ALGORITHMS IN ADVANCED ARTIFICIAL INTELLIGENCE

Edited by
R. N. V. Jagan Mohan, B. H. V. S. Rama Krishnam Raju,
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Algorithms in Advanced Artificial Intelligence

Artificial Intelligence's impact on decision-making is growing, but understanding is limited. Legislation is needed to understand AI's effects and improve human-centric design. Generative Artificial Intelligence (GenAI) uses large database patterns to generate new data instances, while Explainable Artificial Intelligence (XAI) allows human users to understand and trust the results of machine learning algorithms, providing a platform for conference attendees. The ICAAAI-2024 conference will focus on generative adversarial networks (GANs), variational autoencoders (VAEs), and transformers for natural language processing tasks. Large language models (LLMs) are used for language generation, classification, and more. Both fields are crucial for AI advancement, addressing challenges in creative fields and regulated industries. Generative AI is revolutionizing academia and industry 6.0 by enabling machines to participate in creative processes. Explainable AI is essential for trust and accountability, requiring interdisciplinary approaches in mathematical modeling and statistical AI. Techniques like SHAP, LIME, and ALE are used to provide global and local explanations of a model's operating rules. Statistical AI models like linear regression, logistic regression, decision trees, SVMs, Naive Bayes, KNN, and neural networks are used for various tasks. AI models are made simpler with explainable algorithms such as LIME, SHAP, and SBRL, which also improve user experience and cut down on errors. There's been an increase in calls for operational openness as AI becomes more commonplace in daily life. However, poor societal outcomes from AI conclusions can include prejudice against disabled communities and erroneous apprehensions. To follow the guidelines of Information Communication Technology (ICT), which focuses on improving data generation, handling, and exchange methods by infrastructure and tools for Advanced Techniques of ICAAAI-2024.

Algorithms in Advanced Artificial Intelligence is a collection of papers on emerging issues, challenges, and new methods in Artificial Intelligence, Machine Learning, Deep Learning, Cloud Computing, Federated Learning, Internet of Things, and Blockchain technology. The book addresses the growing attention to advanced technologies due to their ability to provide "paranormal solutions" to problems associated with classical Artificial Intelligence frameworks. AI is used in various subfields, including learning, perception, and financial decisions. It uses four strategies: Thinking Humanly, Thinking Rationally, Acting Humanly, and Acting Rationally. The authors address various issues in ICT, including Artificial Intelligence, Machine Learning, Deep Learning, Data Science, Big Data Analytics, Vision, Internet of Things, Security and Privacy aspects in AI, and Blockchain and Digital Twin Integrated Applications in AI.

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113. An Novel Technique for Forecasting of Weather Interactive Predictive Using Hybrid Machine Learning **744**
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1

Emotional People's Views of Oropouche Virus Disease-Cuba while Checking Doctor's Examination: A Hybrid Model Analysis

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Abstract: Unexpected illness symptoms include bewilderment, lightheadedness, disorientation, breathing difficulties, paleness, and perspiration. While we may not know the cause, medical practitioner supports are needed. This study evaluates an undistinguishable analysis of people's lookouts. Emotional well-being can be significantly impacted by health concerns, leading to issues like Oropouche virus disease and other related problems. Oropouche virus disease, caused by the Oropouche virus, has been detected in Santiago de Cuba and Cienfuegos backwaters, indicating a high susceptibility to the disease, with no human-to-human transmission evidence. To enhance patient satisfaction and well-being, it is crucial to identify and address diseases promptly, solve problems efficiently, and personalize services using Fuzzy Classification. Through social media analysis and patient input, this investigation simulates the framework and operations of the brain of an individual using neural network models. The experiment result is to utilize deep learning to analyze people's opinions on healthcare-related tweets and patient feedback, employing a hybrid approach of RNN and LSTM to accurately predict model performance and loss.

Keywords: Deep learning, Fuzzy classification, Long short-term memory, Oropouche virus, Recurrent neural network

1. Introduction

Social media serves as a pivotal medium for human connection, content sharing, and relationship building. With the Oropouche virus disease affecting Cuba, individuals are increasingly turning to platforms such as Facebook, WhatsApp, Twitter, and others to voice their emotions and concerns. This trend provides a unique opportunity to analyze how the disease impacts public sentiment and emotional well-being [1,3].

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Emotions profoundly influence our daily lives, shaping our decisions, actions, and perceptions. Understanding the drivers of these emotions is essential for addressing both the psychological and emotional aspects of health crises. Various theories have been proposed to categorize and explain human emotions. For instance, Paul Ekman, in the 1970s, identified six fundamental emotions that are universally recognized across cultures: happiness, sadness, fear, disgust, anger, and surprise. Robert Plutchik expanded on this by proposing a "wheel of emotions," where basic emotions blend to form more complex ones [4,5].

Happiness, associated with contentment and joy, is linked to overall well-being, while sadness involves feelings of disappointment and grief, which can lead to withdrawal from daily activities. Fear triggers physiological responses that prepare the body for action, and disgust acts as a protective mechanism against harmful stimuli. Anger, if not managed effectively, can result in aggression and negative health outcomes. Surprise, often caused by unexpected events, can leave a lasting impression due to its novelty [6,7].

Sentiment analysis, which assesses the emotional tone of textual content, is increasingly utilized in healthcare to gain insights into patient feedback and monitor public sentiment. This study focuses on sentiment analysis related to the Oropouche virus disease in Cuba. By examining social media posts, we aim to understand the emotional responses of individuals affected by the virus and how these responses influence their overall well-being.

The use of sentiment analysis in healthcare offers significant potential for improving patient care and informing public health strategies.Based on data from social media, the investigation analyses and forecasts emotional reactions using sophisticated neural networks, particularly RNN and LSTM networks. These methods provide a thorough understanding of public opinion, providing insightful information that can improve patient support and medical services. The work delves into the emotional impact of the Oropouche virus in Cuba, emphasizing the importance of sentiment analysis in comprehending healthcare providers' viewpoints.

The seven elements of this paper's response are explained as follows: Section 1's wide introduction. Section 2: Work Proposal. Evaluation of the Clinical Trail Process. In Section 3, the use of fuzzy logic is discussed. The experimental results are shown in Section 4. The conclusion is in Section 5. There are references in Section 6.

2. Projected Method

The study looks at how Cubans feel about the Oropouche virus condition, emphasizing the importance of prompt diagnosis and individualized medical care to increase patient satisfaction. For sentiment analysis in medical contexts, this study uses LSTM networks rather than more conventional RNNs. By preserving long-term dependencies and managing information flow, LSTMs solve gradient vanishing and explosion problems, which makes them perfect for evaluating sequential data like as sentiment in social media posts. In order to improve healthcare services and discover emotional reactions, LSTM networks are utilized to monitor public opinion and patient comments regarding the Oropouche virus. This improves patient treatment and public health responses.

2.1 Clinical Trail Process Examination Using Fuzzy Logic

A mathematical method known as fuzzy logic, is used to describe ambiguity and uncertainty in decision-making when dealing with imprecise or uncertain information. It allows varying truth values from 0 to 1. Artificial intelligence, medical diagnosis, and natural language processing all use it. An assessment of a patient's behaviour that takes into account their appearance, awareness, physical and language function, emotion, perception, hypothetical, attitude, and ability to think is called a mental status examination. Understanding the true nature of mental illness requires a careful and reliable prediction, which calls for tremendous insight, in-depth knowledge, and integrity.

Fuzzy Logic's membership function defines Questionnaire input value membership to a set or category, mapping from 0 to 1, where 1 indicates full membership and 0 indicates not being a member. Fuzzy Logic is a mathematical method for representing uncertainty in decision-making, allowing partial truths, and is implemented using Fuzzy Rules. It uses if-then statements to express relationships between input and output variables, resulting in a fuzzy set. Whereas fuzzy logic has an intermediate value that is partly accurate and partially false, boolean systems use 1.0 and 0.0 to represent true and incorrect values, respectively[11].

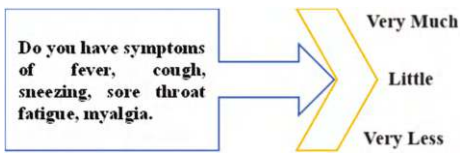

Fig. 1.1 Clinical process examination using fuzzy logic[10]

2.2 Oropouche virus Disease Using Recurrent Neural Networks (RNNs)

Sentiment analysis of the Oropouche virus disease in Cuba is done using RNNs, a kind of deep learning approach.

[2]. An RNN is a kind of neural network that can perform the same action across several inputs because it has internal memory and integrates information from previous computations. This feature makes RNNs suitable for tasks involving sequential data, such as sentiment analysis of social media posts [8,9].

Feedforward neural networks process inputs independently, RNN maintain connections between inputs through their internal state or memory. This enables them to perform tasks such as unsegmented handwriting recognition or speech recognitionby retaining context across sequences of data [10,12].

RNNs are machine learning algorithms that can efficiently process input sequences by utilizing their internal state or memory. These methods can be applied to problems such as speech detection or unsegmented, connected identification of handwriting.None of the inputs in additional neural networks are related to one another. However, in an RNN, every input is connected to every other input[13].

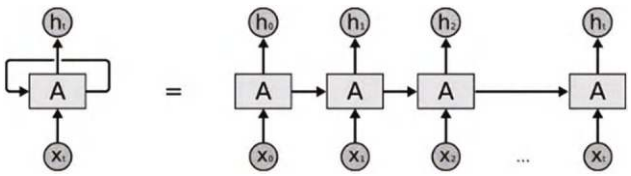

Fig. 1.2 An unfurled RNN[1]

After first collecting X(0) from the input sequence, it produces h(0), which is then combined with X(1) as the input for the next phase. Therefore, the input for the next step is h(0) and X(1). The input for the subsequent phase is similarly provided by X(2) with h(1) from the previous stage, and so forth. It maintains its context memory throughout training in this manner. The formula for the present state is

$$h_t = f(h_{t-1}, X_t) - 1$$

A description of the activation function's use:

$$h_t = \tan h(W_{hh}\, h_{t-1} + W_{xh} X_t) - 2$$

The activation function, Tanh, applies a non-linearity that squashes the activations to the range where h is the only hidden vector and W is the weight, the weight at the moment's input state is W_{hx}, while the weight in the before state of concealment is W_{hh}[–1.1].

$$Y_t = W_{hy}\, h_t - 3$$

The output state, denoted by $\mathbf{Y}_t$, is a crucial factor in determining the overall output state. Assuming that each sample is reliant on the one before it, the models use RNN data sequences. Because activation functions are unable to handle lengthy sequences, convolutional layers are utilized to expand the effective pixel neighbourhoods, or relu, which makes RNN training challenging.

2.3 Oropouche virus Disease Using LSTM

A sophisticated artificial intelligence technique for sentiment analysis of public opinions about the Oropouche virus disease in Cuba is offered by LSTM networks. Among the shortcomings of traditional RNN that LSTM are designed to solve are the disappearing and ballooning gradient problems, which can hinder the learning process. LSTM, an advancement over RNN, boosts the network's ability to retain previously taught information. This is particularly useful for forecasting, classifying, and analyzing time series data with different time delays. Examining sequential data, like social media posts on the Oropouche virus, requires the LSTM architecture's improved capacity to manage long-term dependencies [14]. Three essential parts, or gates, are incorporated into the LSTM network to regulate the information flow:

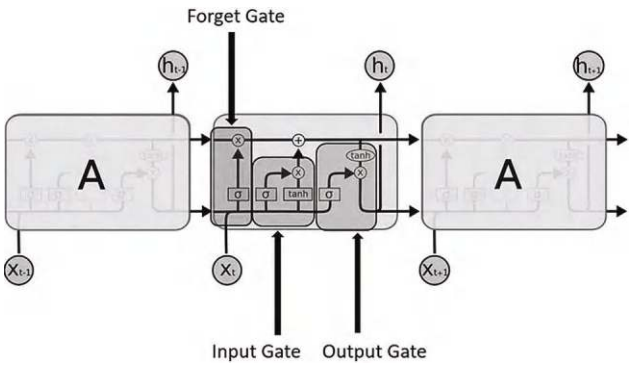

Fig. 1.3 LSTM gates[11]

Gate of Input: Choose the appropriate input value to use with the input gate to modify the memory. The values that are permitted to pass (0,1) are chosen by the sigmoid function. and the supplied values are given a weight by the tanh function, which rates their importance on a range from -1 to 1.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

Forget Gate: Use the Forget Gate to determine which details need to be erased from the block. That decision is made by the sigmoid function. It looks at the content input (X_t) and the preceding state ($h_t - 1$) for each number in the cell state $C_t - 1$, producing a number between 0 (omit this) and 1 (keep this).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Gate of the Output: The block's intake and storage are used to determine the result. The tanh function increases

the result of the Sigmoid function by the weight it gives the values that pass, assessing their significance on a scale from -1 to 1. The values to pass via 0, 1 are determined by the Sigmoid function.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

3. METHODOLOGY

The framework provides a detailed test procedure for Oropouche virus disease and sentiment analysis using deep learning models.

3.1 Clinical Testing for Oropouche Virus Disease

The objective is to identify and confirm cases of Oropouche virus disease.

Sample Collection

Patient selection involves identifying patients with Oropouche virus symptoms, collecting blood, CSF, or other biological samples, and following standard clinical protocols to avoid contamination and ensure accuracy.

Diagnostic Testing

The RT-PCR method extracts RNA from samples, converts it to cDNA, and amplifies specific Oropouche virus regions. Real-time PCR quantifies viral load, while serology tests detect antibodies against the virus, interpreting results based on standard markers.

Data Recording and Analysis

The process involves systematic recording of test results and a thorough review of these results within the clinical context to ensure accurate diagnosis.

3.2 Sentiment Analysis Using Deep Learning Models

The use of deep learning models for sentiment analysis.

Objective: The study aims to assess public perception of Oropouche virus disease through a comprehensive analysis of social media and patient feedback.

Data Collection

The study uses social media and healthcare reviews to identify sources of Oropouche virus disease symptoms, ensuring data privacy, anonymization, and necessary permissions.

Data Pre-Processing

The text undergoes cleaning, tokenization, stop word removal, and stemming/lemmatization to improve sentiment analysis by removing irrelevant content, splitting text into individual words, and reducing common words.

Model Training

The process involves data preparation, feature representation, model selection using Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, and training using sequence data with a loss function, focusing on long-term dependencies.

Model Evaluation

The model's performance is assessed using metrics such as accuracy, precision, recall, F1-score, and loss, while the confusion matrix analyses classification errors.

Result Interpretation

The study analyses social media posts and patient feedback, assesses public emotional response to Oropouche virus disease, and uses graphs and charts for visualization.

Report and Recommendations

The report provides insights into public sentiment and emotional well-being related to the Oropouche virus disease, suggesting targeted healthcare interventions to address specific concerns and improve public health responses.

3.3 Follow-Up

While feedback refining entails regularly upgrading the sentiment analysis model in light of fresh data and input, feedback collecting entails obtaining input on the efficacy of the intervention.

In order to address both the physical and emotional elements of Oropouche virus sickness, this test procedure integrates sophisticated sentiment analysis algorithms with clinical diagnostic procedures. You can obtain thorough insights into the disease's influence on public opinion and develop efficient healthcare plans by methodically gathering and evaluating data.

4. EXPERIMENTAL RESULT

In the experimental phase, a dataset consisting of 1001 samples was used, with 40% allocated to the test set. A deep learning approach was employed to analyze public opinions on the Oropouche virus disease in Cuba, utilizing social media data.The model demonstrated high effectiveness in classifying tweets related to the Oropouche virus, achieving notable accuracy. The application of a hybrid deep learning technique, combining RNN and LSTM network, facilitated accurate sentiment classification. This hybrid approach proves beneficial for healthcare professionals and representatives in managing public sentiment and

improving response strategies. The accuracy and loss metrics of the model were evaluated, with results presented in the graph below. These metrics illustrate the model's performance in classifying and predicting sentiments related to the Oropouche virus disease. Additionally, a study of patient feedback highlighted that oral health problems were commonly reported in areas such as Peda Malam, China Malam Palem, and Bhimavaram Mandalam. These findings underscore the impact of the Oropouche virus on public health, particularly in relation to oral health issues, and emphasize the importance of targeted healthcare interventions.

Do you have symptoms of fever, cough, sneezing, score throat fatigue, myalgia.

Do you have difficulty in breathing?

Have you travelled outside the country in past 30days?

Have you travelled inside India to other cities in past 15 days?

Exposure to a confirmed Oropouche virus disease – Cubaor to Suspicious patient in the last two weeks?

Have you visited a health care facility in the past two weeks?

Figure 1.4's model accuracy is shown by the y-axis, which shows accuracy, and the x-axis, which shows the data used for testing and training set epochs. The lines in blue and orange grow from 0.45 accuracy to 0.70%. In addition to that Model Loss is also observed in the Fig. 1.4. The model loss estimates on training samples and validation dataset using RNN and LSTM. In the model loss of Fig. 1.4 is to observe the y-axis starting 0.0 to -15.0 decreases the value of lines either test and train sets. The accuracy is 62% of patients suffering dental problems and remaining 38% peoples not suffering the dental problems in the survey villages of Peda Malam, China Malam Palem of Bhimavaram Mandalam.

Table 1.1 Sample dataset questionnaires of patient with doctor observations

```
29/29 [==============================] - 5s
37ms/step - loss: 0.6214 - accuracy: 0.5033 - val_loss:
0.5272 - val_accuracy: 0.4600
Epoch 2/10
29/29 [==============================] - 0s
6ms/step - loss: 0.2983 - accuracy: 0.5100 - val_loss:
0.0829 - val_accuracy: 0.4900
Epoch 3/10
29/29 [==============================] - 0s
7ms/step - loss: -0.4072 - accuracy: 0.4989 - val_loss:
-0.7254 - val_accuracy: 0.4600
Epoch 4/10
29/29 [==============================] - 0s
6ms/step - loss: -1.7917 - accuracy: 0.4644 - val_loss:
-2.4059 - val_accuracy: 0.4500
Epoch 5/10
29/29 [==============================] - 0s
6ms/step - loss: -4.2976 - accuracy: 0.4578 - val_loss:
-4.9795 - val_accuracy: 0.4500
Epoch 6/10
29/29 [==============================] - 0s
7ms/step - loss: -7.4509 - accuracy: 0.4700 - val_loss:
-7.8738 - val_accuracy: 0.6000
Epoch 7/10
29/29 [==============================] - 0s
7ms/step - loss: -10.4705 - accuracy: 0.6044 -
val_loss: -10.1842 - val_accuracy: 0.6900
Epoch 8/10
29/29 [==============================] - 0s
6ms/step - loss: -12.8674 - accuracy: 0.6122 -
val_loss: -11.9734 - val_accuracy: 0.6200
Epoch 9/10
29/29 [==============================] - 0s
7ms/step - loss: -14.6611 - accuracy: 0.5733 -
val_loss: -13.4169 - val_accuracy: 0.6200
Epoch 10/10
29/29 [==============================] - 0s
6ms/step - loss: -16.1650 - accuracy: 0.5733 -
val_loss: -14.6863 - val_accuracy: 0.6200
4/4 [==============================] - 0s
3ms/step - loss: -14.6863 - accuracy: 0.6200
```

Test score: -14.686322212219238
Test accuracy: 0.6200000047683716.
Source: Authors

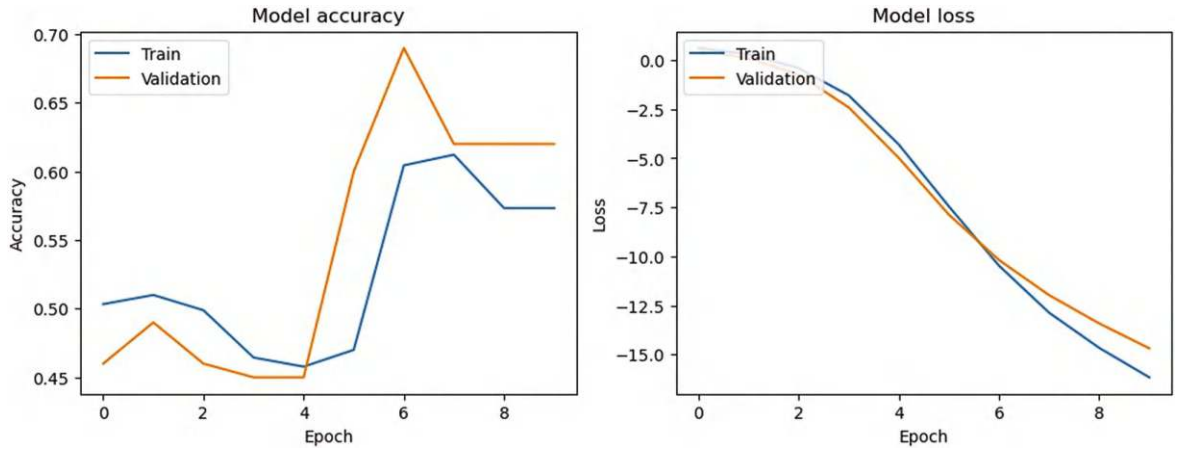

Fig. 1.4 Exploring the model accuracy and model loss of train and validation data set[2]

The model is in selecting epoch tests according to the RNN with LSTM machine learning operational distribution. The machine learning software reliability is estimated by

$$\widetilde{R}(1) = 1 - \frac{n_f}{n} = \frac{8}{10} = 0.8$$

Where n = total number of epochs runs, n_f = number of failed runs out of these n runs.

The size of the errors or the probability of inputs in uncovering these errors, remaining in the machine learning methods, $M(E_r) = 1 - \widetilde{R}(1) = 1 - 0.8 = 0.2$.

The estimate of $M(E_r)$ is given by $M(E_r) = \frac{n_f}{n} = 0.8$.

5. Conclusion

This article assessed the effectiveness of a hybrid deep learning model in analyzing patient opinions regarding periodontal diseases, specifically in the context of the Oropouche virus disease. The study highlights that the Oropouche virus has led to an increase in psychological disorders and oral health issues. Healthcare organizations are using LSTM networks instead of traditional ANN for sentiment analysis due to their improved performance in handling sequential data and long-term dependencies. Oral health issues remain a common complaint among Oropouche virus patients, emphasizing the need for targeted healthcare interventions.

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Leveraging Backpropagation to Forecast Dengue Fever Based on Weather Conditions

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Abstract: Artificial Intelligence (AI) in healthcare enhances patient care, reduces labor costs, simplifies procedures, automates administrative tasks, and customizes treatment options through Machine Learning (ML), Natural Language Processing (NLP), and Deep Learning (DL). This paper will study describes a machine learning method for forecasting dengue cases, a problem for worldwide health. The dengue fever is on comprehensive of weather and environmental parameters, including temperature, humidity, and precipitation. To compare various approaches and implement to accurate predict dengue case, enhancing preventive measure and save lives on the environment is a main challenge. The proposed paper is to estimate parameters like high fever, severe headache, and muscle pain that rely on weather conditions like temperature, humidity, and precipitation to significantly predict dengue fever in people, highlighting the potential of the backpropagation method in machine learning in real-world health challenges. In order to accurately predict the weather conditions of dengue cases data collected from West Godavari District from June to July 2024, the experimental study will compare different machine learning models, which include linear regression (LR), decision tree regression (DTR), random forest regression (RFR), support vector regression (SVR), and XG boost regression (XGBR). Dengue fever will be analyzed using the backpropagation method.

Keywords: Artificial intelligence, Backpropagation, Dengue, Machine learning, Weather condition

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1. Introduction

The development of ML and AI is causing changes in our surroundings, paving the way for the Fourth Industrial Revolution, despite human fears [1]. AI is expected to change the workforce, creating 133 million more engaging and less repetitive roles. AI-powered language tools are bridging social and cultural divides in workplaces and classrooms [2]. AI can transform government by reducing paperwork and improving efficiency. It can also make healthcare more accessible and affordable, with apps like Babylon Health providing accurate, safe, and convenient advice to millions of residents. Additionally, computational creativity is transforming art, with software becoming a creative collaborator, merging computer scientists with artists. However, governments must be prepared to navigate the risks and opportunities of AI. AI aims to create machines capable of perceiving, analyzing, making decisions, communicating, and learning.

Machine learning (ML) is the most advanced approach, utilizing neural networks to recognize statistical patterns and solve complex tasks. AI has achieved impressive milestones, such as computer vision systems identifying objects better than humans, autonomous cars driving millions of kilometres with few accidents, and AI predicting protein structures. However, deep learning-based AI faces challenges such as bias, inefficiency, and large data requirements. Despite these challenges, AI researchers believe continued scaling could resolve these challenges and prepare society for its disruptive effects. AI in healthcare streamlines tasks, automates administrative tasks, and personalizes treatment options, reducing human labor costs and improving patient care.AI in healthcare uses machine learning, natural language processing, and deep learning to improve healthcare experiences. It enhances resource management, enables quicker diagnoses, faster electronic health record retrieval, and provides personalized treatments for patients [3,4].

AI uses neural networks to process data, mimicking the human brain's functions. Backpropagation is a crucial algorithm in neural networks. Backpropagation is an algorithm used in artificial intelligence and machine learning to train neural networks through error correction. It works backward from output nodes to input nodes to reduce the loss function. Neural networks are used in AI and machine learning, with demand increasing by 40% and 23% by 2032. Understanding backpropagation is crucial for career advancement in these fields. Backpropagation in neural networks reduces errors and improves machine responses by analyzing them, comparing them to the anticipated response, and re- running the model until the desired outcome is achieved. This process mimics the human brain's learning process through trial and error [5]. An example of backpropagation is in an autocorrect feature that uses deep learning to learn misspellings, such as "broccoli" on a smartphone. After a series of forward and backpropagations, the machine can correctly interpret the misspelling and correct the error. Backpropagation is a technique used in neural networks for identifying patterns and making predictions. It can be static or recurrent. Static backpropagation is used in feedforward neural networks, like email spam detectors and optical character recognition software. Recurrent backpropagation, on the other hand, uses data sequences as a feedback loop, enabling future learning.

The AI model correctly detects diseases and tumors in medical photos, giving physicians a map to follow, confirm accuracy, and share findings with patients [7.8]. Enhances the prediction of dengue fever by offering a novel method for modeling and predicting dengue cases. Mokhalad A. Majeed et al, 2023[6] has suggested that the SSA-LSTM model with spatial attention outperforms other LSTM models for dengue prediction, demonstrating the effectiveness of attention mechanisms and stacked layers.

AI research explores protein-based anti- dengue medicines, analyzing immune repertoires, potentially influencing vaccine design and discovering novel antibody treatments. Fever is a higher-than- normal body temperature, often indicating abnormal processes. Diagnosis is done using digital thermometers, with rectal temperature being most accurate for children under 3. Dengue fever is a viral infection spread by mosquitoes, primarily in tropical and subtropical climates. High temperature, headache, bodily aches, nausea, and rash are some of the indications. The virus replicates in the mosquito midgut and disseminates to secondary tissues. AI's potential in drug repurposing, precision treatment, health management, and personalized services is vast, but numerous challenges must be addressed for full realization. Half of the world's population suffers from dengue, a viral sickness brought on by the dengue virus. It occurs in tropical and sub-tropical climates, mainly in urban areas. Prevention relies on vector control, with early detection and proper medical care reducing fatality rates. This paper presents the contributions of various individuals and organizations to the field of research.

- The frequency of dengue cases is significantly predicted by weather variables like temperature, humidity, and precipitation.
- Health officials can effectively plan and deploy resources to contain epidemics by having precise forecasts of dengue cases.

The following is an explanation of the seven sections of this paper's response: The general introduction in section 1. In

Section 2, Use Fuzzy Classification to Estimate Dengue Fever. Dengue Data Analysis using Backpropagation is covered in Section 3. Section 4 presents the experimental results. Section 5 includes the conclusion. Section 6 contains references.

2. Develop a Fuzzy Nomenclature for Dengue Fever Estimate

Any input dengue fever pattern $v \in V$ may or may not be a member of the designated class in two- state analysers, where a class D_c is described as a portion of the universal set V. This characteristic determines whether a pattern v in the universal set is a member of the class D_c has an attribute or function that defines it $\mu_{D_c} = V \to \{0,1\}$ as follows:

$$\mu_{D_c}(x) = \begin{cases} 1 \text{ if and only if } v \in D_c. \\ 0 \text{ if and only if } v \notin D. \end{cases}$$

The lines separating the classes may overlap in real-life circumstances. From this point on, it is unclear if a method of input is entirely part of the class D_c. The idea

of the characteristic function has been changed to the fuzzy inclusion function in fuzzy collections to account for such circumstances.

$$\mu_{D_c} = V \to \{0,1\}.$$

It classifies mosquitoes like Dengue illness using discrete-valued factors, aiming to identify fevers in rural areas through surveys, inform municipal authorities, and address potential issues through binary classification issues. The classification problem assigns fevers to positive or negative classes, with negative classes indicating absence and positive classes indicating presence.

3. Dengue Data Analysis using Backpropagation

This explores the concept of backpropagation for classification, a fundamental principle in machine learning models, its operation, and its significant role in dengue data analysis [9,10]. A neural network is a structure with computing units (neurons) connected via edges, assigned an activation function, and adjustable parameters [11,12]. The activation value determines the function to be computed, with higher values indicating greater activation.

Backpropagation is a crucial machine learning method for training artificial neural networks, particularly feed-back neural networks. In order to optimize the cost function, the weights and prejudices in dengue data are found via the backpropagation procedure. By adjusting the weights and biases at each epoch, the model learns to minimize the loss by approaching the error gradient. Gradient descent and stochastic gradient descent, two of the most popular optimization strategies, are therefore discussed. By navigating through the intricate layers of the neural network using the calculus chain rule, the gradient calculation in the backpropagation process can assist reduce the cost function [13,14,15].

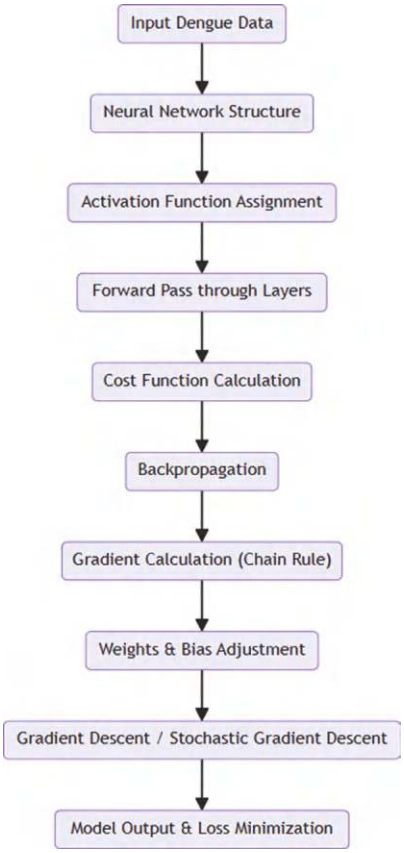

Fig. 2.1 Dengue data classification using backpropagation

4. Experiment Result

Backpropagation is a method that calculates the loss function's gradient based on each neuron's weight and bias, and updates it to minimize loss. The test aims to identify dengue by assessing three symptoms: high fever(x_1), severe headache(x_2), and muscle pains (x_3), **with a result of 1 (dengue) or 0 (no dengue).**

Condition of Process: A person with dengue high fever, minor headache, and muscle pain can be trained a neural network based on their patient trials data.

Step-1 involves evaluating three inputs: high fever (x_1 = 0.9), severe headache (x_2 = 0.8), and muscle pains (x_3 = 1) to determine the severity of the symptoms.

Step-2 involves transitioning from the input layer to the hidden layer.

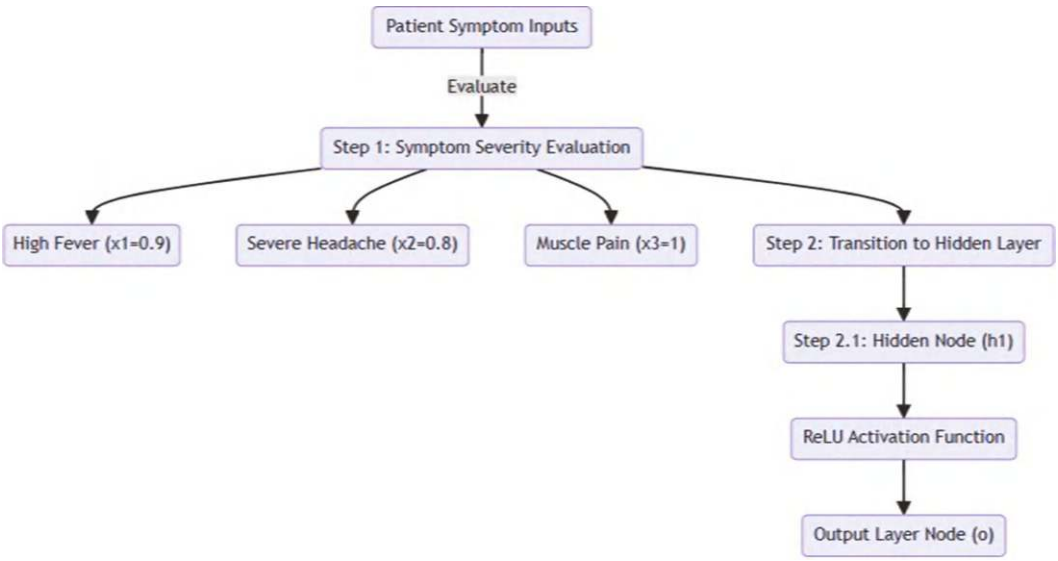

Fig. 2.2 Input layer and hidden layer

Step-2.1 involves the first hidden node (h_1) sums all inputs with assigned weights and performs a mathematical operation (ReLU) on the values, then transmits the output to the output layer node (o).

The hidden node h_1 connects each input to every hidden node with assigned weights.

Weights: w_{11} = .5, w_{12} = .2, w_{13} = .8 Bias: b_1 = –0.1

Calculation:

$$h_1 = \text{ReLU}\,(x_1 \times w_{11} + x_2 \times w_{12} + x_3 \times w_{13} + b_1)$$

$$h_1 = \text{ReLU}\,(.9 \times .5 + .8 \times .2 + 1 \times .8 - .1)$$

$$h_1 = \text{ReLU}\,(1.31)\ h_1 = 1.31$$

The output was obtained from the first hidden node. In step 2.1, inputs with assigned weights are combined by the second hidden node (h_2), which performs a mathematical operation (ReLU) and transmits the output-to-output layer node "o".

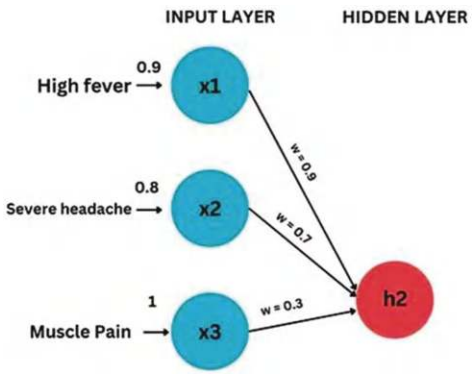

Fig. 2.3 Input and hidden layer process

Hidden Node h2:

Weights: w21 = 0.9, w22 = 0.7, w23 = 0.3

Bias: b2=0.2

Calculation:h2 = ReLU (x1 × w21 + x2 × w22 + x3 × w23 + b2)

h2 = ReLU (0.9 × 0.9 + 0.8 × 0.7 + 1 × 0.3 +0.2) X h2 = ReLU (1.87)

h2 = 1.87

The step-3 involves transitioning from a hidden layer to an output layer.

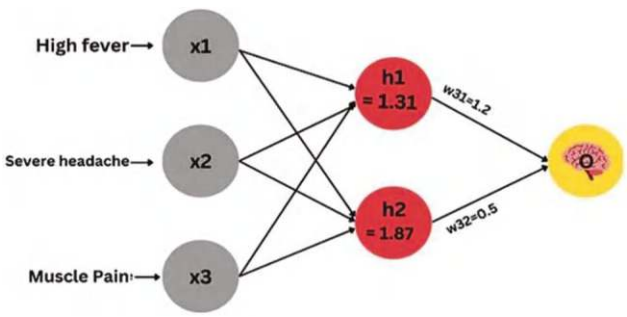

Fig. 2.4 Output layer process

The output node receives the inputs from the hidden nodes, each with its own weights. It then adds up the outputs, applies a sigmoid mathematical operation on the value, and determines whether to output 0 or 1.

Output Node:

Weights: w31=1.2, w32=0.5 Bias: b3=–0.3

The activation function is a crucial aspect of any system or process that requires energy to function properly.

Activation Function: Sigmoid i.e., $\frac{1}{(1+\hat{e}-x)}$

Calculation (output node) = sigmoid (h1×w31 + h2×w32 + b3)

$$o=\text{sigmoid}\ (1.31 \times 1.2 + 1.87 \times 0.5 - 0.3)$$

$$o = \text{sigmoid}\ (2.207) = 0.90$$

The network predicts that the person has dengue due to the output 0.743 exceeding 0.5.

The neural network correctly predicted 0.90, but a prediction close to 1 (e.g., 0.99) would have been more robust and effective on new hypothesis data.

The statement is expressing our loss

$$= \frac{1}{2}\ (\text{Predicted} - \text{Actual})$$

$$= \frac{1}{2}\ (0.9 - 1)^2 = 0.005.$$

Backpropagation is used to adjust weights and biases to reduce loss and improve network accuracy.

5. Comparative Analysis

Dengue is a viral infection primarily spread by mosquitoes, causing high fever, headache, body aches, nausea, and rash in most cases. Dengue, a global viral infection primarily affecting urban populations, is primarily caused by infected mosquitoes, and early detection and proper medical care are crucial for prevention. We study tested and compared various machine learning models for specific fever out of all actual cases, such as Dengue or No.

Case 1: The individual is suspected to have dengue, and the prediction is that they have dengue (TP).

Case 2: The individual is predicted to not have dengue (TN).

Case 3: The individual is not confirmed to have dengue, but it is predicted that they may have a mild form of dengue (FP) that won't cause any issues.

Case 4: The individual is suspected to have dengue, but the prediction is that they do not have dengue, which could lead to issues (FN).

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{900}{900 + 40} = 41$$

accurately predicting based on weather conditions of dengue cases in West Godavari District from June-July 2024 data shown in Table 2.1.

Table 2.1 Error rate of dengue cases

Regression Methods	MSE	R-Square Score
Linear Regression	0.66	0.26
Decision Tree	1.18	0.11
Random Forest	0.53	0.11
Support Vector	0.53	0.11
XGBoost	0.64	0.11

Recall: The proportion of true positive predictions among all real positive occurrences in a dataset is known as recall**.** We must therefore now decrease FN. So, in this case, recall is necessary. What proportion of the actual outcomes closely reflect the forecasts? Remember that we want to increase TP and decrease FN.

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{900}{900 + 60} = 61$$

Accuracy: The percentage of all forecasts made by the early version that were accurate, including true positives and true negatives.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} = 1000$$

6. Conclusion

The x-axis in Fig. 2.6 above represents the several regression techniques, including LR, DT, RF, SV, and XGBoost and y-axis denotes the estimated values of mean square error rate.

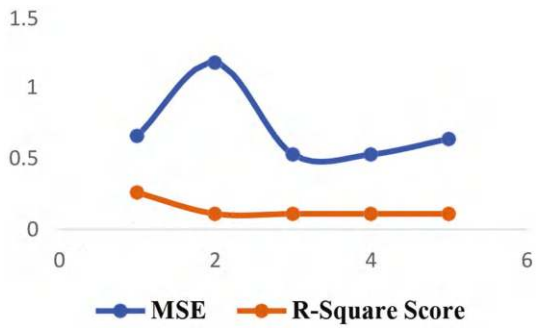

Fig. 2.5 Dengue case of error rate prediction

Performance measurements like precision, recall, accuracy, and F-beta score are crucial for evaluating machine learning models' efficacy and precision, requiring accurate measurements alongside an imbalanced dataset. Our model's efficiency would be 90% if we instructed it to consistently predict Dengue out of 1000 entries in our dataset, of which 900 belong to Positive Cases of Dengue Fever and 100 to Not Positive of Dengue Fever Cases.

Precision: Precision refers to the percentage of accurate positive predictions within a model's positive predictions. Recall in medical diagnosis refers to the percentage of correctly identified patients with a Dengue fever is a viral infection spread by mosquitoes, primarily in tropical and subtropical climates. High temperature, headache, bodily aches, nausea, and rash are some of the complaints. Dengue, a global viral infection primarily affecting urban populations, is primarily caused by infected mosquitoes, and early detection and proper medical care are crucial for prevention. Backpropagation is a method that calculates the loss function's gradient based on each neuron's weight and bias, and updates it to minimize loss. The test aims to identify dengue by assessing three symptoms: high fever(x1), severe headache(x2), and muscle pains(x3), with a result of 1 (dengue) or 0 (no dengue). In addition, tested and compared various machine learning models for accurately predicting based on weather conditions of dengue cases in West Godavari District from June-July 2024 data. Future research should explore transfer learning, expert knowledge, attention mechanisms, time scale evaluation, and model distillation techniques to improve dengue prediction performance across different regions.

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3

Artificial Intelligence Techniques for the Early Diagnosis of Cardiovascular Disease Among Diabetes Patient: A Review

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Abstract: Globally, cardiovascular disease (CVD) is the most prevalent cause of morbidity and mortality. Consequently, the efficient treatment and prevention of complications are contingent upon their early and precise detection. This is crucial because patients with diabetes are at a significantly increased risk of developing cardiovascular disease (CVD). It is likely that the deep learning and machine learning techniques in AI will be beneficial in the early detection of cardiovascular disease (CVD) in patients in this category, as evidenced by recent research. The assessment of the accuracy and efficiency of AI techniques and tools designed to diagnose cardiovascular malfunctions in diabetic patients, in conjunction with other scientific methodologies, will be a focus. We anticipate that the clinical application of these AI solutions will expand the scope of conventional screening procedures and expedite the implementation of treatment strategies, thereby improving the health of high-risk patients.

Keywords: Artificial intelligence, Early diagnosis, Cardiovascular disease, Diabetes, Machine learning techniques

1. Introduction

It is now understood that cardiovascular disease (CVD), in all its manifestations, remains a major contributor to the world's population health and is recognized as one of the health care problems among many other patients, especially those with diabetes. A report recently released by the World Health Organization (WHO) outlined that CVD has accounted for 38% of all deaths, from more than 17 million medical conditions, below the age of 70 World Health Organization (2020). While the risk factors of most cardiovascular diseases remain elusive, risk factors are salient to diabetic patients, increasing their risk of developing an ailment of the heart. Such common risk factors, especially pertinent to the management of diabetes mellitus and which can be considered as potential for the development of CVD among patients, include smoking activity, hypertension, obesity, hypercholesterolemia, family history, and older age.

Effective assessment and management of diabetes patients to avoid deterioration of the patient's condition relies on early detection and appropriate treatment of heart diseases

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American Diabetes Association (2018). Apart from the apparent utility of researched AI applications like machine learning and deep learning, there is rapidly growing interest in the application of such technologies in identifying and diagnosing heart diseases in diabetic patients. Places where AI is thought to be most useful include the prediction of health events, which is done with impressively high accuracy and sensitivity and is effective in spotting early warning signs of CVD and offering interventions for high-risk individuals in good time. Several research works had been carried out to determine the effectiveness of these artificially intelligent strategies in the identification of CVD in people living with diabetes. For evaluation purposes, data on these methods have been employed on different datasets, which have shown that the use of AI technologies helps in improving better diagnosis of CVD among the high-risk populations. Intense. Here, this paper is mostly based on the effect of differential ownership holdings.

The alarming rate of heart disease calls for advanced cardiovascular disease risk stratification measures. Given the relative importance of the several diagnostic measures in the diagnosis of CVD and CVD-related conditions, their use in the clinic may be restricted by the need for interpretation by a clinician McClellan et al. (2019). To solve this problem, machine learning approaches are being developed to raise the level of diagnosis. The addition of AI improves the trueness of diagnosis, enables timely treatment of patients, and therefore enhances their overall effectiveness and promotes more widespread use of the technology in normal clinical practice.

The review is divided into different sections, with each addressing specific issues. The first section describes some of the contemporary AI methods concentrating on the ML and DL. The second part includes a survey of the most relevant works around the topic of this research. The third section discusses how this evidence can be translated into practice. Ultimately, the conclusion stresses that AI methods can help to prevent and treat cardiovascular disease in diabetic patients earlier than it is usually possible; therefore, their more active implementation in clinical practice would be advisable to ensure better health outcomes.

2. AI Techniques for the Early Diagnosis

2.1 Modern AI Techniques in Detecting Cardiovascular

Artificial intelligence has created a new position for the health sector with advanced possibilities to accurately diagnose and predict certain diseases. Artificial intelligence has proven itself as an integral instrument that is being used to diagnose diseases in their early stages, find risks, and, thereafter, help doctors make decisions about starting a treatment early Basu et al., (2020).

2.2 Role of Machine Learning in Cardiovascular Detection

Machine learning has managed to influence a lot in regard to cardiovascular disease detection, which means that there is efficiency in diagnosing and predicting cardiac and vascular diseases. Instead of programming a machine with a preexisting set of rules, machine learning applies a class of algorithms to data that can be improved upon as an experience. It can be divided into three major classifications: supervised learning, which seeks to instruct models about which causal relationships exist between the input and the supplied output with some provided annotations; unsupervised learning, which strives to extract the structure of the data with no fruitless attempts at making any claims of hypotheses; and reinforcement learning, where algorithms learn by doing in interaction with their environment. The use of these techniques helps in improving the detection and control of cardiovascular diseases, in turn improving the outcomes of the patients Choy et al. (2018).

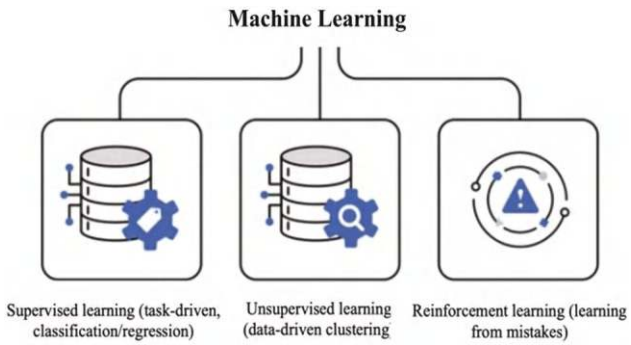

Fig. 3.1 Types of machine learning

2.3 Role of Deep Learning in Cardiovascular Detection

Deep learning is now considered one of the branches of machine learning; it can be used in molecular phenotyping, image analysis, and diagnostics. This advanced computational technique utilizes neural networks with multiple layers to model complex patterns in large datasets. By automatically extracting features from raw data, deep learning eliminates the need for manual feature engineering, making it particularly effective in fields requiring nuanced analysis. There is especially high interest in cardiology in implementing this method, as it can classify and characterize data based on quantitative and semantic

criteria, structure decision-making, and provide optimal classifications for diagnosing cardiovascular disturbances. For instance, deep learning algorithms can analyze medical images to detect anomalies, assess risk factors, and predict outcomes based on patient data. Therefore, deep learning is key to cardiology's progressive development and has a profound impact on the advancement of personalized medicine and the utilization of diverse data forms. Its ability to integrate various types of data—such as imaging, genetic, and clinical data—further enhances its potential to improve patient care and outcomes Krittanawong et al. (2019).

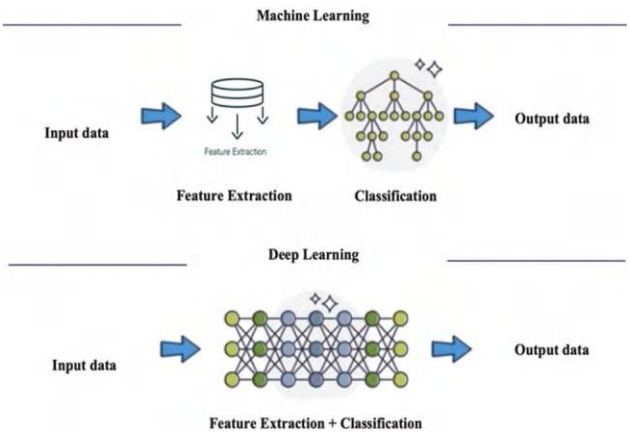

Fig. 3.2 Machine learning vs deep learning

3. Literature Review

Patients with diabetes are at a considerably increased risk of developing cardiovascular disease (CVD); therefore, it is important for them to be screened for this condition. This requires proper blood glucose control along with identification and monitoring of CVD risk markers. If detected early enough, interventions can be started in good time, thus avoiding serious consequences on health as well as enhancing overall health.

In the study by Kulkarni et al., integrating machine learning with data from electrocardiograms (ECG) opens the door to a wide range of opportunities for the early diagnosis of diabetes and prediabetes. Among 1,262 individuals residing in Nagpur, India's high-risk territories, research using the XGBoost model for diabetes classification achieved a remarkable accuracy of 97%. So this is an important study because it portrays how easily affordable and efficient ECG could be used for screening, making it a good alternative to invasive procedures. Also, the DiaBeats algorithm had been found useful in identifying risky individuals. However, there is still need for further tests on efficacy before these screening tools can gain wide acceptance in clinical practice for all populations Kulkarni et al., (2023). The following study by garcia et al. employed the technique of pulse wave velocity (PWV) together with different machine learning approaches like LASSO regression to forecast cardiovascular outcomes among high-risk groups of patients who are obese, hypertensive, and hyperglycemic. The results indicated that arterial stiffness determined by PWV is an independent prognostic factor forecasting contrived major adverse cardiovascular events. This brings out the promising aspect of PWV as a non-invasive gadget with efficient potential use within early diagnosis of cardiovascular disorders, primarily among those having no prior history of such diseases Garcia-Carretero et al. (2020). Dinh et al. applied their robust methodology using several machine learning techniques thereby contributing vital knowledge on how diabetes and cardiovascular diseases can be predicted which will eventually lead to significant health care practices. An evaluation on the applicability of supervised machine learning algorithms in identifying individuals with higher chances of being diagnosed with both diabetes and a cardiovascular disease based on laboratory tests results and survey responses would be done. The team, whose training was based on the NHANES data, used logistic regression, support vector machines, random forest, and the gradient boosting method. As a result of the research, XGBoost boosted performance in cases of no lab data with an AU-ROC score of 83.1% and cases of lab data with an AU-ROC score of 83.9%, respectively. It states that ML technology can even produce an instant life-saving diagnosis for the demographic that is prone to diabetes and heart-related diseases Dinh et al. (2019). Subsequently, Mayya and Solieman (2022) did a further investigation by developing a framework based on machine learning to forecast cardiovascular diseases among diabetics using the NHANES database. Thus, the quality of the set was enhanced, and algorithms from Random Forest Classifier and XGBoost were used to obtain an optimal result of 93.1% based solely on laboratory data and 88% by adopting both physical and laboratory data. This study highlighted the importance of balancing datasets and identified important predictors for CVD in diabetic patients, such as eosinophil count and GGT, among others. Unlike previous studies, this research demonstrated a remarkable improvement in predictive performance made possible by thorough data preprocessing and extensive model tuning to point out the potential of these models to enhance early diagnosis and reduce related diagnostic costs. Rejath Jose and his colleagues conducted research to demonstrate how they can forecast the future reading of hospital admissions and the degree of diabetes using the PyCaret library. It identifies a subset of patients who are vulnerable to problems and enables highly precise machine learning techniques. where this study adopts

the Light Gradient Boosting Machine classifier and other advanced modelling techniques to improve the level of interpretation among other features where necessary. This research examines the usefulness of machine learning in the prediction of diabetes regarding outcomes and readmission rates and establishes influential parameters such as accuracy, precision, recall, and area under the curve of ROC. It assesses the reliability of the machine learning models and spots the factors predictive of diabetes and readmissions Jose et al. (2024). The relationship between early-stage diabetes symptoms and cardiovascular disease is investigated by Julian Borges using logistic regression and Random Forest models. In developing the severity score as a quantification of the burden of diabetes symptoms, it has been an important predictor in the models. The dataset is split into an 80%-20% training and test split. Logistic regression yielded a moderate predictive accuracy of 76.3% with an AUC of 0.78, but the Random Forest handled the complex interactions better. The McNemar test confirmed significant differences in model performance. This result shows that machine learning models have great potential to predict heart failure among diabetic patients and that further research needs to be done with a larger dataset for the confirmation of these results Borges, (2024). The objective of the study by Haiyun Chu et al. was to innovate a cardiovascular disease (CVD) risk prediction model for clients from China who have type 2 diabetes mellitus (T2DM), which takes into account both biological and psychological factors usually neglected by existing models. The model relied on dependable information from hospitals and determined key clinical parameters, including HbA1c, BMI, blood pressure, cholesterol levels, anxiety, and depression. The prediction model established with deep neural networks (DNN) attained an accuracy level of 87.50%, where anxiety and depression were identified as significant indicators of CVD risk alongside BMI, total cholesterol, and systolic blood pressure. This investigation emphasizes the importance of comprehensive treatment strategies that consider both physical and mental health in managing T2DM with a view to preventing cardiovascular complications Chu et al. (2021). According to Saraswat et al., machine learning algorithms have potential applications in predicting cardiovascular diseases in diabetic patients. This paper proposes an IFANN (Improved Fuzzy Logic

Table 3.1 Artificial intelligence in cardiovascular disease detection in diabetic patients

References	Datasets used	Model used	Outcomes
Kulkarni et al. (2023)	1,262 individuals and 10,461 heart beats from the diabetes in Sindhi Families in Nagpur	Extreme Gradient Boosting (XGBoost)	Precision of 97.1%, recall of 96.2%, accuracy of 96.8%, and F1 score of 96.6% in the independent test set
Garcia-Carretero et al. (2020)	A 88 high-risk patients with obesity, hypertension, hyperglycaemia, and preserved kidney function, followed over 12.4 years	Cox regression combined with the least absolute shrinkage and selection operator (LASSO)	Nonfatal cardiovascular events, with PWV as a significant predictor of cardiovascular disease development
Dinh et al. (2019)	DNational Health and Nutrition Examination Survey (NHANES) data	Weighted Ensemble Model (WEM) and eXtreme Gradient Boosting (XGBoost)	an AU-ROC score of 83.1% for cardiovascular disease detection and 86.2% for diabetes detection without laboratory data, with improved scores when laboratory data was included.
Mayya & Solieman (2022)	NHANES database	Random Forest (RFC) and XGBoost (XGB)	Laboratory data accuracy was achieved at 93.1%, while combined physical and laboratory data are at 88%.
Jose et al. (2024)	Kaggle dataset	Light gradient boosting machine classifier and other by PyCaret machine learning library	Enhanced disease prediction and management, focusing on reducing hospital readmission rates
Borges (2024)	Heart failure dataset with diabetes-related symptoms	Logistic Regression and Random Forest	Logistic Regression had 76.3% accuracy, and Random Forest identified serum creatinine, ejection fraction, and age as key predictors.
Chu et al. (2021)	834 patients with type 2 diabetes from Harbin Medical University Hospital, China	Deep Neural Network (DNN)	Anxiety and depression significantly impacted CVD risk among T2DM patients.
Saraswat et al. (2022)	ECG dataset containing records from 245 individuals, including 160 non-diabetic volunteers and 85 diabetic volunteers	K-Nearest Neighbor (KNN), multi-layer Perceptron (MLP), and Support Vector Machine (SVM)	SVM achieved the highest accuracy of 96.25%, followed by MLP with 93.8% and KNN with 80%.

Centric Artificial Neural Network) classifier that is aimed at prognosis of coronary artery heart diseases among diabetes mellitus patients. In comparison with other existing methods based on different performance parameters, this form of classifier shows its effectiveness in improving predictive accuracy. These are K-Nearest Neighbor (KNN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) models, which the authors examine for improving prediction accuracy. The study uses ECG data on 245 subjects and notes that in terms of accuracy, specificity, and sensitivity, SVM is more efficient than KNN and also MLP. Furthermore, it addresses overfitting issues faced by many researchers as well as computational inefficiency issues related to this area of research. This demonstrates how much machine learning can help to improve clinical diagnostics in diabetic patients. Future research may focus on utilizing deep learning techniques for better prediction accuracy (Saraswat et al., 2022).

4. Discussion

Along with timely medical treatments provided by specialists, the supportive role of artificial intelligence in assisting the diagnosis of heart diseases when diagnosed early helps to quickly commence treatment. A prominent example present in the literature is the application of algorithms along with electrocardiograms in one of the studies aimed at the diagnosis of diabetes at an early stage, which is also cheaper and easier for mass testing. Conversely, for such practice to be workable, there should be sufficient digital electrocardiography equipment, advanced skills for health workers, as well as population-based verification studies. Furthermore, PWV ability-predicting models for cardiovascular outcomes demonstrated the potential of combining PWV with machine learning, which enables targeting of specific high-risk groups. Although the early reports were encouraging, additional studies are necessary to recognize promising factors and formulate basic clinical pathways. According to another study, machine learning models, particularly XGBoost and weighted ensemble models, help in assessing the cardiovascular risks in patients suffering from diabetes. These models help in rendering timely management and more individualized treatment. Incorporation of these models in electronic health records (EHR) can bring about a shift from reactive healthcare to proactive healthcare through automation of risk assessments and risk reduction options. Furthermore, more recent studies have added psychological risks such as anxiety and depressive symptoms in addition to conventional biological risks using deep neural networks (DNN). This opinion is also consistent with the current tendency towards rather greater personalization in health management, which allows one to better estimate the patient's risk. And even though it can be readily concluded that AI is capable of great potential in this specific area, additional investigation and practical implementation should be conducted to ensure successful clinical application of the proposed technologies. Figure 3.3 shows the main findings of this review.

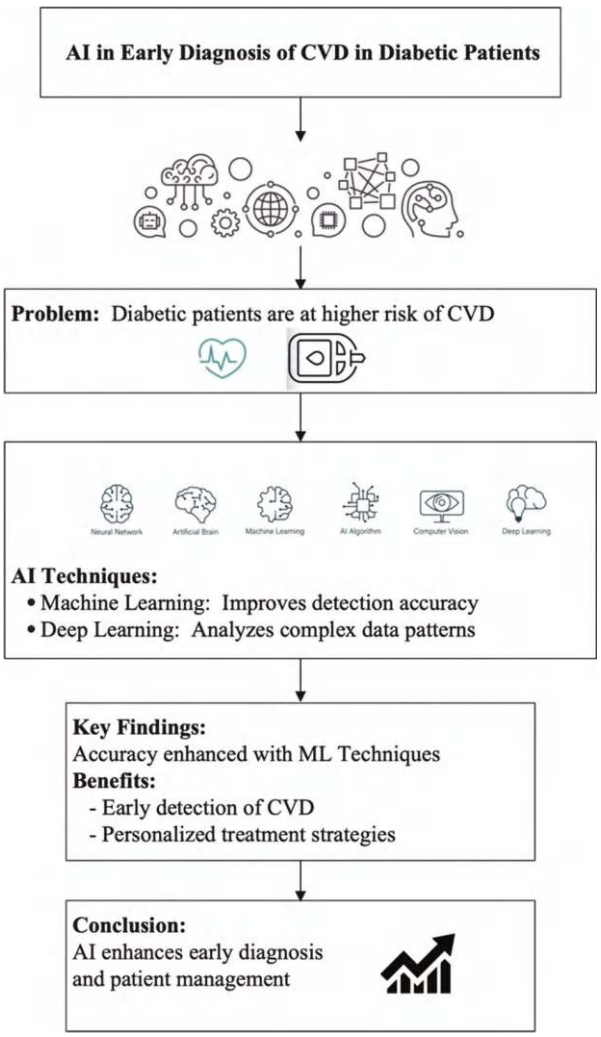

Fig. 3.3 Main findings of using AI to enhance early diagnosis and patient management

5. Conclusion

Artificial intelligence (AI) is very effective in improving the early diagnosis of cardiovascular diseases (CVD) in diabetic patients. With the help of machine learning and deep learning techniques, the diagnosis can be performed more accurately, which will lead to more timely treatment and more effective individual treatment tactics. XGBoost, weighted ensemble methods, and DNNs have provided

solutions that effectively predicted cardiovascular risks among diabetic patients, and the approaches are less invasive and cheaper than the former methods. As much as the research conducted thus far is good, there are barriers to implementing the clinical solutions in practice. These barriers include the validation study and the need for utilization of appropriate facilities and adequate training of the healthcare practitioners. Also, the implementation of these AI tools within EHR systems is not only limited to the passive assessment of risk but may revolutionize the way risk is evaluated as well as help achieve better outcomes by signalling the application of preventive measures to the patient. Further, the importance of including anxiety and depression to assess cardiovascular disease over and above purely biological parameters is in line with policy guidelines towards the deficit model. Such AI tools for the management of diabetic patients will address both mental health and physical health, therefore making smarty.

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4

Bone Fracture Detection Using Residual Neural Network

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Abstract: A fracture is a broken bone, whether fully or partially, that can be open or closed, with the latter revealing the bone through the skin. An orthopaedic expert diagnoses and treats bone, joint, muscle, and ligament problems, frequently treating ailments caused by accidents or diseases. The study recommends developing a big dataset of X-ray images specifically for applications that use computer vision to detect bone fractures. Deep learning techniques, such as Convolutional Neural Networks (CNNs), are revolutionizing image segmentation by extracting high-level features from multiple filters using a hierarchical approach. To detect bone fractures, images are trained and evaluated using bounding boxes or respirators, which segment pixels at the pixel level. This makes it easier to detect and evaluate cracks. Developing a deep learning model to detect bone fractures in X-ray pictures. The goal is to improve patient care and medical diagnostics by speeding the development of computer vision systems for fracture identification Using ResNet.

Keywords: Convolutional neural networks, Bone fracture, Deep learning, X-ray images, ResNet

1. Introduction

By recognizing and understanding objects and people in photos and videos, robots may mimic human senses such as vision and perception thanks to a branch of computer science called computer vision [1, 2]]. It is necessary for contemporary inventions and solutions like on-site and cloud computing [3, 4]. Sensing devices, such cameras or medical imaging equipment, are used by computer vision to evaluate images. After receiving the image,

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an interpreting device uses pattern recognition to break it down, compares it to known patterns, and evaluates whether any material matches [5]. The device then provides the required information by analyzing the image. More and more contemporary computer vision applications are using deep learning, a neural network-based technique, to deliver more precise image processing and data retention [7,8]. The applications are consequently getting increasingly effective. The method allows computers to recognize faces in images and count the number of people there by classifying objects. The gadget recognizes a specific object in an image, video, or snapshot [9,10]. Using object identification, for instance, the system might identify individuals in a picture and infer characteristics or identities from the way they appear. To process the location of a moving object over time, the system watches a video. Using object tracking, a parking lot security camera, for instance, would be able to recognize the cars in the lot and offer details about their movements and locations over time. When the system has recognized the letters and numbers in an image, the data is transformed into machine-encoded text. This enables users to use other computer programs to read or alter the content [11.12].

Because computer vision has so much potential, it can be used with different applications and sensor devices to provide a wide range of real-world purposes. An example of a computer vision program that can be used for something similar to bone-breaking identification or detection [13,14]. By examining pictures or photographs captured by various medical devices, doctors can identify problems and provide diagnoses more quickly and accurately. In the medical field, deep learning (DL) has gained importance in the detection of bone anomalies in orthopaedics, especially in musculoskeletal disorders such as tendinitis and arthritis. Bone fractures from X-rays are common injuries, but doctors face difficulties in evaluating images due to obscured bone traits, expertise required, and fatigue. Efficiency in assessing musculoskeletal radiographs decreases at the end of the workday. The prevention of chronic pain and disability is largely dependent on early identification. Evaluation of bone fractures, a common injury, is challenging because of weariness, the need for expertise, and sometimes hidden bone features [17,18].

GANs are adversarial networks with a generator and discriminator. The generator learns features and generates feature maps, while the discriminator distinguishes between these and the true data distribution. Attention gates efficiently represent important feature vectors, which are then fed into an image encoder. After work, radiologists are less effective at identifying fractures, and proper categorization among standard types is critical to the outcome of treatment. Patient outcomes may be directly impacted by a system that supports physicians [19].

This paper is organized as follows: there are different sections; the first one is the introduction. Section 2 deals with proposed work. The 2.1 section is a deep learning approach to bone fracture image segmentation. Section 3 is the process of bone fracture using residual neural networks. Section 4 deals with the conclusion, and finally the reference is Section 5.

2. Proposed Work

The study suggests creating a large dataset of X-ray pictures specifically for applications using computer vision in order to detect bone fractures. The collection of images is used to categorize images of different types of bone fractures, such as fractures to the elbow, fingers, forearm, humerus, shoulder, and wrist.

- Deep learning techniques like Convolutional Neural Networks (CNNs) are revolutionizing image segmentation by extracting high-level features from multiple filters using a hierarchical approach.
- The technique for detecting bone fractures involves training and evaluating images using bounding boxes or respirators that segment pixels at the pixel level. This makes it easier to identify and analyze cracks.
- The development of a deep learning model is being initiated for the detection of bone fractures in X-ray images.
- In order to improve patient care and medical diagnostics, this project aims to accelerate the development of computer vision solutions for programmed fracture recognition.

2.1 Deep Learning for Bone Fracture Image Segmentation

Segmentation, a critical process in computer vision, is the division of an image into distinct sections depending on particular criteria such as color or texture, also known as pixel-level categorization. Deep learning is a powerful technique for image segmentation, particularly for bone fractures, as it can learn complex characteristics from Bone Fracture image. Convolutional neural network (CNN) is appropriate for this task due to their direct learning of fracture properties.

CNN perform at image semantic segmentation due to its sequential analysis and ability to learn long-term dependencies, allowing for accurate interpretation of feature changes over time. The Bone Fracture Recognition and dataset define the deep learning architecture used, with powerful GPUs allowing for large-scale training and cross-device flexibility. Image segmentation is critical in computer vision, with applications including self-driving automobiles and medical image analysis. Deep learning

image segmentation divides images into parts using a neural network. The network learns on interpreted images, marking each one with the correct segmentation.

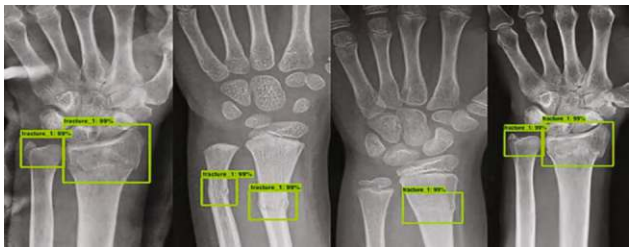

Fig. 4.1 Bone fracture image segmentation

3. Bone Fracture Recognition Using ResNet

ResNet is designed deep learning architecture for Bone Fracture image recognition, the ImageNet Large Scale Visual Recognition Challenge by training residual functions using weight layers [6]. The term "residual connection" refers to the distinct architectural a design of $I \rightarrow f(I) + I$, where f represents any random neural network module. It is a variation on the "short-cut connection" or "skip connection". ResNet is a neural network that gained popularity in feedforward networks after its debut. It replaces residual connections in recurrent the LSTM algorithm and feedforward highway networks. Residual connection maintains the training and convergence of deep neural networks with hundreds of layers, which is a typical feature in Transformer models [16].

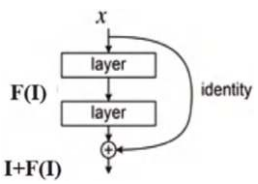

Fig. 4.2 Bone image using ResNet

The methodology discusses the use of ResNet for Bone Image Recognition, a deep learning technique for detecting bone fractures. The methodology for bone fracture image using ResNet is presented in the following.

Bone Fracture Image Exploration and Visualization: We analyzed the Bone fracture dataset, which exclusively included X-Ray images of bone fractures. We presented Bone Fracture photos from training, validation, and test sets to guarantee proper Bone fractures data loading and presentation.

Unique Bone Fracture Image Dataset Processing: To handle our Bone Fracture images dataset more efficiently, we designed a unique dataset class in Jupitar. This class addressed preparation steps such as resizing images like NxN and turning into tensors, preparing for use in model training.

Fig. 4.3 Bone fracture of test image dataset

Bone Image Fracture Model Training: We chose a pre-trained Res Net model and fine-tuned it for our particular aim. We train the model to recognize bone fractures accurately with GPU acceleration. Over ten epochs, the model is implausible evolution.

Outcome: The outcome of Bone Image Fracture Model Training is as follows

Bone Image Fracture Model Training Loss: The model demonstrated exceptional performance with a training loss of 0.0000, indicating excellent performance on the training Bone Fracture images.

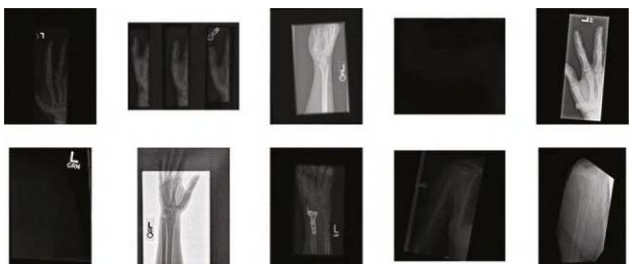

Fig. 4.4 Bone fracture of training dataset

The argument 'pretrained' is deprecated since 0.13 and may be deleted in the future; instead, use 'weights'. Arguments other than a weight enum or 'None' for 'weights' have been deprecated since version 0.13 and may be removed in the future. The current behaviour equates to passing.

Epoch 1/10, Loss:0.0092
Epoch 2/10, Loss:0.0001
Epoch 3/10, Loss:0.0001
Epoch 4/10, Loss:0.0000
Epoch 5/10, Loss:0.0000
Epoch 6/10, Loss:0.0000
Epoch 7/10, Loss:0.0000
Epoch 8/10, Loss:0.0000
Epoch 9/10, Loss:0.0000
Epoch 10/10, Loss:0.0000

Bone Image Fracture Model Validation Loss: The validation loss of 0.0000 indicated the model's great adaptation ability. The following phases include fine-tuning the model, investigating strategies to increase its precision and dependability, and assessing possible uses and practical implications.

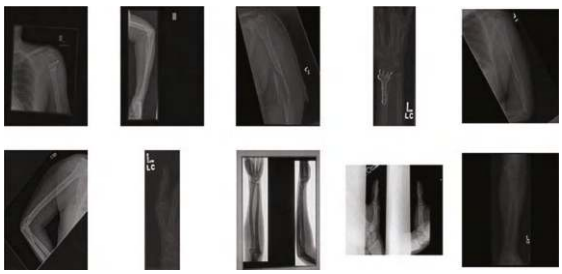

Fig. 4.5 Bone fracture of validation images

4. Conclusion

Developed a deep learning model to detect bone fractures in X-ray images using convolutional neural networks (CNNs). By employing respirators or bounding boxes to segment pixels at the pixel level, the model enhanced patient care and medical diagnosis. help speed up the development of computer vision techniques for automatic bone fracture detection. ResNet was used for bone fracture identification. The models for fractures from damaged bone images are trained and verified. The Bone Image Fracture Model Validation Loss has been identified. The Bone Image Fracture Model Training demonstrated exceptional performance with a training loss of 0.0000, indicating excellent performance on training Bone Fracture images. The model's great adaptation ability was indicated by a validation loss of 0.0000. Further phases include fine-tuning, investigating strategies to increase precision and dependability, and assessing practical implications.

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5

Protection of Sensitive Information Utilizing AutoML and Merkel Tree based on AONT-EHR

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Abstract: Digital medical data can be entered, stored, and maintained electronically due to the widespread interchangeability of Electronic Health Records (EHR). To speed up the model-building process, AutoML automates a number of processes, including feature engineering, data preparation, model selection, and hyperparameter modification. EHRs maintain data over time and include patient records, including demographics, test results, medical history, and prescriptions. Cybercriminals use this EHR data for a variety of purposes, including extortion, fraud, identity theft, data laundering, hacktivist activities, promoting political agendas, and sabotage. The EHR data is kept in certain, recognizable physical places on dedicated servers. This paper uses Merkle Tree and All or Nothing Transform (AONT) techniques to classify EHR inconsistencies between servers, demonstrating the effectiveness of this approach in protecting sensitive data processing. The EHRs face a security threat from employees and cyber attackers, compromising patient information and privacy. It is to protect the EHR by restrict access, uses firewalls, uses strong encryption, and uses VPNs. Only authorized individuals can access data. AI/ML can enhance security by detecting and blocking cyber-attacks. Faster deployment methods, shorter cycle times, improved interoperability, and inclusive digital health platforms can enhance EHRs, enhancing patient care and decision-making.

Keywords: All or nothing transform (AONT), Client-server, Electronic health record, Merkle tree etc.

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1. Introduction

Information security, hacker fragility, data corruption or deletion, incorrect transmission, and treatment errors are among the dangers associated with EHRs that arise from user-related, monetary, and design problems [2]. Cybercriminals are attracting EHRs due to Protected Health Information (PHI) and potential profit on the dark web or black market. Thieves and professionals present a privacy risk to EHRs, compromising patient confidentiality [3]. Use firewalls, virtual private networks, robust encryption, and access restrictions to protect EHRs [4]. Only those with permission can access data. AI and ML can improve security by recognizing and combating dangers on the internet. Subsequent investigations ought to concentrate on the intrusion and detection capabilities of firewalls, restricted entry to devices, operating systems, and databases, and inclusive digital health platforms [5].

Artificial intelligence (AI) is the study of enhancing computer intelligence to match human intelligence in performing tasks. AI facilitates faster and better decision-making as well as process automation in complicated IT processes. AI mimics how clever machines make decisions [8]. Others frequently confuse artificial intelligence (AI) with machine learning (ML), which is an essential aspect of Intelligence. The capacity to continually "statistically learn" from data without the need for explicit programming is known as machine learning. As networks get more distributed and complicated, the advantages of using AI/ML technology in networks are becoming more and more clear [9]. AI/ML facilitates faster issue resolution, enhances troubleshooting, and offers remedy advice. It provides important insights to enhance the application and user experience. Real-time problem solving and proactive problem prediction are both possible with AL/ML. Through enhanced threat response and mitigation, it further enhances security insights. By optimizing network baselines and minimizing noise and false positives, network analytics leverages AI and ML to help IT workers precisely detect problems, trends, anomalies, and underlying causes. Crowdsourced data and AI/ML approaches are also utilized to lower unknowns and raise the degree of certainty in decision-making. It is possible to apply the knowledge gathered by collecting anonymized telemetry data from thousands of networks on particular networks. AI techniques allow us to pinpoint common issues and occurrences and guide remedial action, even though every network is unique. There are times when machine learning algorithms are specifically targeted at a single network. Even more data may be used if the procedure is trained on a greater range of anonymous datasets in various applications.

AI/ML and analytics help IT automate network policies, manage zero-trust security solutions, and identify devices. Networks will be able to learn, self-optimize, and anticipate service degradations because of AI, lowering costs and providing an optimal connected experience. AI/ML models provide users with network-health benchmarks, enabling insights for optimization, including long-term performance trends and comparisons with industry peers. The network controller and management dashboard utilize AI/ML engines to analyze network telemetry data, Machine reasoning (MR) is a crucial aspect of AI that uses learned information to identify optimal solutions to deep domain problems. It complements machine learning (ML) by analyzing causes and improvement options, requiring explicit knowledge capture.

Predictive analytics uses machine learning to anticipate network failures and performance issues using historical data, enabling mid- and long-term planning to prevent degradations or outages. The range of uses for networking technologies with AI support. In order to help IT workers take remedial action, machine learning can predict network problems such as Wi-Fi interference, congestion, and office traffic loads. By recognizing and classifying objects through network probes or application layer discovery approaches, AI/ML supports IoT deployments. Policy-making to allow or prohibit interactions is made possible by machine learning (ML), which analyses traffic flows from endpoint groups and provides comprehensive information such as source and destination, service, protocol, and port numbers. Operations can propose changes since machine reasoning can quickly and effectively scan a large number of network devices to make sure they have the most recent software image and identify any potential risks.

The paper organize into several sections are as follows, Section 1 is Introduction of sensitive information of Electronic Health Records. Section-2 deals with proposed work includes 2.1 deals with sensitive data and 2.2 deals with Classifying Electronic Health Records (EHR) inconsistencies between Servers Using Merkle Tree. 2.3. deals with Electronic Health Record (EHR) Move and Encrypt with All or Nothing Transform (AONT). Section-3 deals with Client-Server AutoML Design to Protect Processing of Sensitive Data. The experimental result is in the section 4. Finally, Conclusion and References.

2. Proposed Work

Electronic Health Records (EHRs) face a security threat from employees and cyber attackers, compromising patient information and privacy [11]. To protect EHRs, restrict access, use firewalls, strong encryption, and VPNs. Research should focus on enhancing firewalls' intrusion

and detection capabilities, limited access to databases, operating systems, and devices, and access control methods. Integration with telehealth platforms can enhance patient care and decision-making. The following is how the work is to contribute:

- To use the process of EHR-sensitive information.
- To use Merkle Tree to categorize the disparities in Electronic Health Records (EHR) between servers.
- To use the All or Nothing Transform (AONT) Algorithm for Moving and Encrypting Electronic Health Records (EHRs).
- Client-Server AutoML Architecture to Safeguard Sensitive Data Processing.

2.1 Sensitive Information of EHR

To maintain privacy and prevent destruction, firms must protect sensitive data, including health records and private information. Inadequate cooperation can lead to legal consequences, and protecting sensitive data poses numerous risks for modern enterprises. Sensitive data, including medical records, is crucial for organizations to prevent theft or unauthorized access, as failure to implement these measures can lead to data breaches [13]. Data classification is crucial for data privacy, categorizing data based on sensitivity, value, and criticality, enabling organizations to implement protective measures and maintain data privacy. Sensitive data protection, each with unique privacy and security implications [14]. According to the suggested paper, compromised protected health information, such as test results, insurance information, billing information, and medical records, may result in privacy violations and possible harm to one's personal and professional life. Access credentials, such as usernames, passwords, PINs, and biometric data, are crucial for granting or denying data access and can be hacked, violating data protection regulations [15]. Especially in nonproduction situations, sensitive data should be protected using methods like data masking and pseudonymization to guarantee that workers only have access to the information that need. To safeguard sensitive data, they should also encrypt it, monitor usage, train employees data security techniques, and set access controls in effect [12].

2.2 Classify Electronic Health Records (EHR) Inconsistencies between Servers using Merkle Tree

A mathematical method for verifying the integrity of data chunks transmitted back and forth between peers in a peer-to-peer network is called a Merkle root. Merkle trees are a structured data encoding method used to classify EHR inconsistencies between servers, providing easy verification and security through visual representations resembling upside-down trees. Merkle trees are used to find discrepancies in EHR data between systems [1].

A model can contain a lot of EHR data. Naively splitting up the entire range to calculate checksums for comparison is not very feasible. There is simply too much records to be transferred. Instead, we can use Merkle trees to compare models of range.

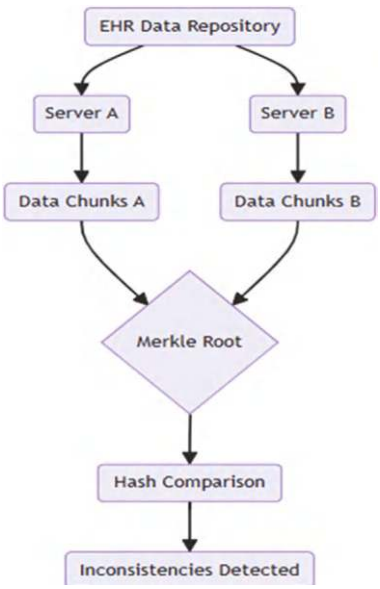

Fig. 5.1 Merkel tree of EHR

2.3 Electronic Health Record (EHR) Move and Encrypt with All or Nothing Transform (AONT) Algorithm

The All or Nothing Transform (AONT) technique, which effectively and consistently protects electronic health records [6], is explained in detail below:

1. **Data Encryption:** Begin with the initial electronic health data (D). Create a random AES256 key (K) that is unique to the version of your Record.
2. **Cipher Creation:** Encrypt the Electronic Health data (D) with the key (K) to produce a cipher (C).
3. **Hashing:** Create the hash (H) of the cipher (C).
4. **Key Transformation:** Apply an XOR operation between the hash (H) and the key (K) to get a new value (K').
5. **Data Formation for AONT EHR:** To create the AONT data (C+K'), combine the cipher (C) with the altered key (K').

By using this technique, it is ensured that the full AONT EHR data is required in order to obtain the original EHR data (D). An attacker cannot recover the data without the

full encryption, even if they are able to breach a portion of it (C). In addition to being effective at managing keys, AONTs provide improved security by protecting against incomplete breaches and are adaptable enough to be used to any kind of information. AONTs provide enhanced safety [6, 7]. The keyless, independent key management system offers enhanced security, able to withstand partial ciphered data theft attacks, and offers versatility in protecting any type of EHR data.

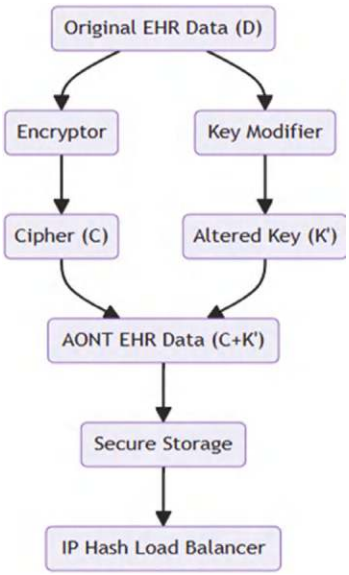

Fig. 5.2 Electronic health records using AONT

By dividing up incoming requests among several servers, distributing the load ensures the best possible speed, availability, and scalability. The **IP Hash** method assigns requests to a server based on the client's IP address, creating a personalized queue and potentially faster response times [10].

3. Client-Server AutoML Design to Protect Processing of Sensitive Data

AutoML software is a crucial task solution since it automates the process of creating ML models, encompassing feature engineering, data preparation, model selection, and hyperparameter tweaking. Additionally, contemplate about putting strong security measures in place to safeguard private information while it's being processed and a monitoring system to keep an eye on the model's performance over time [16]. **The various elements of auto machine learning to take into account are:** The AutoML process involves providing pre-processed, cleaned EHR data to the system for training a machine learning model. The system then trains multiple models using various algorithms and hyperparameters to find the best fit. The best model is then selected and used as the output. The trained model can be used for predictions or actions based on new EHR data, typically deployed as a web service accessible to other applications or users.

Frontend Client: To build up the model training and begin the process, we must let the user enter parameters. The outcomes of a particular run and the metrics associated with it ought to be visible to the user. In order to improve the model selection procedure, we may additionally offer a means of comparing training runs.

Backend Server: The front-end logic implementation point is at this point. It establishes a connection with a Run Metadata database, which records the various run metrics and settings. This database ought to hold all the data required to perform comparable training runs again. One great illustration of a training run management system is Machine Learning Flow (MLFLow).

Message Queue for Training Request: Given that multiple requests from distinct users may come in at once, we must buffer training requests. If we are limited in the number of training servers we can use at once, it is better to buffer requests until there are enough machines available for the subsequent requests.

Orchestration Scheduler: In the event of a failure, the control system can arrange the different steps and resume one at a time. Systems are instances of such systems. When a user request is received, the scheduler will start a training pipeline and monitor the message queue.

Training Pipeline: The orchestration workers manage the various steps, which are recorded in a Tree.

Data Pull Module: To get the right data from the feature store, we must develop a logic. After the data is extracted, it needs to be verified to make sure it complies with the specifications for that specific training run and features metadata.

Data Processing Module: To assess the model's effectiveness after data is available, it is necessary to create a validation set.

Model Selection Module: The majority of the procedure will be completed inside. The model selection procedure is managed by that module, which also selects the ML model, model architecture, hyperparameters, and features. A trained optimal model is the output of the above module.

Model Validation Module: Following model training, we must record the many validation metrics that will enable the user to choose the output model with knowledge. We need to record hardware utilization data, such as memory

and CPU consumption, in addition to ML metrics. The generated metadata must be sent to the Run Metadata database.

Model Push Module: It is necessary to push the generated model together with its version number to a model registry. In order to protect sensitive data processing, the Auto Machine Learning Client Server Architecture is built as follows.

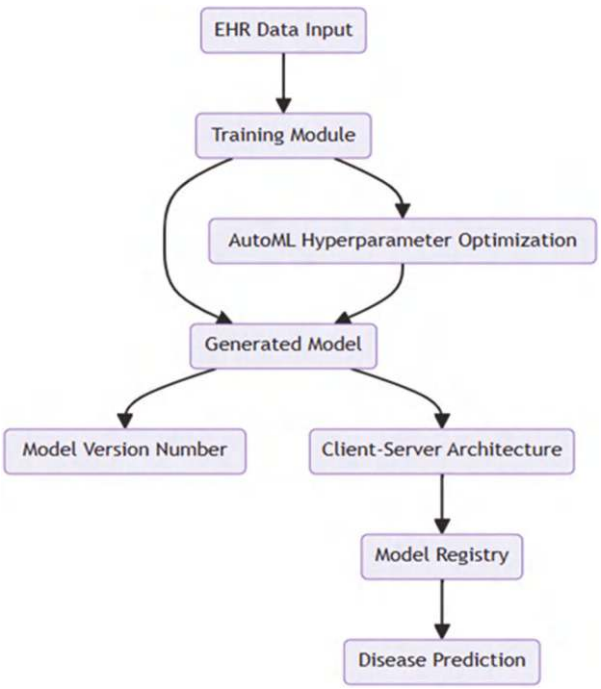

Fig. 5.3 Client-server architecture with auto-machine learning to protect sensitive data processing

Supervised machine learning models predict Healthcare Disease based on EHR data, learning the relationship between data and outputs during training to make new predictions. The quality of EHR data input is crucial for machine learning models as it directly impacts model accuracy and performance, preventing incorrect or misleading relationships between input and output. Hyperparameters, such as learning rate and neural network number, control model behaviour and performance. AutoML systems optimize hyperparameters by automatically finding the best combination for a model, by training the model on EHR data and evaluating each combination's performance.

3.1 Procedure of Sensitive Information of EHR

Step-1: First, we submit the Dataset EHR input. The form of the input EHR is automatically adjusted. But the EHR that is seen here is still utilizing the original. Step-8 displays the actual record that was used in this AutoML.

Step-2: Select the Filter option. Once the required keys are generated, the EHR is encrypted.

Step-3: The task is to create the private key.

Step-4: AONT encrypts Electronic Health Records (EHR) using a filter and sends encrypted output to the server. The output is not accessible to the server, and execution time is minimal. AutoML displays the encrypted output, with a random private key for decryption. An attacker can only see an EHR with a random EHR.

Step-5: The encrypted EHR should be sent to the server.

Step-6: Run the AONT execution.

Step-7: The server has been encrypted and the output EHR has been received. The output is decrypted and compared to the original EHR, with the user only knowing the transformed version and the original EHR.

Step-8: Decrypt the output. The EHR is displayed on the input record used in the previous steps, with the output visible on the right.

The above EHR process was built with Concrete-ML is a Privacy Preserving AutoML open-source tool by Zama.

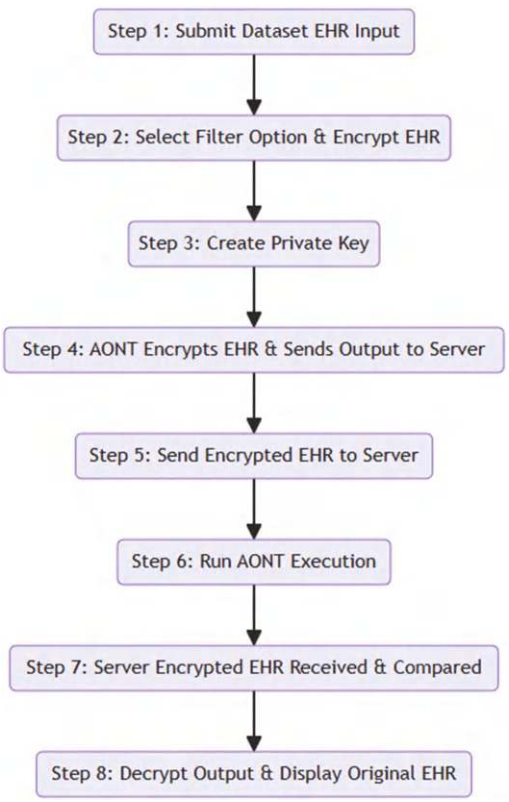

Fig. 5.4 Procedure of sensitive information of EHR

4. Experimental Result

The experiment indicates that while simulation-based methods can reduce errors, systems-based solutions should still be used. Following simulation-based training, the clinicians' capacity to recognize and manage patient care risks improves. The safeguarding concerns continue after the first begin operation phase, emphasizing the need for ongoing monitoring and maintenance. Simulation-based medical data access programs should be high fidelity, incorporating deliberate practice, feedback, outcome measurement, and transfer to practice. Because many EHR vulnerabilities reflect the difficulty of creating a scaled, integrated, and globally deployable medical data system, enhancing EHR design is essential for patient safety.

Initial Risk Assessment: The initial risk rating is crucial in determining the most effective control measures to minimize risk within a specific time frame of Electronic Health Records.

Provider A: Total Risk = 0.39

Provider B: Total Risk = 0.52

Post-Training Risk Assessment: The training covers EHR impact, security concerns, hazards, best practices, risk assessments, legal compliance, and risk management advantages, emphasizing best practices and comprehensive risk assessments.

Provider A: Total Risk = 0.29

Provider B: Total Risk = 0.44

Risk Assessment After EHR Reconfiguration: Implementing an EHR system requires network and infrastructure setup, employee onboarding, patient engagement, care coordination, and wait time to ensure smooth operations.

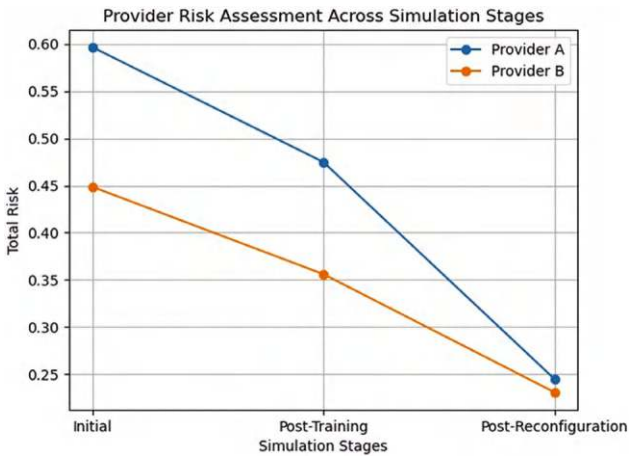

Fig. 5.5 Provider risk assessment across simulation stages

Provider A: Total Risk = 0.19

Provider B: Total Risk = 0.27

5. Discussion

Although simulation-based approaches lower mistakes, systems-based solutions are still necessary. They enhance physicians' capacity to recognize and manage risks to patient care. Intentional practice, feedback, and practice transfer are necessary for high-fidelity simulation programs. Enhancing the design of EHRs is essential for patient safety.

By using an interactive approach, providers' error susceptibility is evaluated in a safe, realistic setting with high-fidelity feedback. Through practice, feedback, and practice transfer, in situ simulations in clinical treatment enable prompt learning.

Analyses based on EHRs minimize errors and detect safety hazards. It is preferable to reconfigure the current system rather than alter human behaviour. Since it necessitates creating a scalable, integrated software suite, improving EHR design is essential for patient safety.

6. Conclusion

Simulation-based methods can reduce errors but not replace systems-based solutions. Providers improve risk identification and management, but protection risks persist. High-fidelity simulation-based medical data access programs and improved EHR design are crucial for patient safety. The training covers EHR impact, security concerns, hazards, best practices, risk assessments, legal compliance, and risk management advantages, emphasizing best practices and comprehensive risk assessments for smooth EHR system implementation.

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6

Sustainable Shrimp Farming Aquaculture Using Approximate Nearest Neighbour

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Abstract: Shrimp is a crustacean in zooplankton, are facing water quality issues due to overstocking, increased feeding, and tainted water, which can lead to their death due to copper fertilization. The ecological circumstances that exist on shrimp farms have a big impact on whether the shrimp farming sector succeeds or fails. The improper setting of the farms is the main factor contributing to the socioeconomic and environmental implications of shrimp farming, including nutrient loading and salinization of the land and drinking water. Finding the right location could help avoid several problems that affect shrimp creators and the environment. The given solution makes use of a method called Approximate Nearest Neighbor (ANN) finds the number of prawns and the disease in a data collection that are somewhat close to the query point, but may not be exactly the same. The chi-square test is on prawns' data collection during disease and quality testing for the purposes of pre-process. A test for evaluating how expectations match actual observed data or model outputs is the chi-square (χ^2) statistic. The study predicts Total Ammonia Nitrogen (TAN) levels using NH_3 and pH concentrations, examining the correlation between water quality parameters and shrimp farming through multi-regression analysis.

Keywords: Approximate nearest neighbor, Chi-square, Multi-regression analysis, Shrimp farming

1. Introduction

Shrimp farming places should consider factors such as mangrove forests, sensitive environmental areas, potential social unrest, and environmental issues. Because mangrove trees are vital to coastal ecosystems and livelihoods, their disappearance might have dire consequences. Shrimp farms are not best placed in marine parks or in acidic mangrove environments [1]. Converting arable land into a shrimp farm could have social consequences, but only if

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the government reclassifies the area. Buffer zones for soil conditions are required because shrimp farms near other land uses may experience seepage of water. Shrimp farms should be strategically positioned to prevent flooding in populated areas. Larger farms should be 5 hectares apart, while smaller ones should be 20 meters apart. 60% of land should be used for water spread, and new farms should be allowed after creek capacity. Soil quality is crucial in culture systems, with low pH, acid-sulfate, and high heavy metal content indicating the need to avoid these types of soil. Clayey loam soils are preferred for farm maintenance due to lower capital and operational costs, while sandy soils can cause salinization and high maintenance costs. Sustainable aquaculture requires good quality water in required quantities, requiring careful study of source, quantity, and quality during farm site location. Shrimp farming requires gravity-drainable ponds, with a minimum elevation of 0.45-0.6 m for proper drainage, as proper water exchange and drying of the pond bottom are crucial for success.Hydro-meteorological data, including rainfall, tidal fluctuations, wind direction, flood levels, and natural calamities, are crucial for farm design, avoiding construction in cyclone-prone areas. When choosing a shrimp farm location, consider basic features like highways, power, and accessibility to incubators, freezing vegetation, and processing plants to ensure profitability [2].

Building lakes, waterways, and levees, which collectively account for between 35 and 50 percent of construction expenditures, can significantly reduce capital costs and increase profitability. Proper farm layout reduces construction costs and ensures smooth operation [3]. Farm planning and building are critical components of effective management and environmental preservation. The selection of a site and the addition of mitigating features can stop problems like water loss, subsidence, hurricanes, and water levels. A site-specific approach and experienced construction teams, under the supervision of a qualified aquaculture engineer, are necessary. The peripheral dyke of a farm is crucial for protection against floods, tidal thrusts, and cyclones, influenced by soil load capacity and compactability [4]. A retaining wall or a berm with stone pitches facing the river should be present on the outside of the dike. The pond dike must be roughly fifteen meters high, with 0.6–0.7 meters of free board required above, in order to contain one meter of water. The supply channel should be on the crest, and the slope should be 1:1 for clayey soil and 3:1 for sandy soil. The daily water requirements of the farm dictate the construction of the supply canal, whether it is made of concrete, lined, or earthen canals. In small farms, PVC tubes with valves are used.

The nourishment leave of a pond must be made of concrete or wood, with areas designated for harvest bags, strain nets, and wooden shutters. Its diagonally opposite the inflow location is ideal for efficient water exchange. The width of the exit sluice should be three percent to one-point meters, with a one-meter minimum bottom width. Square or rectangular ponds with their longest axis parallel to the wind direction are perfect for shrimp culture because they provide the best natural aeration. Positioning ponds perpendicular to wind direction is recommended for high wind action. Rearing ponds should have a minimum depth of 1m and a slope of 1:2000. A turbid, suspended solids source water necessitates a reservoir pond for settlement and chemical treatments, with site-specific design characteristics essential for effective pond construction. Effluent treatment ponds (ETP) are crucial for semi-intensive farms, releasing drainage water back into creeks. Common ETPs prevent nutrient loading, and mollusc and seaweed cultures purify suspended solids and dissolved nutrients. Saline water contamination is avoided in lakes with proper design and lining materials by employing techniques like cementing, compaction, and clay lining. on order to avoid disease contamination on large farms, drainage canal lining is essential. Using paddle wheel aerators, which work best in rectangular ponds and have an average oxygen transfer efficiency of 2.13, which is kg Oz/Kw-hr, dissolved oxygen levels in shrimp ponds can be raised.A skilled aquaculture team, supervised by a qualified engineer, should construct ponds using earthmoving equipment. In low-soil areas, remove and relaid fertile soil, and construct sluices and supply channels carefully [5].

This paper is organized in the different sections follows; section-1 deals with the introduction of Shrimp.The section-2 deals with proposed work contains different subsections. The section 2.1 indicates prawn optimal points and values. Section 2.2 deals with shrimp detection using approximate nearest neighbour. The section 2.3 deals with Shrimp Water Test Using Chi-Square Method. In the section 2.4 deals with Shrimp Water Parameters Test Using Multiple Regression Analysis. The experimental result in section 3. Section-4 deals with conclusion. Section-5 deals with discussions. Section-6 deals with references.

2. Proposed Work

Shrimp, a crustacean in zooplankton, are at risk of death due to excessive iron fertilization, overstocking, and tainted water due to their sensitivity to changes in water chemistry.

- To utilize the Prawn Population Optimal Points and Values.
- To use the nearest neighbor search method for shrimp detection.
- The Chi-Square Method is used to conduct a shrimp water test.

- The shrimp water parameters test is conducted through multiple regression analysis.

The utilizes Prawn Population Optimal Points and Values, Nearest Neighbor Search for shrimp detection, Chi-Square Method for shrimp water testing, and multiple regression analysis for shrimp aquaculture improvement.

2.1 Prawn Optimal Points and Values

The high-dimensional space where the prawn data are represented as points contains an embedded query, which could be a word or image that needs to be matched to a shrimp's point. The prawns detect that are nearest to the search is wherever the illness identification application responds appears. The section deals with optimal prawn in the pond. Vector optimization emphasizes the prawn's situation. The sustainable shrimp farming Aquaculture reflects the optimal set of prawn ponds and values [6].

$$\text{Shrimp} = \{f_0(x) | \exists x \in t, f_i \text{ (Prawns s)} \leq 0, \\ i = 1, 2, 3, \ldots, n, h_i \text{ (pond)} \\ = 0, i = 1, 2, \ldots, p\} \subseteq R^q$$

Set of feasible target values has the set of feasible values represented by sustainable shrimp farming Aquaculture prawns in the ponds. The prawns by considering the shrimp based on identification and disease are targeted(t) value in a sustainable aquaculture farming. The optimization method should be applied to eliminate any other potential quantities. Model developers utilize prawn's estimates for approximate nearest-neighbor search methods since it takes time to calculate the distance between prawns. The shrimp farming aquaculture that is sustainable suggests using an algorithm to find the closest prawn ponds to the study [6].

2.2 Shrimp Detection Using Approximate Nearest Neighbor

Nearest-neighbour search is a widely used technique in modern machine learning (ML) applications. The focuses on the method of detecting shrimps using an approximate nearest neighbor. ApproximateNearest Neighbor (ANN) search is an effective way to find prawns in a high-dimensional space that are near the input region. ANNs can be used to evaluate photographs, converting them into vectors that image recognition systems can subsequently compare to a database of vectors. This is helpful for tasks like object recognition and picture classification since it enables ANN to identify images that share features or content. This technique uses preprocessing to create an efficient index, including vector transformation and vector encoding. The approach uses the Metasearch procedure to find a prawns data point close to the query point, but not absolute closest. It then sorts the neighbourhood by distance from the object being added, connecting the new object with the first K nearest elements [7].

ANN algorithms work by transforming higher-dimensional data sets into lower-dimensional ones, making predictive models more efficient. They use metric spaces to define distances between data points, adhering to rules like non-negativity, identity, symmetry, and triangle inequality. ANN also uses indexes to improve efficiency by pre-processing data into them, allowing faster navigation of the search space. This approach can be Shrimp for finding prawns.

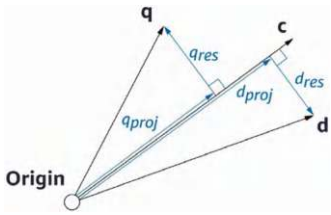

Fig. 6.1 ANN estimates distances between prawns

A digit finger calculates the distance between a query vector (q) and a fresh graph node vector (d) by using the vector of an already investigated node(c). The sum of projections along c (q_{proj} and $d_{\mathbf{proj}}$) and "residual" vectors (q_{res} and d_{res}) orthogonal to c can be used to represent both q and c. It is possible to treat c as a basis vector of the space by representing q and d as the sum of projection along c and "residual vectors" perpendicular to c.

The algorithm has already determined the distance between **c** and **q** if it is investigating **c**'s neighbors. The artefact demonstrates that the distance between q and d can be estimated by estimating the angle between their residual vectors using existing calculations and precomputed node vector values. The angle between a graph's residual vectors and its immediate neighbors can be approximated using the relationships between the residual vectors of nearby neighbors, suggesting that if q is close enough to c, it's likely one of its nearest neighbors. The Digit finger method demonstrated superior efficiency in estimating methods on pond datasets, demonstrating its effectiveness across different exploration rates, as illustrated in Table 6.1.

2.3 Shrimp Water Test Using Chi-Square Method

The weekly Shrimp Water Test, conducted using the Chi-Square Method, yielded the following results as shown in Table 6.1. Chi-square (χ^2) is a statistical measure that compares observed and expected frequencies of events or variables [8-12]. It's useful for analyzing categorical variables, especially nominal ones. It determines the relationship between variables and the fit between observed

Table 6.1 Multi regression values of shrimp water quality test

S. No	pH (X_1)	NH_3 (X_2)	TAN (y)	X_1^2	X_2^2	(X_1X_2)	X_1Y	X_2Y
1	7.4	0.02	1	54.76	0.0004	0.148	7.4	0.02
2	8.2	0.1	0.9	67.24	0.01	0.82	7.38	0.09
3	7.9	0.07	1.2	62.41	0.0049	0.553	9.48	0.084
4	8.7	0.03	0.1	75.69	0.0009	0.261	0.87	0.003
5	8.4	0.1	0.7	70.56	0.01	0.84	5.88	0.07
6	9.2	0.3	0.5	84.64	0.09	2.76	4.6	0.15
TOTAL	**49.8**	**0.62**	**4.4**	**415.3**	**0.1162**	**5.382**	**35.61**	**0.417**

and theoretical frequencies. The following is the formula for a Chi-Square (χ^2) statistic:

$$x_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Wherec = Degrees of freedom, O = Observed value(s), E = Expected value(s).

A chi-square (χ^2) statistic is a test that compares a model to observed data, using random, raw, and mutually exclusive data from independent variables. It is commonly used to test hypotheses, comparing discrepancies between expected and actual results. Degrees of freedom determine null hypothesis rejection, with larger sample sizes resulting in more reliable results. Chi-square tests are statistical analysis methods used to evaluate categorical variables [13]. The test of independence examines the relationship between student gender and course choice, particularly when variables are nominal. The χ^2 test compares the frequencies of male and female students selecting courses, determining the probability of random chance explaining observed differences [14].

2.4 Shrimp Water Parameters Test Using Multiple Regression Analysis

To predict the value of a response variable, a statistical technique known as multiple linear regression (MLR), or simply multiple regression, uses a large number of explanatory factors [15]. The goal of multiple linear regression (MLR) is to model the linear relationship between the response (dependent) variables and the explanatory (independent) variables [16].

$$\mathbf{Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} + \epsilon}$$

where Y_i is the dependant variable for i = n observations. X_i = explanatory factors, β_0 = the constant term y-intercept. Each explanatory variable's slope coefficients are denoted by β_p, and the model's error term, or residuals, is represented by ϵ.

3. Experimental Result

A statistical method called multiple regression analysis examines the relationship between two or more variables and uses the results to calculate the values of the dependent variables. In order to comprehend the link, anticipate future observations, and manage operations, multiple regression is a technique used to explain or predict a single Y variable from several X variables. Assume for the moment that we wish to forecast TAN levels using NH_3 and pH concentrations: Y, the dependent variable Total Ammonia Nitrogen (TAN) pH and NH_3 levels are independent variables (X_1 and X_2).

Using the values from the table:

- $\sum y = 4.4$
- $\sum x_1 = 49.8$
- $\sum x_2 = 0.62$
- $\sum x_1^2 = 415.3$
- $\sum x_2^2 = 0.1162$
- $\sum x_1x_2 = 5.382$
- $\sum x_1y = 35.61$
- $\sum x_2y = 0.417$
- $n = 6$

Substituting into the first normal equation:

$$4.4 = 6b_0 + 49.8b_1 + 0.62b_2$$

Substituting into the second normal equation:

$$35.61 = 49.8b_0 + 415.3b_1 + 5.382b_2$$

Substituting into the third normal equation:

$$0.417 = 0.62b_0 + 5.382b_1 + 0.1162b_2$$

The values of the coefficients based on solving the given normal equations are:

b_0 (intercept) = 7.304
b_1 (coefficient for pH, x_1 = –0.829
b_2 (coefficient for NH_3, x_2) = 3.032

The values of b_0, b_1 and b_2 can now be used in the regression equation: $y = 7.304 - 0.829x_1 + 3.032x_2$

This equation can be used to predict the Total Ammonia Nitrogen (TAN) levels given the supplied pH and NH_3 values. The Chi-square test is a statistical method used to compare observed and expected values of TAN, ensuring a significant difference between observed and expected outcomes.

Calculation of Chi-Square Statistic: The Chi-square statistic (χ^2) is calculated using the formula:

$$x_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where $\mathbf{O_i}$**:** Observed values (actual TAN values from the table).$\mathbf{E_i}$**:** Expected values (predicted TAN values calculated using the regression equation).

The Chi-square test's degree of impartiality is computed as: df = n−k−1.

Wheren: Number of observations (here, n=6),

k: Number of independent variables (here, k=2),

So, df= 6−2−1=3.

The Chi-square statistic should be calculated using the observed and expected (predicted) values:

$$E_1 = 7.304 - 0.829\,(7.4) + 3.032(0.02) = 1.009$$
$$E_2 = 7.304 - 0.829\,(8.2) + 3.032(0.1) = 0.930$$
$$E_3 = 7.304 - 0.829\,(7.9) + 3.032(0.07) = 0.976$$
$$E_4 = 7.304 - 0.829\,(8.7) + 3.032(0.03) = 0.361$$
$$E_5 = 7.304 - 0.829\,(8.4) + 3.032(0.1) = 0.657$$
$$E_6 = 7.304 - 0.829\,(9.2) + 3.032(0.3) = 0.466$$

Calculate χ^2 for each observation:

$$\chi_1^2 = \frac{(O_i - E_i)^2}{E_i} = \frac{(1 - 1.009)^2}{1.009} = 0.00008,\ \chi_2^2 = 0.00097,$$

$\chi_3^2 = 0.0504$, $\chi_4^2 = 0.173$, $\chi_5^2 = 0.0033$, $\chi_6^2 = 0.0025$.

Sum up these values to get the total Chi-square statistic:

$$\chi^2 = 0.00008 + 0.00097 + 0.0504 + 0.173 + 0.0033 + 0.0025 = 0.164.$$

4. Conclusion

Shrimp, sensitive to water chemistry changes, are facing increasing water quality issues due to overstocking, feeding rates, and tainted water. The success of shrimp farming is influenced by ecological conditions. The Approximate Nearest Neighbor method helps identify optimal locations and chi-square tests evaluate data accuracy. A study examined the correlation between water quality parameters and shrimp farming.

5. Discussion

Shrimp are sensitive to water chemistry changes, especially copper, and excessive iron fertilization can cause death. High stocking, increased feeding rates, and polluted water contribute to water quality issues. Warmer weather increases prawns' susceptibility to illness and slower growth rates, affecting their oxygen needs.

Ammonia toxicity in water is influenced by pH, with high levels of hazardous unionized ammonia causing stress and gill damage to prawns. Maintaining pH values between 7.5 and 8.5 is crucial to minimize ammonia toxicity. Temperature can also affect pH, with increased biological activity releasing CO2 and carbonic acid, which can reduce pH. Alkalinity, which neutralizes acids, helps maintain pH by preventing sharp changes and promoting a stable environment for prawn growth.

Understanding water quality indicators is crucial for prawn culture balance. Proactive management strategies, including feeding, aeration, biofiltration, and frequent water exchanges, support healthy growth and minimize stress.

Prawn culture relies heavily on water quality parameters like pH, ammonia toxicity, and alkalinity, which are interdependent and can impact prawn health and growth. Total ammonium in water, ionized and un-ionized, is known as TAN. To evaluate the total ammonia concentration in aquaculture systems, TAN is a metric that is frequently evaluated. This is ammonia in its unionized form, which is poisonous to aquatic life, especially prawns. (NH_3) can be hazardous at even low quantities. The pH of the water determines the ratio of ionized ammonium (NH_4^+) to unionized ammonia (NH_3). The majority of ammonia resides as the less harmful ionized form (NH_4^+) at lower pH values (acidic conditions). An increase in pH (more alkaline circumstances) causes an equilibrium shift that raises the amount of un-ionized ammonia (NH_3).The relationship between pH, ammonia (NH_3), and total ammonia nitrogen (TAN) can be studied with multiple linear regression, where one of these factors is the dependent variable and the others are the independent variables. This will enable us to understand how TAN levels are affected by pH and NH_3, or vice versa.

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7

Unveiling the Power of Classic ML Techniques in Text Classification: A Comparative Approach

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Abstract: Text data preprocessing plays a crucial role in machine learning, as it transforms unstructured content into a structured format suitable for model training. This research enhances the effectiveness of several well-known machine learning algorithms, including Gaussian Naive Bayes (GNB), Multi-Layer Perceptron (MLP), Decision Tree (DTC), Random Forest (RFC), Support Vector Machine (SVM), Logistic Regression (LRC), and K-Nearest Neighbors (KNN).We demonstrate the use of these models on four diverse datasets, focusing on improving key performance indicators such as Correctness (accuracy), Exactness (precision), Sensitivity (recall), and Harmonic Score (F1-score). The preprocessing involves heavy cleaning and transformation, which is said to be quite crucial in order to change model effectiveness and efficiency. The experimental results have demonstrated massive improvements within classifier performance and thus proved that thorough model tuning and preprocessing may lead to scalable and efficient text classification systems. This proves to be effective and adaptable in various application domains, suitable for a wide variety of text classification tasks.

Keywords: Machine learning, Text classification, Classifier optimization

1. Introduction

Text classification is a key aspect of machine learning, with applications in sentiment analysis, spam detection, and topic modeling. Although deep learning has recently led to notable advancements, traditional machine learning algorithms continue to perform well when carefully tuned and applied to well-prepared data. The effectiveness of

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these models often depends on labeled data, which is scarce and costly to obtain. Labeling requires specialized expertise and is a time-consuming process, making it one of the major challenges in developing high-precision models [1], [9]. This paper explores several machine learning algorithms aimed at implementing efficient text classification models, focusing on standard classifiers such as (LRC), (SVM), (DTC) among others [2], [4].

In this study, we conducted experiments using four datasets from diverse domains, placing strong emphasis on thorough preprocessing to ensure high-quality inputs for the models [5], [6]. The results indicate that traditional machine learning models, when optimally tuned, can deliver competitive performance in text classification tasks even with limited labeled data [3], [10]. This research demonstrates that traditional machine learning methods, when enhanced by specific optimization techniques, can achieve results comparable to those of more complex models, underscoring the importance of preprocessing for model efficiency and effectiveness [8], [9]. Our findings highlight the potential of scalable, resource-efficient text categorization techniques across various domains, reinforcing the value of machine learning in both academic and practical applications [7].

2. Related Work

Text classification is a key area in natural language processing, where traditional machine learning models serve as foundational tools for various classification tasks. Early research focused on simple models, such as (GNB) and (SVM), utilizing feature engineering techniques like bagof-words and TF-IDF. While effective for basic text classification, these approaches often failed to capture nuanced contextual information, limiting their accuracy on complex datasets[1], [6].

To address these limitations, subsequent studies expanded the range of algorithms to include Decision Trees, Random Forests, Logistic (DTC), (RFC), (LRC), and (KNN). These models have proven effective in applications like spam detection and sentiment analysis, where interpretability and computational efficiency are crucial[1], [9]. However, they remain sensitive to input data quality, necessitating rigorous preprocessing steps—such as text cleaning, tokenization, and normalization—to enhance performance[3], [5].

Recent findings indicate that traditional machine learning models can achieve competitive results against complex deep learning architectures with careful preprocessing and tuning[2], [4]. Ensemble methods, like Random Forest, which combines multiple decision trees, have shown effectiveness in improving accuracy and robustness. The Voting Classifier, which aggregates predictions from various models, has also been explored to enhance performance, particularly in scenarios with limited labeled data[7], [8], [10].

Given the high computational demands of deep learning, traditional machine learning models offer a valuable alternative in resource-constrained environments. Their shorter training times and greater interpretability make them appealing, especially when optimized through preprocessing and hyperparameter tuning[1], [3]. This study evaluates the performance of seven widely used classifiers—(GNB), (MLP), (DTC), (RFC), (SVM), (LRC), and (KNN)—across four diverse datasets. By adopting a comparative approach, we aim to identify best practices in preprocessing and model selection that can lead to scalable and efficient text classification solutions adaptable to various application domains[1], [2], [10].

3. Methodology

3.1 Datasets

This research evaluates traditional machine learning models for text classification using four datasets: the IMDB Dataset with 50,000 movie reviews for sentiment analysis, the SMS Spam Collection Dataset with 5,574 labeled SMS messages, the Amazon Product Review 2 Dataset with consumer reviews for binary sentiment analysis, and the Movie Review Polarity Dataset containing 2,000 balanced reviews for testing sentiment distinction [1], [2], [4], [5], [6], [9], [10].

- **IMDB Dataset:** This dataset includes 50,000 movie reviews in English, categorized into positive and negative sentiments. It serves as a vital resource for assessing the effectiveness of sentiment analysis models in distinguishing between positive and negative sentiments, as it is utilized for binary sentiment classification [1], [3], [6].
- **SMS Spam Collection Dataset:** Comprising 5,574 SMS messages in English, this dataset is labeled as either spam or ham (non-spam). It is essential for evaluating model performance in identifying unsolicited messages, as it is employed for binary text classification [2], [4], [9].
- **Amazon Product Review Dataset:** This dataset consists of numerous consumer reviews and star ratings from Amazon. The ratings are categorized for binary sentiment analysis, where ratings of 4 and 5 are

marked as 1 for positive reviews, while ratings of 1 and 2 are marked as 0 for negative reviews. Ratings of 3 are excluded from the analysis. This classification ensures a clear distinction between positive and negative sentiments, enhancing the effectiveness of sentiment categorization [6], [7].

- **Movie Review Polarity Dataset:** Containing 2,000 movie reviews, this dataset is evenly split into 1,000 positive and 1,000 negative reviews. It is a critical resource for evaluating the capability of sentiment analysis models to differentiate between positive and negative sentiments, as it is used for binary sentiment classification [8], [10].

3.2 Data Pre-Processing

Data preprocessing is vital for improving text classification model performance. It includes tokenization, lowercasing, and punctuation removal for clarity, along with eliminating stopwords to emphasize key terms. Numbers are discarded or transformed, and text normalization standardizes formats. Stemming and lemmatization refine words to their root forms, while removing special characters and HTML tags enhances content focus[1], [2], [3], [4], [5], [6], [7], [8], [9], [10].

- **Tokenization:** The text is divided into smaller units, such as words or tokens, to facilitate processing [3].
- **Lowercasing:** Text is converted to lowercase to maintain consistency and prevent confusion between similar words, like 'The' and 'the' [5].
- **Removal of Punctuation:** Punctuation is removed from the text to enhance clarity and focus on significant words [4].
- **Stopword Removal:** Common words like "and" and "the," which do not carry significant meaning, are eliminated to emphasize the most important terms in the text [7].
- **Number Handling:** Numbers are either omitted or transformed to maintain focus on textual content and minimize potential distractions [6].
- **Text Normalization:** Standardization of common text formats, such as dates, is performed to ensure consistency throughout the dataset [8].
- **Stemming:** Words are reduced to their root forms (e.g., "walking" to "walk") to facilitate searches by grouping related terms [9].
- **Lemmatization:** A more precise technique than stemming, lemmatization reduces words to their dic3 tionary forms (e.g., "better" to "good"), improving model accuracy during training [2], [9].
- **Special Character Removal:** Characters such as @, ^, *, (, and) are removed to improve clarity and conciseness [1].
- **Removal of HTML Tags:** HTML tags are stripped from the extracted text to focus solely on the content, which is essential for effective model training [10].

3.3 Approaches to Text Classification Using Machine Learning

Text classification has evolved significantly, driven by advances in (ML) algorithms and the availability of large labeled datasets [1], [6]. For tasks like sentiment analysis and spam detection, many approaches are utilized widely, such as (LRC), (SVM), (DTC), (RFC), (GNB), (MLP), and (KNN). [2], [3], [4].

- **Logistic Regression:** A binary classification's probability is modeled using logistic regression as follows: [5], [9]

$$P\left(y=1|x\right)=\frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\ldots+\beta_n x_n)}}$$

- **Support Vector Machines (SVM):** SVMs maximize the margin between classes, formulated as: [7], [8]

$$\min_{w,b}\frac{1}{2}\|w\|^2\ y_i\left(w\cdot x_i+b\right)\geq 1$$

- **Decision Trees Decision:** Trees used feature values to divide datasets, and the Gini impurity was determined by: [2], [6]

$$\text{Gini}(D)=1-\sum_{k=1}^{K}(p_k)^2$$

- **Random Forests:** For increased accuracy, Random Forests merge several Decision Trees; they are shown as: [9], [10]

$$\hat{y}=\text{majority}\left(\hat{y}_1,\hat{y}_2,\ldots,\hat{y}_M\right)$$

- **Gaussian Naive Bayes Gaussian Naive:** Bayes assumes Gaussiandistributed features, with the conditional probability given by: [8], [10]

$$P\left(x|C\right)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- **Multi-Layer Perceptrons (MLP):** MLPs are neural networks where the output y is computed as: [2] ,[4]

$$y=\sigma\left(\sum_{i=1}^{n}w_i x_i+b\right)$$

- **K-Nearest Neighbors (KNN):** KNN uses the majority class of the K closest neighbors to classify: [7], [6]

$$\hat{y} = \arg\max_{c \in C} \sum_{i=1}^{K} I\left(y_i = c\right)$$

4. Result and Analysis

4.1 Models Comparison

Following the fine-tuning process, all models exhibited an average enhancement of roughly 3 (Percentage) in their performance metrics. This fine-tuning involved the application of techniques such as grid search and random search to determine the best hyperparameter settings. Moreover, cross-validation methods were employed to ensure thorough evaluation and mitigate the chances of overfitting, which facilitated improved generalization on new, unseen data. These approaches aided in the more accurate calibration of each model, leading to consistent improvements in Correctness, Exactness, Sensitivity, Harmonic Score. In summary, the finetuning phase underscored the essential importance of optimizing parameters to boost the performance of machine learning models across various datasets.

Table 7.1 Comparison of various machine learning models on the IMDB dataset

Models	Correctness	Exactness	Sensitivity	Harmonic Score
(LRC)	**0.92**	**0.90**	**0.87**	**0.90**
(SVM)	0.90	0.87	0.89	0.88
(DTC)	0.75	0.73	0.71	0.73
(RFC)	0.88	0.85	0.82	0.83
(GNB)	0.85	0.81	0.83	0.82
(MLP)	0.90	0.89	0.87	0.88
(KNN)	0.82	0.79	0.76	0.80

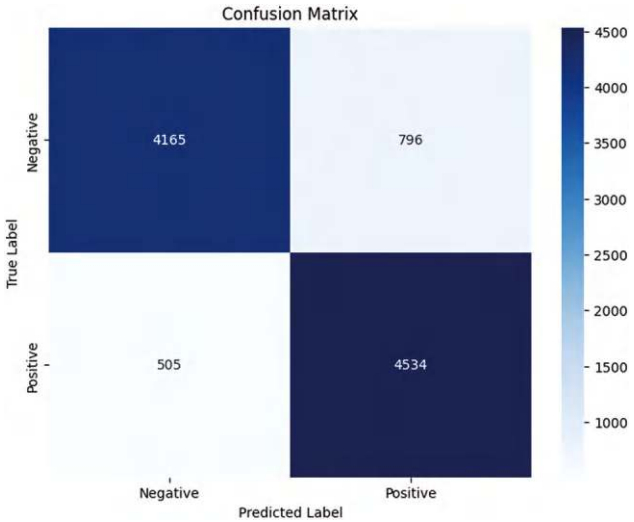

Fig. 7.1 Logistic regression achieves highest accuracy on the IMDB dataset

Table 7.2 Comparison of various machine learning models on the SMS spam collection dataset

Models	Correctness	Exactness	Sensitivity	Harmonic Score
(LRC)	**0.98**	**0.98**	**0.87**	**0.99**
(SVM)	0.97	0.85	0.85	0.99
(DTC)	0.97	0.93	0.86	0.99
(RFC)	0.97	0.98	0.83	0.90
(GNB)	0.87	0.53	0.89	0.93
(MLP)	0.98	0.98	0.89	0.92
(KNN)	0.87	0.87	0.99	0.93

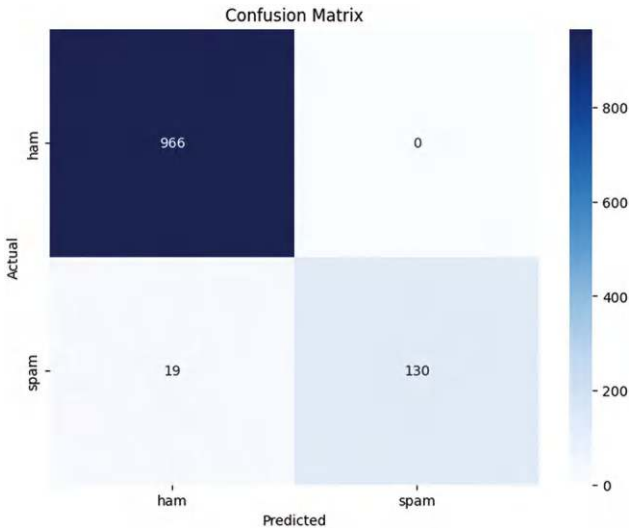

Fig. 7.2 Logistic regression achieves highest accuracy on the SMS spam collection dataset

Table 7.3 Comparison of various machine learning models on the amazon product review dataset

Models	Correctness	Exactness	Sensitivity	Harmonic Score
(LRC)	**0.88**	**0.86**	**0.84**	**0.86**
(SVM)	0.80	0.81	0.84	0.82
(DTC)	0.84	0.73	0.80	0.78
(RFC)	0.86	0.82	0.86	0.83
(GNB)	0.78	0.75	0.77	0.74
(MLP)	0.86	0.82	0.84	0.83
(KNN)	0.83	0.86	0.81	0.82

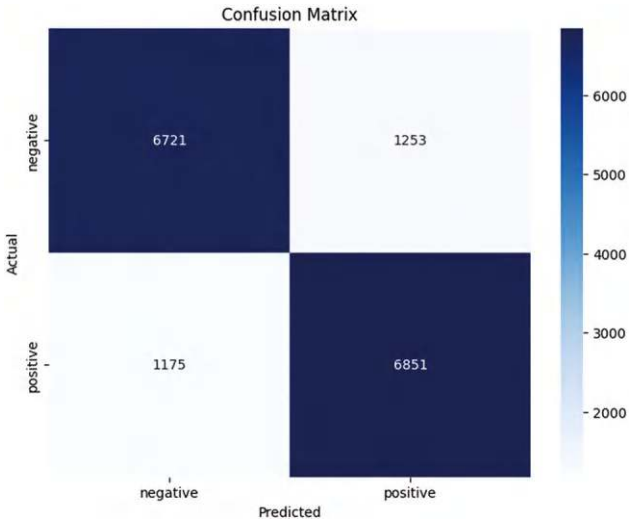

Fig. 7.3 Logistic regression achieves highest accuracy on the amazon product review dataset

Table 7.4 Comparison of various machine learning models on the movie review polarity dataset

Models	Correctness	Exactness	Sensitivity	Harmonic Score
(LRC)	0.86	0.84	0.85	0.83
(SVM)	0.82	0.81	0.80	0.82
(DTC)	0.75	0.72	0.73	0.71
(RFC)	0.84	0.83	0.80	0.81
(GNB)	0.84	0.81	0.83	0.80
(MLP)	**0.87**	**0.84**	**0.85**	**0.84**
(KNN)	0.85	0.82	0.80	0.85

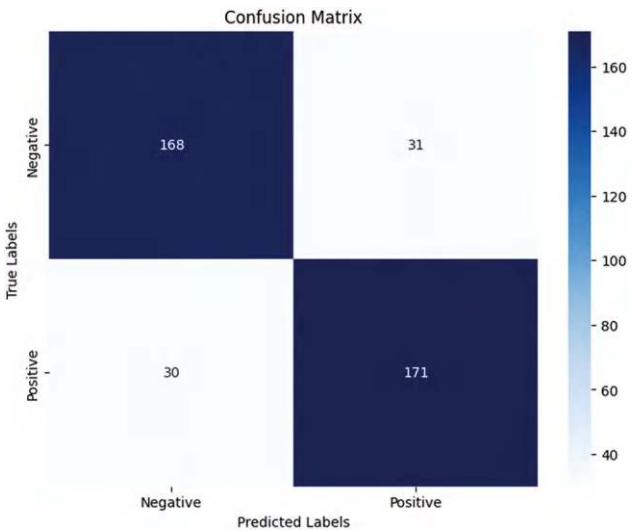

Fig. 7.4 MLP achieves highest accuracy on the movie review polarity dataset

Comparison of Datasets Params

Table 7.5 Parameter comparison across datasets

Datasets	IMBD	SMS Spam	Amazon N	Movie Reviews
Models	(LRC)	(LRC)	(LRC)	(MLP)
Train Params	40,000	4,457	64,000	1,600
Test Params	10,000	1,115	16,000	400

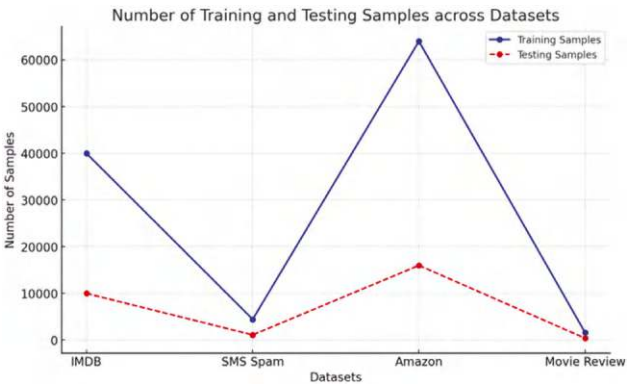

Fig. 7.5 Comparison of training and testing parameters across four different datasets

5. Conclusion

The present study undertakes an extensive analysis of various machine learning algorithms on text classification across diverse datasets, underlining the challenges posed by smaller datasets. We used four major datasets: IMDB movie reviews, SMS Spam, Amazon Product Reviews, and Movie Reviews, along with seven machine learning models: (LRC), (SVM), (DTC), (RFC), (GNB), (MLP), and(KNN).

Our findings show that (LRC) consistently delivered the best Correctness (accuracy) on the IMDB, SMS Spam, and Amazon Product Review datasets, proving its reliability for binary classification and sentiment analysis tasks. In contrast, the MLP model excelled on the Movie Review Polarity dataset, showcasing its strength in handling more complex sentiment analysis tasks.

These results indicate that (LRC) performs best for simpler text classification tasks, while (MLP) is better suited for more complicated sentiment polarity detection. Future work will expand on this by exploring these models across a wider range of data types, from simple to complex, and by incorporating advanced techniques such as deep learning and transfer learning. This aims to further optimize text classification systems and adapt them to increasingly complex, multi-modal datasets.

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8

Resilient Frequency Control of Islanded Microgrid Using Mother Optimization Algorithm

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Abstract: An islanded AC micro-grid system's robust frequency regulation under various uncertainties is demonstrated in this article using a PID controller based on the Mother Optimized Algorithm (MOA). By integrating multiple distributed generation systems (DG) based on renewable energy, a micro-grid is integrated. The energy storage of batteries (BES) and flywheels (FES) are two of energy storage devices included in the suggested micro-grid system, which is also equipped with wind turbine generators (WTG), photo voltaic systems, diesel engine generators (DEG), micro-turbines (MT), and aqua electrolyser based fuel cells (FC). In addition, a micro-grid system's frequency control mechanism receives input from an electric vehicle with a charging plug as load side demand. All DG systems have low inertia, high dynamics, and inherent uncertainties, which have a significant impact on system performance, particularly with regard to frequency. An innovative Mother Optimized Algorithm based PID controller is proposed in this paper to ensure that distant customers receive high-quality electricity in light of the need for a reliable control mechanism in islanded micro-grid systems. The effectiveness of the suggested MOA optimized PID controller is evaluated against traditional PSO and WOA technique based PID controllers to demonstrate the superiority of the suggested methods. It has finally been established that the proposed MOA based PID controller was more effective than earlier optimized controllers.

Keywords: Distributed generation system (DG), Frequency deviations, Islanded AC microgrid, Mother optimized algorithm (MOA), PID controller

1. Introduction

The majority of the conventional producing stations in the electricity system are negatively impacted by the paucity of fossil fuels. The idea of a microgrid and the renewable energy resources have been included into power system to address the lack of electrical power. Micro-grids are typically tiny digital grids with multiple distributed

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generators (DG) interwoven into them (Sahu et al., 2021). DG systems are specifically referred to as micro sources because they primarily rely on renewable energy sources for their power generation. From an economic perspective, a variety of micro sources provide electricity to far and isolated locations, however the usage of combustible fuels results in high CO2 emissions and higher transportation costs to these areas. Due to these drawbacks, alternative renewable energy sources (RES) are now being considered for the production of electricity. Sustainable energy sources, including solar, wind, biomass, tidal, and geothermal energy, are increasingly being used with microgrid systems to electrify the system. Because of their many benefits such as being environmentally benign and having minimal transmission losses these alternatives are becoming more and more popular for use in power systems. Although solar and wind power are widely employed, the addition of fuel cells (FC) to the power system guarantees a civilization free of carbon (Neeli et al., 2023). Because the specifications and operational conditions of wind generator systems and solar cells are constantly changing, isolated coordinate power systems are unable to provide continuous power (Sahu et al., 2018). Power is unstable as a result of these variable sources. Various energy storing system (ESS) will serve as power substitute source in a microgrid to ensure an uninterrupted power supply (Neeli et al., 2022). Because the specifications and operational conditions of wind generator systems and solar cells are constantly changing, isolated coordinate power systems are unable to provide continuous power (Sahu et al.,2019). Power is unstable as a result of these variable sources. Different energy storage systems (ESS) are being utilized as backup power sources within microgrid systems to guarantee a continuous and reliable power supply. (Saeedi et al., 2019). When there is not enough power, it supplies the extra electricity that is produced. The two types of energy storage systems employed nowadays are flywheels (FES) and battery energy storage systems (BES) (Neeli et al., 2020). This oscillation from the renewable energy source also results in a highly deviant voltage and frequency, which in turn leads to an undesirable imbalance between supply and demand. In order to provide electricity, particularly in rural and distant places, a microgrid is a compact digitally managed grid to which a numerous distributed generators (DG) were linked.

There are two main modes of operation for micro-grid structures: grid-connected mode and off-grid, or islanded mode (Clairand et al., 2018). Multiple instabilities arising in the micro-grid system have little effect on the micro-grid while it is connected to the grid; but, in off-grid or island scenarios, various uncertainties related to renewable sources have a significant impact on the micro-grid control. For power engineers, micro-grid regulation in an island setting presents enormous hurdles. In addition, a micro-grid system's frequency can be significantly impacted by a nonlinear electrical load, such as a large number of plug-in electric cars (EVs) (Faisal et al., 2018). Therefore, in order to control the power supplied by the swinging power sources, an efficient control strategy is always required. The best solution for these problems has not been shown to be conventional controllers. Driven by these issues, academics are focusing on strong controller design to achieve frequency balance, which would reduce the disparity between supply and demand for electricity. Because of these reasons, the current paper suggests using a Mother Optimized Algorithm (MOA) based PID controllers for the frequency regulation of electric vehicle operated with AC off grid based microgrid system in order to circumvent a few of the limitations of the preceding methodologies.

This manuscript makes the following contribution:

(1) Modeling a microgrid system is done using penetration of different renewable-sources, like fuel cells (FC), wind turbine generators (WTG), photovoltaic cells (PV), and micro sources, like micro turbines (MT) and diesel engine generators (DEG), along with some energy storage devices, such as flywheel and FES.

(2) To assess the microgrid system's dynamic performance, an electric vehicle's simplified transfer function model is applied as a load.

(3) The study suggests a strong PID controller to keep the AC microgrid system's frequency stable in the face of a variety of uncertainties, such as load fluctuations, variations in wind power, and variations in solar radiation power.

(4) To design the PID controller optimally across a range of working regions, a nature inspired mother optimization algorithm (MOA) is proposed.

(5) A relevant comparison study between WOA and PSO based PID controllers is used to validate the MOA based PID controller's effectiveness.

(6) Using various comparison analyses, it is demonstrated that the suggested MOA algorithm based controller is more viable than the Whale optimization algorithm (WOA) and Particle swarm optimization (PSO) based controllers.

2. Modelling of Proposed Islanded Microgrid

Transfer function expressions that have been simplified are used to model the suggested microgrid system. An

assortment distributed generation (DG) units, including diesel powered engine generators (DEG's), wind powered turbine generators (WTG's), photovoltaic cells (PV's), micro turbines (MT), & fuel cells based on aqua electrolysers (FC), are included in the microgrid. The conventional distributed generation system incorporates a few energy storage devices (ESD) such FES and BES to enhance power quality and reaction time. The microgrid system's secondary frequency control loop is made up of the DEG, MT, and FC. Nevertheless, because of their significant reliance on the environment, there is no secondary frequency control loop participation for WTG or PV. In order to test the microgrid system's dynamic characteristics, a battery-operated car is used as the load. Figure 8.1 shows a model of transfer function's basic concept of a microgrid system powered by electric vehicles. The corresponding transfer function expression for each component of the microgrid system is used to express it.

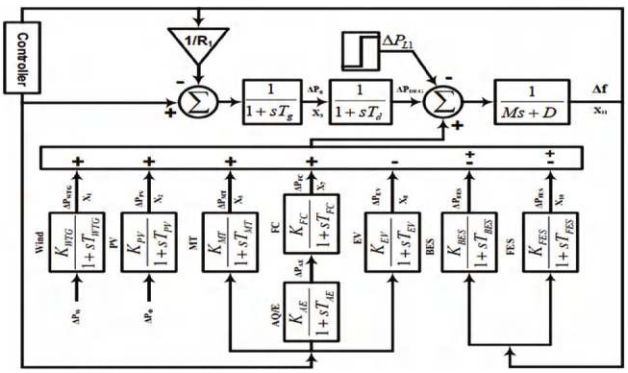

Fig. 8.1 Transfer function modelled of suggested system {9}

2.1 Wind Turbine Generator (WTG) System

One of the renewable energy sources that is reportedly expanding the fastest is wind energy, with a mean growth rate of roughly 21% over the last several years (Gao et al., 2019). Wind power is produced by converting the kinetic energy of moving air. Because the wind turbine is a nonlinear system, its pitch controller counteracts frequency oscillations in the power grid. Because of this, the pitch mechanism creates nonlinearities by adjusting the pitch angle in response to wind speed. The transfer function model for wind turbine generators (WTG's) in first order, is supplied by

$$G_{WTG}(s) = \frac{K_{WTG}}{1 + sT_{WTG}} \tag{1}$$

2.2 Solar (PV) System

Solar photovoltaic systems are another rapidly growing renewable energy mechanism. Solar radiation, which is variable owing to weather, is used to generate electricity in solar photovoltaic cells. The generated d.c. electricity is converted to a.c. by means of an inverter. The transfer function model base of the PV system can have represented in the following way

$$G_{PV}(s) = \frac{K_{PV}}{1 + sT_{PV}} \tag{2}$$

2.3 Diesel Generator Engine

When a diesel engine is used to drive the synchronous generator, it produces a sufficient amount of power output and the required torque. It acts as a backup generator to maintain the required load in the event that solar and/or wind power become unavailable. Because sudden variations in the customer's load are typical in microgrid, the prime mover at the diesel generator must be adequately effective in addition to having a quick, strong reaction. Diesel engine generators are non-linear models with respect to the time variable dead time between fuel injection and mechanical torque production. The governor adjusts the engine's fuel injection to make sure that the required amount of power is produced to keep the balance between generation and demand. This research looks at the first-order transfer function model for diesel generators

$$G_{DG}(s) = \frac{K_{DG}}{1 + sT_{DG}} \tag{3}$$

2.4 Plug-in-Electric Vehicle (PHEV)

Plug-in hybrid electric vehicles (PHEVs) are automobiles that run on super capacitors or batteries in addition to conventional gasoline (Hemmati et al., 2020). The plug-in hybrid electric vehicle (PHEV) harvests power from the grid, stores it for use during off-peak hours, and then feeds it back into the grid during peak hours. Its dual fuel capability (gas and electricity) makes it a great option for long-distance travel. The PHEV transfer function, according to first order

$$G_{PHEV}(s) = \frac{K_{PHEV}}{1 + sT_{PHEV}} \tag{4}$$

2.5 Power and System Frequency Deviations

When a disruption occurs in the system, the primary factor affecting the frequency is the imbalance in total power, also known as active power, or ΔPe. It is challenging to maintain system frequency in a microgrid that is fuelled by wind and solar energy. The selection of a suitable control method that effectively preserves active power balance through adjustments to the generator component's output and controlled load guarantees the microgrid stable operation. Since active power mismatch is the primary cause of

frequency variation, the main objective is to maintain the balance between active power generation and demand. For the purpose of referencing the difference between power generation (PS) and load demands (PLOAD)

$$\Delta P_e = P_S - P_{LOAD} \tag{5}$$

ΔPe is expressed through equation

$$\Delta P_e = P_{WTG} + P_{PV} + P_{DEG} + P_{MT} + P_{FC} \pm P_{BESS} \pm P_{FESS} - P_{LOAD} - P_{EV} \tag{6}$$

System frequency variations and power discrepancies in real-world scenarios are accompanied by an inherent temporal lag. Thus, represents the transfer function model of the power system for the system frequency variations to their active power deviations per unit.

$$G_{sys}(s) = \frac{\Delta f}{\left[P_S - P_{LOAD}\right]} = \frac{1}{K_{sys}\left(1 + sT_{sys}\right)} = \frac{1}{Ms + D} \tag{7}$$

3. Formulation of the Problem

The microgrid (PID) controllers have optimized parameters to minimize the goal function. ISE, or integral square error, of the frequency deviations is the chosen objective function (J) and can be shown as follows:

$$J = \int_0^{T_{Sim}} \left(\Delta f\right)^2 dt \tag{8}$$

The objective is to reduce J while taking into account the following restrictions,

$$\begin{aligned} K_P^{\min} \le K_P \le K_P^{\max} \\ K_I^{\min} \le K_I \le K_I^{\max} \\ K_D^{\min} \le K_D \le K_D^{\max} \end{aligned} \tag{9}$$

The greatest and lowest values for the Kp, Ki, and Kd values for controller are in the range of [0 and 1].

4. Outline of MOA Algorithm

The metaheuristic optimization method known as the Mother Optimization Algorithm (MOA) is inspired by the natural reproductive process (Matoušová et al., 2023). In order to find the best answers within a given search space iteratively, it imitates the processes of reproduction, mutation, and selection. MOA technique can be used for effectively distribute and to control the vitality flow from distinct renewable energy sources, including wind and solar power, in addition to conventional ones, such grid connectivity, concerning energy control in a renewable energy hybrid system (Sailaja et al., 2024). MOA contributes to improving energy efficiency, lowering costs, and guaranteeing system dependability by dynamically modifying the patterns of production and utilization of energy according on system restrictions. It is an affirmative technique for maximizing the hybrid renewable power system's efficiency due to its capacity to tackle intricate, nonlinear, and multi-objective optimization issues.

The Algorithm steps are furnished below

Step 1: Initialization procedure

Set up the input parameters initially.

Step 2: Arbitrary vector creation

The input parameters are randomly generated by the random vectors once they are configured.

$$Z = \begin{bmatrix} Z_1 \\ Z_j \\ Z_M \end{bmatrix}_{M \times E} = \begin{bmatrix} Z_{1,1} & Z_{1,i} & Z_{1,E} \\ Z_{j,1} & Z_{j,i} & Z_{j,E} \\ Z_{M,1} & Z_{M,i} & Z_{M,E} \end{bmatrix} \tag{10}$$

Utilizing the interval [0,1] and the function rand (0, 1), a random uniform value is generated, where Z represents the population matrix of the proposed MOA, M represents the total number of persons in the population, E denotes the number of decision variables, and Zj,i is the ith variable.

Step-3: Computing the fitness-function

Fitness is dependent on the objective function. The fitness function is defined as

$$J = \int_0^{T_{Sim}} \left(\Delta f\right)^2 dt \tag{11}$$

Table 8.1 Gain values of MOA, WOA and PSO optimized PID controllers

Parameters	Case 1			Case 2			Case 3		
	MOA	WOA	PSO	MOA	WOA	PSO	MOA	WOA	PSO
KP	0.8147	0.6872	0.4613	0.9005	0.8474	0.2254	0.8258	0.6705	0.4313
KI	0.2576	0.3868	0.2309	0.6627	0.6070	0.6342	0.8363	0.4727	0.4961
KD	0.6557	0.3918	0.3387	0.4971	0.3032	0.2904	0.7057	0.9616	0.1338
ISE	**0.0394**	**0.0524**	**0.0742**	**0.0036**	**0.0047**	**0.0122**	**0.2486**	**0.4032**	**0.8653**

Step 4: Education (The Exploration stage)

Children's education serves as an inspiration for the "Education" phase of population update in the planned MOA strategy. Through major positional changes, it aims to enhance global search and an explorations capability. In the MOA design, the mother was observed as the most knowledgeable person among the population, so her behaviour as a teacher is emulated during the education phase. During this step, a unique position is determined for each member using Equation (12). The objective function value grows at the novel site, indicating that it is the proper member's position, as shown by Eq. (13).

$$Z_{j,i}^{Q1} = Z_{j,i} + rand(0,1) \cdot (N_i - rand(2) \cdot Z_{j,i}) \quad (12)$$

$$Z_i = \begin{cases} Z_j^{Q1}, E_j^{Q1} \le E_j \\ Z_j, \quad else \end{cases} \quad (13)$$

where Ni represents the ith dimension of mother positions and Zji denotes the ith dimension of the member of the jth population's position. For every individual in the jth population, the new location Zj, ZjQ1 is formulated based on the initial phase of the MOA. Function rand (0, 1) provides same count at the random in the interval [0,1] and rand (2) is the random function that reliably generates a random count from the set {1,2}. Its jth dimension is shown by ZjiQ1, and its objective function value is indicated by EjQ1.

Step 5: Guidance/Advice (The Period of exploitation)

Among the most important responsibilities of a mother is to counsel her children and to stop misbehaving. The mother's advice to the kids is used to construct the second phase of updating the population in the MOA. The advice phase significantly alters the positions of the population members, enhancing the MOA's ability to conduct global search and exploration. As per the MOA style, when an individual in the population has greater objective function values than those of other population members, their position in relation to other individuals is considered abnormal and should be avoided. The collection of unfavourable actions/behaviours (DDj) for each member is determined by comparing values of the goal function using Eq. (14). From the generated collection of unpleasant behaviours (DDj) for each Xi, a member is randomly selected in an equal manner. To mimic shielding the child from misbehaviour, a novel posture is first created for each member using Eq. (15). Then, if this new location raises the value of the objective function, it replaces the linked member's previous position using Eq. (16).

$$DD_j = \{Z_K, E_K > E_j^K \in \{1,2,.....M\}\} \quad (14)$$

$$Z_{j,i}^{Q2} = Z_{j,i} + rand(0,1) \cdot (Z_{j,i} - rand(2) \cdot SDD_{j,i}) \quad (15)$$

$$Z_i = \begin{cases} Z_j^{Q2}, E_j^{Q2} \le E_j \\ Z_j, \quad else \end{cases} \quad (16)$$

ZjiQ2, on the other hand, denotes the unique position found for the jth population member in subsequent phase of the planned MOA. rand (0, 1) yields an uniform count that is arbitrary in the range [0, 1], while rand (2) is the arbitrary/ random function that reliably yields an arbitrary/ random count from a set {1, 2}. EjQ2 is its value as an objective function. DDj is the collection of inappropriate conduct for the jth member of the population, SDDj,i represents the selected unsuitable behaviours, and SDDj,i is the ith dimension respectively.

Step 6: Raising/Upbringing (the era of exploitation)

Moms help their children in many ways to boost their academic abilities. By gently moving the population members' positions, the parenting enhances the possibility of local search and exploitation during the MOA period. Eq. (17), simulates parenting stage, every member of all population was originally assigned a fresh position depends on modeling of children's personal expansion. According to equation (18) objective function value increases at the fresh place, the respective member new positions are substituted for the previous one.

$$Z_{j,i}^{Q3} = Z_{j,i} + (1 - 2 \cdot rand(0,1)) \cdot \frac{va_i - la_i}{t} \quad (17)$$

$$Z_i = \begin{cases} Z_j^{Q3}, E_j^{Q3} \le E_j \\ Z_{j,} \quad else \end{cases} \quad (18)$$

The rand (0, 1) function randomly produces an integer in an interval period [0, 1], where t denotes real value of an iterations counter, ZjiQ3 is the ith dimension, and EjQ3, its objective function value corresponds to the new position for the jth population member, in accordance with the third stage of the proposed MOA.

Step 7: Criteria for termination

Check if the termination criteria are met; if not, carry out the process again. This indicates that the best solution has been discovered.

5. Simulations and Evaluations

The presentation of several dynamic responses or deviations in area frequency (Δf), in response to diverse system uncertainties (ΔPL, ΔPW, and ΔPϕ) in the presence of various optimal controllers is the subject of this section. In order to produce the above response, the islanded AC Micro grid system's transfer function model

is constructed in the environment for Simulink, and the required programs are written in MATLAB2016 software's (.m file) using a system with an i-5 CPU and 4GB of RAM. In order to identify distinct dynamic responses, the system inconsistencies are first affected discretely and then collectively for load frequency control. Regarding the islanded AC Micro grid system's LFC research, three distinct cases are taken into consideration.

Case-1: Load variation (ΔPL),

Case-2: Wind power fluctuation (ΔPW),

Case-3: Solar irradiation power fluctuation (ΔPϕ)

A nature-inspired Mother Optimization Algorithm (MOA) has been constructed to acquire optimal gain values for the suggested robust PID controller, which is intended to manage the secondary frequency of the island-based MG system's secondary frequency. When considering its performance against WOA and PSO optimized PID controllers, the PID controller's feasibility is validated. A number of comparison investigations show that the suggested MOA algorithm is more effective than WOA and PSO approaches.

Case 1: Load variation (ΔPL)

In this scenario, a random pattern load (RLP), as seen in the Fig. 8.2, is used to determine the LFC of an islanding MG system. is added to the system mean while the impact of wind and solar power disturbances is zero (ΔPW = 0, ΔPϕ = 0). This section shows the varied frequency responses to this disturbance that were caused by various optimal controllers. Figure 8.3 shows the relative frequency deviation caused by MOA, WOA, and PSO optimized PID controllers, respectively. The suggested MOA optimized PID controller has been found to significantly improve all

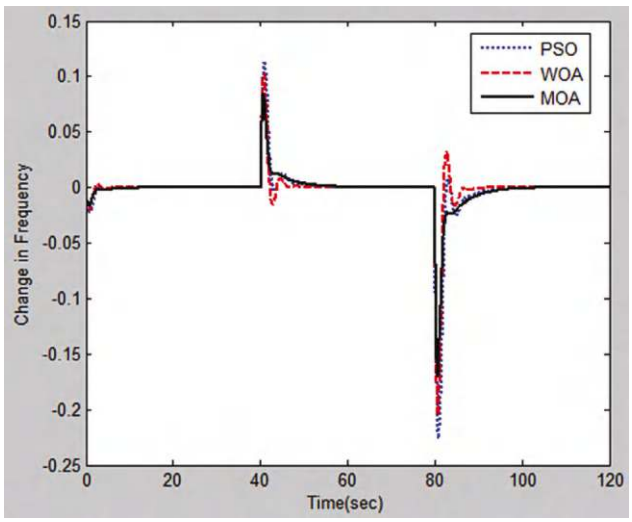

Fig. 8.3 Frequency deviation due to (ΔP_L)

dynamic responses, despite of their settling times, peak overshoots, and peak undershoots. Therefore, compared to previous established controllers for the MG system's load frequency management, our suggested technique shows greater efficacy.

Case 2: Wind power fluctuation (ΔPW)

To examine the frequency responses of islanded microgrid, a randomly produced wind power, as seen in Fig. 8.4, is applied to the micro-grid system. In this context, Figure 8.5 shows the variation in frequency response caused by MOA, WOA, and PSO optimized PID controllers under such uncertainty. In comparison to the other PID controllers, the MOA optimized controller performs better, as seen by the frequency response. Table 8.1 respectively, shows gain values of controllers that have been optimized with

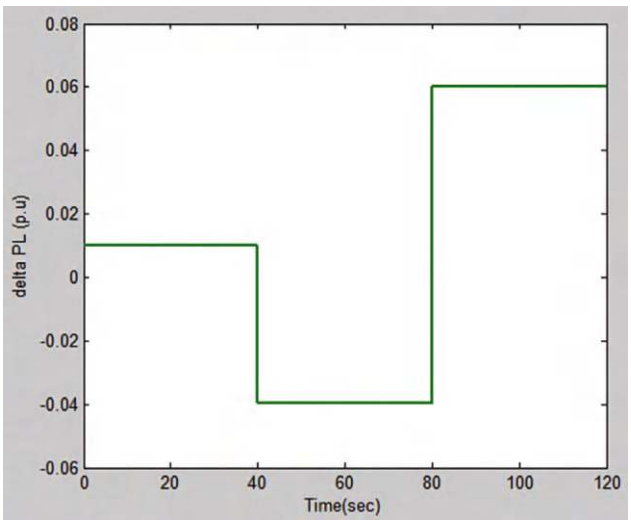

Fig. 8.2 Variation of load (ΔP_L)

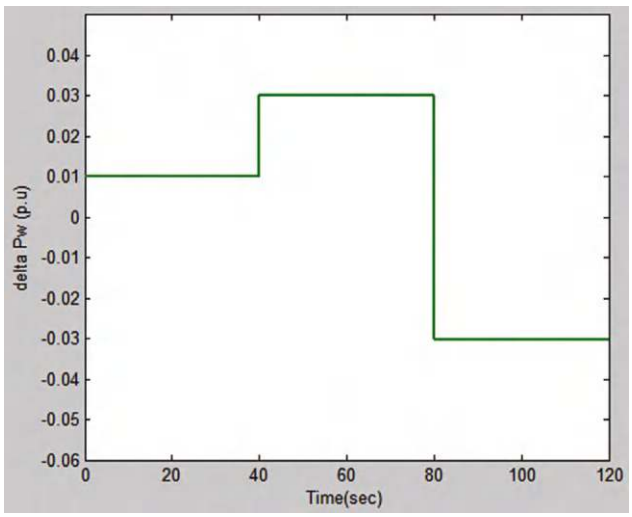

Fig. 8.4 Variation of wind power (ΔP_W)

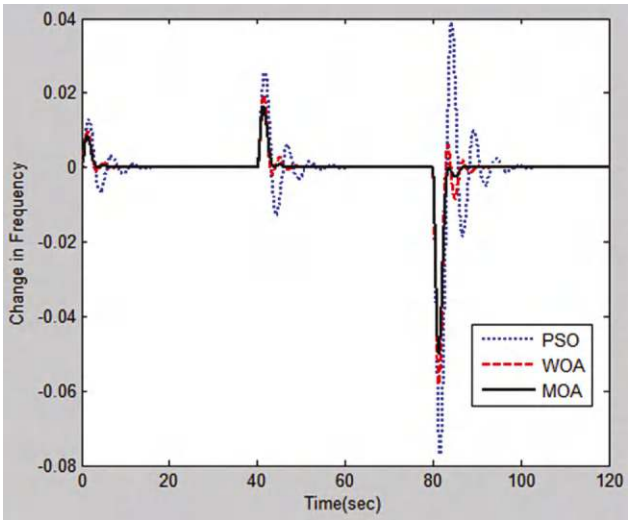

Fig. 8.5 Frequency deviation due to (ΔP_W)

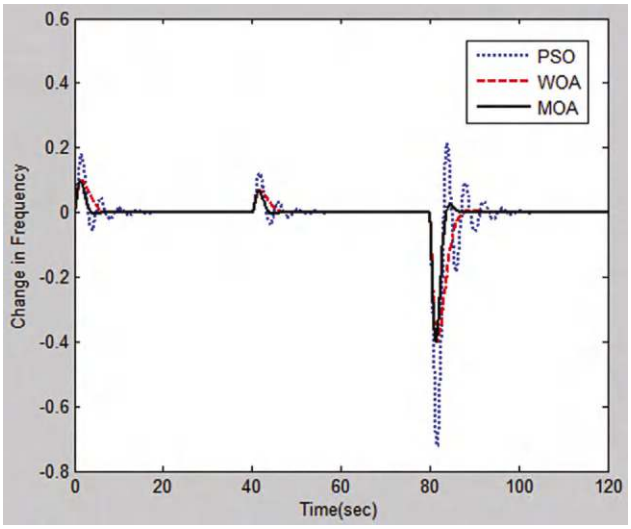

Fig. 8.7 Frequency deviations due to (ΔP_ϕ)

the PSO, WOA and MOA. The performance index such as ISE values are gathered in Table 8.1. The Table 8.1 shows a notable improvement in all performance index values as a result of the MOA optimized PID controller.

Case 3: Solar irradiation power fluctuation ($\Delta P\phi$)

An analysis of frequency regulation under several regulated ways is conducted in the proposed EV based microgrid by varying the solar irradiation power, as depicted in the Fig. 8.6. Figure 8.7 shows the system frequency's regulated dynamic response under such a disturbance. With the MOA optimized PID controller, the frequency response settles more quickly and with less peak overshoot. Nevertheless, a longer settling period and more peak overshoot are necessary to get the frequency response achieved with a WOA and PSO optimized PID controller. This gives the suggested MOA optimized PID controller a quicker reaction time to achieve system stability. The results of the investigation indicate that the suggested MOA optimized PID controller performs better than the optimal WOA and PSO optimized PID controllers and greatly enhances system performances.

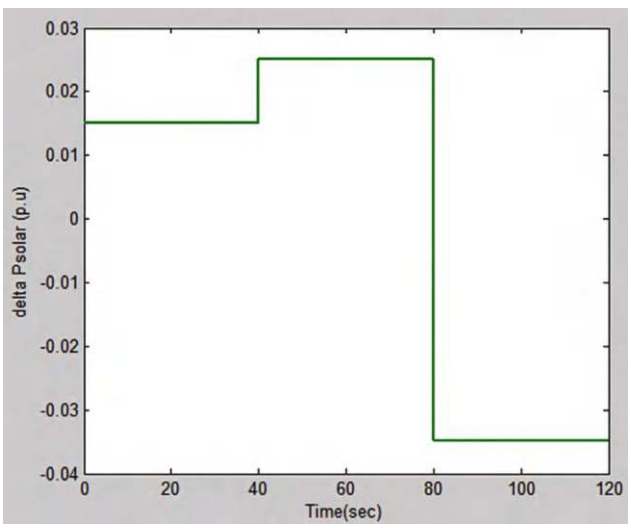

Fig. 8.6 Variations of solar radiation power (ΔP_ϕ)

6. Concluding Remarks

For an EV-powered AC microgrid structure with frequency management, this research recommends a MOA based PID controller. The intense performances of the microgrid were examined beneath a range of uncertainties, including variations in solar irradiation power, wind power fluctuations, and load dynamics. It is discovered that under a variety of uncertainties and with an electric vehicle plugin, the suggested MOA optimized PID controller performs better at controlling frequency in an islanded AC microgrid system. For the purpose of demonstrating the suggested controller's efficacy, its performance has been compared to those of WOA and PSO based PID controllers. An appropriate comparison examination over the PSO and WOA algorithms for the micro-grid control mechanism has demonstrated the viability of the proposed MOA technique. The overall study and the critical discussions of various quantity findings and vibrant response will establish the superiority of the proposed MOA optimized PID controller for islanded micro-grid system frequency management. In light of this, it can be concluded that the proposed control system operates very well in terms of both integral square error and frequency regulation under all circumstances.

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Note: All the figures (except Fig. 8.1) and table in this chapter were made by the authors.

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9

Predictive Analysis of Cloned Voice to Commit Cybercrimes Using Generative AI Scammers

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Abstract: Cyber Crime teams a new impersonation scam using Voice cloning and urges public caution about unsolicited calls on mobile phones. Cyber fraudsters are using advanced AI technology to mimic the voices of trusted individuals, such as family members, over phone calls, according to police. The calls, disguised as emergencies, deceive victims into transferring money quickly, exploiting their trust by creating a sense of urgency or distress. Police emphasise the need for awareness and caution in preventing residents from falling victim to evolving cybercrimes due to their

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sophistication. The Cyber Crime Wing reports that a scam involves a scamster posing as a trusted friend or family member, claiming urgent financial assistance due to a fabricated threat, and using emotional distress tactics to elicit help. Scammers use advanced AI software to impersonate victims, cloning their voice and intonation using social media posts or phone conversations, using 'wrong number' tactics to convincingly impersonate them. Scammers employ an AI-generated cloned voice to commit cybercrimes. Scammers often demand that victims transfer money to resolve crises, often using fast payment methods like the UPI system. Victims may comply without verifying caller authenticity or situation legitimacy. After transferring money, victims may realise they were deceived and suffer financial loss, feeling betrayed, violated, and emotionally distressed. Urges people to ask detailed inquiries and confirm callers' identity, especially when requesting financial assistance. Along with traditional schemes like voice cloning fraud, it also cautions about unsolicited money solicitations. Report it to Cybercrime if a victim is impacted. This paper proposes that the above-mentioned predictive analysis of cybercrimes focuses on clone voices, threatening victims with distress calls, and demanding large sums of money in these types of cases to solve cybercrime cases through Advanced Artificial Intelligence technology.

KEYWORDS: Cyber crime, Voice cloning, Advanced AI technology, Mimicking voices, AI-generated cloned voice, etc.

1. INTRODUCTION

Cybercrime Police warn about a new artificial intelligence (AI) voice copying fraud. According to police, con artists were now using artificial intelligence (AI) to mimic the voices of victims. These victims would receive phone calls sounding like friends or family members who were in need, and they would be requested to send significant amounts of money right away to support their loved ones. The public is being cautioned about unwanted calls they get on their mobile phones by the Cyber Crime Wing of the Police, which has released an advisory regarding a new impersonation fraud that leverages AI (Artificial Intelligence) voice cloning. According to police, cybercriminals increasingly use voice cloning—a sophisticated AI technique—to mimic family members' and other reliable people's voices during phone calls. Under the guise of an emergency, the calls trick victims into sending money immediately by instilling a sense of urgency or concern, taking advantage of their confidence. According to the police, this strategy demonstrates the increasing sophistication of cybercrimes and underscores the significance of awareness and caution in preventing residents from being victims of such fraudulent schemes.

According to the Cyber Crime Wing, the con starts when a con artist calls the victim and pretends to be someone they know and trust, like a friend or family member. Scammers can invent an emergency or threat to justify their desperate need for money. The con artist employs a variety of strategies to make the victim feel rushed and distressed. They may start crying or make imploring sounds, saying they are in a terrible predicament and need assistance immediately. The con artist uses advanced artificial intelligence algorithms to replicate the target's voice behind closed doors. They obtain a voice sample of the individual from social media posts or videos or use the "wrong number" trick to speak with them over the phone. Thanks to this technology, they can successfully impersonate the victim's trusted contact's voice, intonation, and emotional nuances. Cybercrime Division, "In simple terms, the scammers use an AI-generated cloned voice to commit cybercrimes."

The fraudster asks the victim to send money right away in order to help them fix the situation once they have gained the victim's confidence and sense of urgency. They frequently advise using quick and easy payment options like the Unified Payments Interface (UPI) system to speed up the transaction. Motivated by worry and a wish to support their loved one, the victim can heed the scammer's requests without checking the veracity of the scenario or the caller's identity. When the victims independently contact their family members or acquaintances and learn that they were never in difficulty or in need of financial aid after the money transfer is finished, they may later realise that they have been duped. In addition to losing money, the victim may also experience mental pain, feelings of betrayal, and violation after realising they were duped, according to the police.

The public must be sure the caller is who they claim to be before acting, especially if they are demanding emergency financial assistance. They should also ask follow-up questions or contact a friend or relative using a known, trustworthy number. He also asked people to learn to recognise red flags and be cautious of common con tricks, like this voice cloning scam. He cautioned against giving in to sudden demands for money, especially if they involve

emotional blackmail or grave situations, such as if you think you may have been a victim of this type of fraud or have observed any unusual activity.

2. Literature Survey

We are focused on referring to various articles to solve the problem. This involves exploring existing research, studies, and findings on using advanced artificial intelligence technologies for malicious purposes such as impersonation scams. Below is an organised literature survey that covers critical areas of interest, including definitions, techniques, case studies, countermeasures, and future research directions.

Goodfellow et al. (2014) introduced GANs, which consist of two neural networks, a generator and a discriminator competing. This adversarial setup has been extensively utilised in voice cloning to create high-quality, realistic-sounding speech.

Zhang et al. (2021) highlight the effectiveness of data preprocessing, such as noise reduction and segmentation, to improve the quality of cloned voices.

Shen et al. (2018) and van den Oord et al. (2016) emphasise the use of neural network-based voice synthesis models (e.g., WaveNet, Tacotron) that can produce highly realistic cloned voices from minimal data.

Wu et al. (2020) discusses the development of real-time voice conversion tools that allow attackers to modify their voice to mimic others instantly during phone calls or video conferences.

Symantec (2019) described an incident where scammers used AI-based voice cloning to impersonate a CEO's voice, convincing an employee to transfer €220,000 to a fraudulent account.

CNET (2020) covers instances where criminals used cloned voices to mimic distressed family members, requesting urgent financial assistance from relatives or friends.

The Federal Trade Commission (FTC, 2022) documented a rise in AI-generated robocalls that clone voices and automate impersonation attacks at scale, targeting millions of users.

Tiwari et al. (2022) proposed enhancing user authentication with multi-factor verification, combining voice biometrics with other factors like passwords or one-time codes to prevent unauthorised access.

Research by Kim et al. (2021) focused on developing machine learning algorithms to detect anomalies in voice patterns and recognise cloned voices by analysing acoustic features that are hard for AI models to replicate.

Hwang et al. (2021) have pointed out the potential misuse of publicly available audio data. A significant challenge involves balancing the development of voice cloning technology with concerns over privacy, data security, and ethical considerations.

3. Proposed Work

The Cyber Crime Wing is reporting a new impersonation scam using voice cloning. The scam involves scammers impersonating victims using advanced AI technology disguised as emergencies and demanding quick money transfers. The calls are disguised as emergencies, and victims are tricked into transferring money without verifying the caller's authenticity. The paper urges public caution and reporting of unsolicited money solicitations to Cybercrime. It also suggests a predictive analysis of cybercrimes focusing on clone voices, distress calls, and large sums of money to solve these cases.

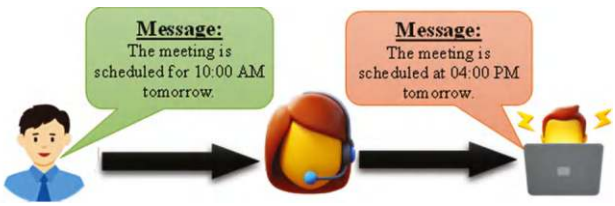

Fig. 9.1 Message transfer without encryption

3.1 Privacy Secure-based Voice Clone Classification

In the ever-evolving digital landscape, safeguarding your data is like finding the perfect match. That's where encryption steps in as your trusty wingman. Encryption is a process used to protect data from unauthorised access and manipulation. It is a way of scrambling data so that it can only be read by someone with the correct "key" to decrypt it.

a) Suppose we are working with a team from Offshore and Onshore; to communicate in between, we would require a network bridge over here to pass the message. Example: Aadhya receives the message from offshore and passes it to the onshore person, but she manipulates it. Due to this, China missed the meeting. We don't have any privacy between the source and destination as the message has to pass only through the third-party person.

   Golden Rule: When it comes to DATA, Never Trust Anyone. Protection of your Data always.

b) To avoid being manipulated data, Raj sends the encrypted message to Aadhya, and Aadhya passes it to China. But how does China read the encrypted

message? That's where Raj will share the standard secure key with China, and China will read the decrypted message using an encrypted key he received. Middleman (Aadhya) will not understand what message it is.

Golden Rule: To protect our data, we must ensure that the encapsulated layer masks the actual data inside it.

c) In an outer layer, Raj encrypts the message and sends it to Chinna; the Encryption Key is used to Cipher/Decipher the message. Finally, Chinna will use the encryption key to decrypt the message for reading.

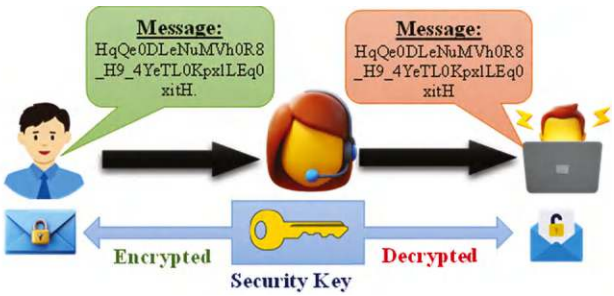

Fig. 9.2 Message transfer with encryption

Masked Language Modelling is a crucial approach in Language Modelling that trains models to predict masked tokens in input data, improving their understanding of word distributions and text generation.

3.2 Large Language Model

Once the model architecture is chosen, the significant steps involved in training an LLM include data preparation (collection, cleaning, deduping, etc.), tokenisation, model pretraining (in a self-supervised learning fashion), instruction tuning, and alignment.

- ***Data Cleaning:*** The effectiveness of language models trained on data depends on its quality. Filtering and deduplication are two examples of data-cleaning procedures that greatly influence model performance.
- ***Tokenization:*** Tokenization breaks up a text sequence into smaller units called tokens. Most tokenization programs rely on a word dictionary, while the simplest one divides text into tokens based on white space.
- ***Positional encoding:*** The original Transformer model used Absolute Positional Embeddings to maintain sequence order information. Therefore, the positioning information of words is added to the input embeddings at the bottom of both the encoder and decoder stacks. Positional encodings come in two varieties: fixed and learnt.
- ***LLM Architectures:*** The three most popular LLM architectures are encoder-only, decoder-only, and encoder-decoder. The majority of them use Transformers as their foundation.
- ***Model Pre-training:*** Pre-training, the initial phase of a large-scale language model training pipeline, aids LLMs in gaining basic language comprehension skills that are useful for a variety of language-related jobs. The LLM is taught on a vast number of (often) unlabeled texts during pre-training, typically under the guidance of a supervisor.
- ***Fine-tuning and Instruction Tuning:*** BERT and other early language models were taught by self-supervision. The foundation model required to be supervised and fine-tuned, or SFT for short, to a particular task with labelled data in order for it to be considered valid.

For example, the model was fine-tuned to different tasks in the original BERT. While more recent LLMs no longer require fine-tuning, they can still benefit from task or data-specific fine-tuning. The figure is prominent, and more parameters must be considered here, like alignment, decoding strategies, etc.

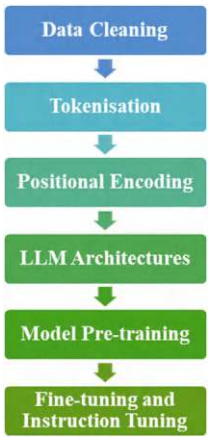

Fig. 9.3 Working structure

3.3 Masked Language Modelling

This method is used to predict the distribution of words in text data, a technique that has been used since BERT. The model trains to learn word probabilities using a prediction matrix with sequence and vocabulary dimensions, focusing on masked words in input data positions. The prediction matrix with a specific dimension depends on the prediction head used. The Language modelling head is a linear layer with input features of [Hidden state size] and output features of [Vocabulary size]. The linear layer is a projection matrix resizing the hidden state to vocabulary size. The model is trained by comparing predictions for masked words, with

all other words ignored, typically using the cross-entropy loss function for LLM prediction. To generate a sequence at inference time, the most straightforward strategy is to choose the word with the highest predicted probability and auto-regress. This involves selecting the word with the highest probability for the second word and then iterating until an ending condition is met.

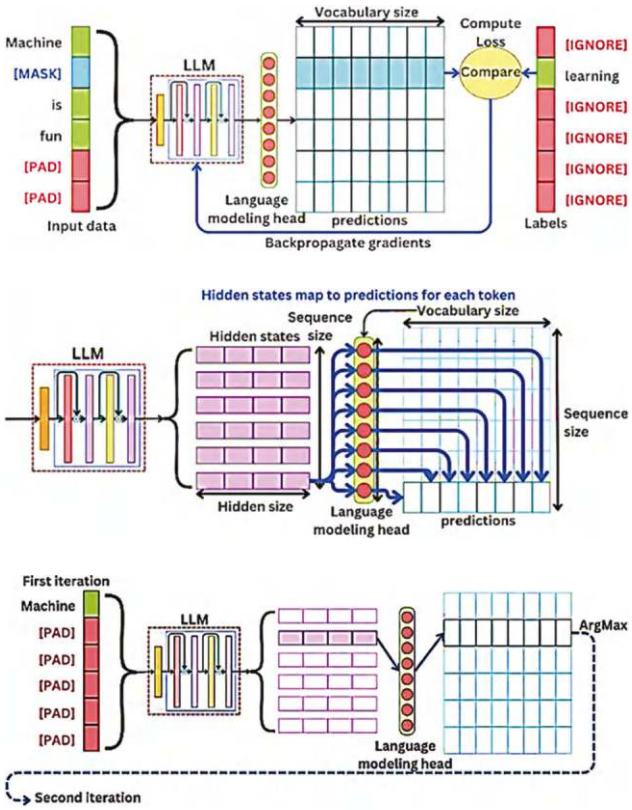

Fig. 9.4 Evaluation procedure

4. Experiment Results

We will simulate a basic communication scenario where data is sent securely between two parties, ensuring an intermediary (a middleman) cannot manipulate or read the message.

Encryption Key Generation: Raj generates a symmetric encryption key using the Fernet algorithm. Symmetric encryption means the same key is used for both encryption and decryption.

Encrypting the Message: Raj encrypts the original message using the generated key, transforming it into an unreadable format.

Passing Through the Middleman: Aadhya, the middleman, sends the encrypted message. Since it is encrypted, Aadhya cannot understand the content.

Decryption by the Recipient: Chinna, the intended recipient, uses the shared encryption key to decrypt the message back to its original form.

The message is protected from unauthorised access or manipulation during transmission. Only the intended recipient with the correct key can read the message.

Encryption is vital in securing communications and protecting sensitive data from cyber threats. For example,

Raj's Original Message: Meeting is scheduled at 10 AM tomorrow.

Raj's Encrypted Message: CchM5oFworOfqgCg8I50Lw

Aadhya receives the encrypted message and forwards it to Chinna.

Chinna's Decrypted Message: Meeting is scheduled at 10 AM tomorrow.

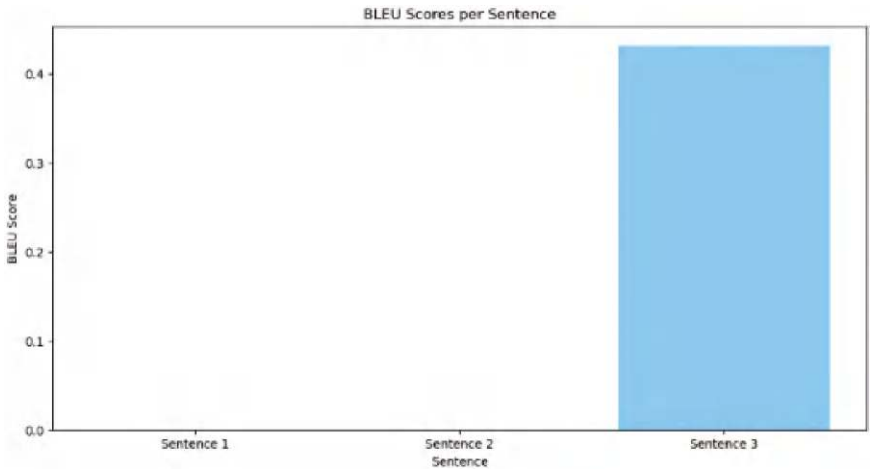

Fig. 9.5 BLEU score report

A Large Language Model (LLM), it's crucial to use a variety of metrics that assess different aspects of its performance, such as its ability to understand context, generate coherent responses, and maintain relevance. Since LLMs are often used for tasks like text generation, translation, summarisation, and question answering, the metrics must capture both general and task-specific aspects.

BLEU Score (Bilingual Evaluation Understudy Score): The BLEU score is commonly used to evaluate the quality of machine-translated text against one or more reference translations. It can also assess LLMs for tasks like text generation or summarisation.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation): ROUGE is a set of metrics for evaluating automatic summarization and machine translation. It compares an automatically produced summary or translation against a reference.

ROUGE-N: Measures the overlap of n-grams.

ROUGE-L: Measures the longest common subsequence between the generated text and the reference.

ROUGE-W: A weighted variant of ROUGE-L.

F1 Score: The F1 score is the harmonic mean of precision and recall. It's beneficial for evaluating tasks involving binary or multilabel classification (e.g., named entity recognition and question answering).

Accuracy: Accuracy measures the proportion of correct predictions made by the model.

BLEU Score: Evaluates the similarity of generated text to reference text using nltk.

ROUGE Score: Computes ROUGE-1 and ROUGE-L scores using rouge_score for different types of n-gram overlaps and longest common subsequence overlaps.

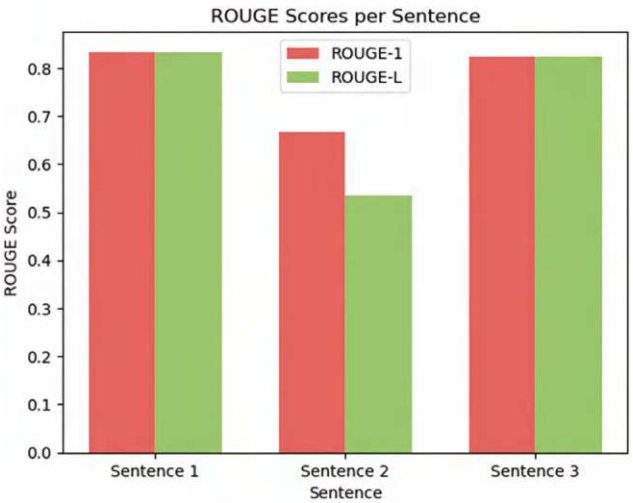

Fig. 9.6 ROUGE Report

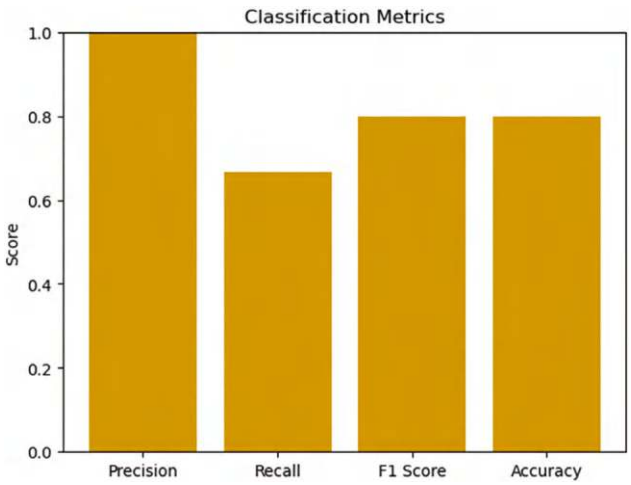

Fig. 9.7 Performance metrics evaluation report

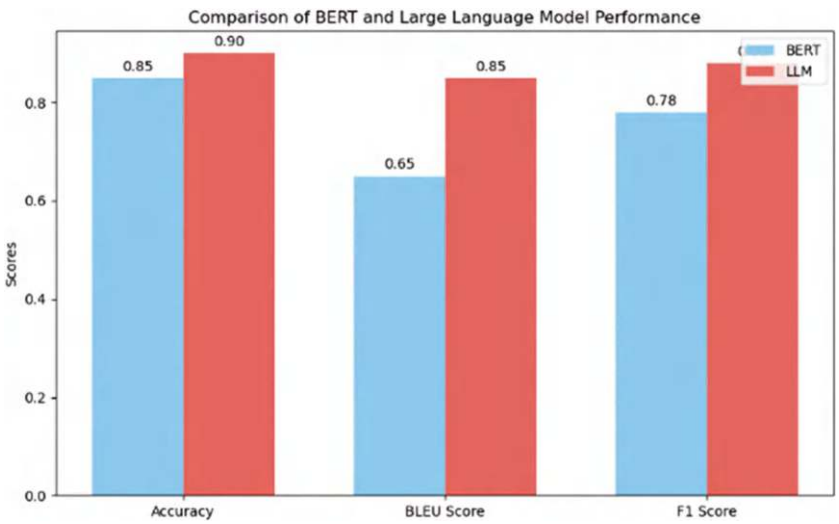

Fig. 9.8 Performance metrics comparison report

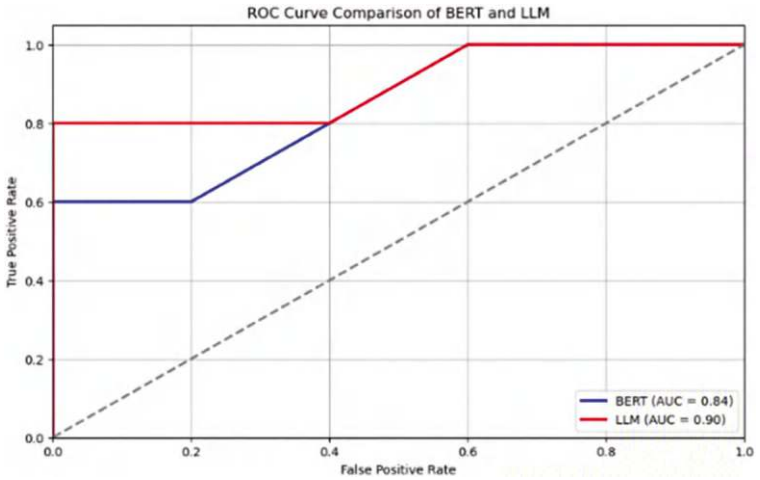

Fig. 9.9 ROC curve comparison BERT and LLM

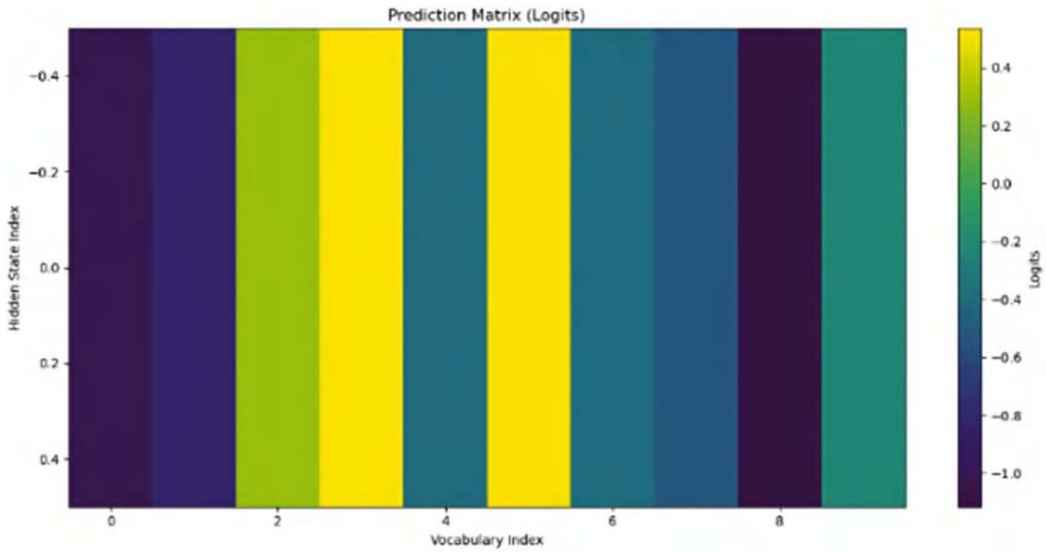

Fig. 9.10 Prediction matrix

Precision, Recall, F1 Score, and Accuracy: Evaluates simulated binary classification task performance.

BERT is a powerful, smaller-scale language model primarily used for tasks requiring deep contextual understanding.

LLMs are larger, more versatile models capable of both understanding and generating text. They are suitable for a wider range of tasks and excel in scenarios where transfer learning or minimal supervision is needed.

Logits: The output of the prediction matrix (logits) for each word in the vocabulary.

Loss: The cross-entropy loss value, which reflects how well the model predicts the masked word.

Generated Sequence: A sequence of words generated by selecting the word with the highest probability iteratively.

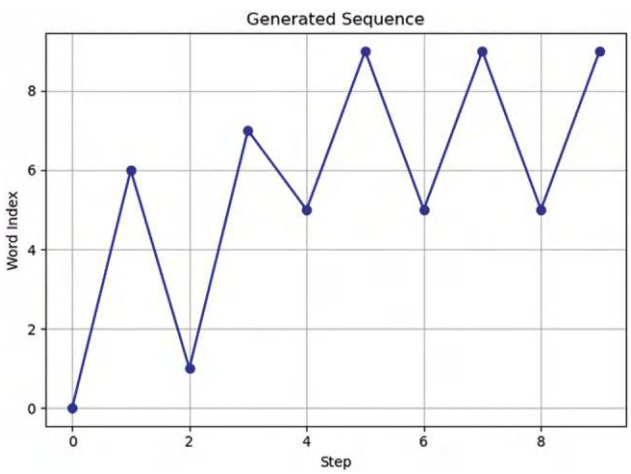

Fig. 9.11 Generated sequence prediction

5. Conclusion

Using voice cloning and AI-based impersonation in cybercrime represents a growing threat driven by advancements in AI and deep learning technologies. The literature suggests that while the technology has significant potential for misuse, various countermeasures exist, including advancements in detection techniques, enhanced public awareness, and stricter regulatory frameworks. Continued research and collaboration across technological, legal, and ethical domains are essential to address these evolving challenges effectively.

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10

Quality Improvement Mechanism for Routing using Throw Boxes in DTN

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Abstract: The End to end connectivity between source and destination nodes is general phenomenon in the Ad hoc networks. Where as in Delay tolerant network there is an intermittent connectivity between both nodes. The major drawback in these kinds of networks is delay in routing. Throw boxes is a novel approach which were used to increase delivery probability and decrease latency of networks. To improve, performance of DTN placing the throw boxes in appropriate locations is a major task where there is a higher chance of relaying the data to other nodes.

Keywords: Throw boxes, Delay tolerant networks, Routing

1. Introduction

The wireless communication had enabled an emergence of the WSNs (wireless sensor networks) era, comprising of a massive amount of sensing devices with each device able to detect, process and relaying the environmental information. The DTN (Delay Tolerant Network) are essentially designed in order to trounce the occurring limitations of connectivity given the conditions such as poor infrastructure, mobility as well as short range of radios. DTNs bank on a natural

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mobility in network for delivery of the packets over extended and frequency network partitions with the help of a forward paradigm and store-carry. The primary aim of a DTN is to enable interoperability between various forms of networks in wide-ranging versions along-with reliable transmission over the relay network. The throw boxes are highly effective in improvement of throughput which can also enable in cutting down data delivery delay. Enhancement in resulting throughput is relatively more substantial as opposed to the delay-based improvement [1].

The throw boxes are highly viable in routing algorithms which employ multi-path routing as the nodes follow a particular mobility pattern. The throw box deployment makes use of knowledge regarding contact opportunities, which performs much better when compared to deployment. In addition to that, when the deployment is customized to present traffic patterns, resulting algorithms are relatively more effective as opposed to assuming that traffic is distributed equally. Method considers these issues, as aligned algorithms are proposed for provisioning high quality solutions to relatively challenging issues. For decreasing the delivery delay along-with enhancing the dependability in mobile DTN, an extra set of stationary nodes known as throw boxes (greater amount of contact opportunities via other nodes are connected). The method also takes in consideration the issue of throw box selection along-with its deployment for cutting down the operating time in DTN.

Essentially, the DTN (Delay Tolerant Network) is a method in computer network architecture which attempts to seek out technical issues in heterogeneous networks which may be deficient in continuous network connectivity. The instances of these networks include those including terrestrial environments and extreme environments, or networks placed in space. Most of the developing wireless networks have differentiable characteristics from internet, including long propagation, instability of a link, high link errors and asymmetric data rate. The DTNs are to provision steady, interoperable and reliable transmission and communication between different ranges of networks. As is the case, the DTNs are essentially shaped to surpass the limitations of connectivity and allay the conditions, including shorter range radio, infrastructure and mobility.

The DTNs hinge on the mobility of the network to enable the packet delivery over network partitions with the help of store-carry or forward paradigm. In any case, the amount of contact opportunities missed are decreased, the throughput is increased along-with the delay in a network is also ramped up. The application of throw boxes in the mobile DTNs for ramping up the amount of contact opportunities, improves the network performance. The primary intention of the DTN is to enable interoperability among the different forms of networks in wide-ranging versions, and facilitating reliable transmission on the overlay network. The application of the DTNs will be a beneficial solution for challenged networks.

2. Literature Review

Network that can tolerate delays is scarce. Due to node mobility and network segmentation, there is no end-to-end connection. It operates on a store and carry system. When a node encounters another node, a message is buffered and sent to the other node. Rural residents are sufficiently impoverished to cover the costs of communication notwithstanding the high cost of infrastructure-based communication. Due to node mobility and network partitioning, delay-tolerant networks feature sparse networks with no end-to-end connection. It operates on a store and carry system. When source is sending a message to destination, it stores the message in its buffer, when it encounters another node it forward it to that node and it stores it into its memory and forwards the message to relay nodes until it reaches destination node.

In the routing protocol known as “Direct Delivery” [2], the source will transmit the message directly to the destination if it matches it; else, it will not relay the message to a different node. The message will never arrive at its destination if source node does not connect with destination node. Message is flooded to every node that epidemic routing [3] encounters. It doesn’t take the buffer space into account. Although this routing system has a high resource consumption rate, it has a maximum delivery ratio. The message is sprayed to T nodes in the routing protocol Spray and Wait [4]. T is a user-defined predetermined value. The direct delivery routing approach is used since there is just one message remaining for the node to process alone. These routing techniques transfer the message to a different node without knowing anything about it or considering its usefulness. The encounter nodes’ past interactions are a factor in the Prophet routing mechanism. If node A frequently interacts with node B then frequently interacts with node C, node A may transmit the message to node C as well. This routing protocol additionally considers the aging issue.

2.1 The Approaches of Routing

The routing ascertains the traffic load and routing paths on every path. The routing ascertains the traffic loads and routing path. The routing approaches will be examined in this research paper:

Epidemic Routing

In this method of routing, the nodes attempt to exchange the buffered messages during the nodal contact is maintained, however, the messages are encoded in this type of network.

In this approach, there is heightened amount of redundant messages, resulting in a lower utilisation of the network resources. However, the epidemic routing is robust in network partitions, and needs no particular data set for operation. Henceforth, no particular explicit method for opting to either paths or traffic load exists on every path [1].

Single Path Routing

In this case, the messages regarding source-destination pair adheres to a singular pathway. As a traffic load for source-destination ascertains traffic load on a particular path, the flexibility to select a predefined set of nodes on path is an added flexibility [5].

Multipath Routing

In this case, the messages are transmitted using multiple paths for a given source-destination pair [5].

As is the case, the throw boxes are essentially powered using batteries, the quantity of the data transmitted is limited for every throw box. Therefore, the multiple throw boxes can be deployed in a particular location for supporting the data being relayed for a particular period of time.

3. Materials and Methods

3.1 SCROP Method

The SCORP is based on a utility function that considers the likelihood of running into nodes with a certain interest among individuals with similar daily routines. Social proximity is utilized with content knowledge for two different purposes. Firstly, it's because nodes with the same day-to-day habits entail higher probability of having the same interest. Secondly, social proximity metrics provide faster data disseminations, exploiting the longer and frequent contacts between the closer nodes [2].

Figure 10.1 presents various social interactions, node A has with the other nodes during its day-to-day routine. For simplicity's sake, on this example, every node encountered has only a single interest. SCORP determines the contacts' duration, indexing such durations to interests the nodes have. The nodes have different measures of social interactions levels with node that have same interests during particular periods of time of their day-to-fay routines. These different social interactions levers are taken into account while making decision whether nodes are classified as good forwarders for messages tagged with given interests.

When node A entails n contacts with other nodes with interest x in the daily sample ΔTi, with every contact k involving a given duration, (CD(a,x)k), at ΔTi end, he total time connected to Interest x is given by the equation below:

$$TCTI(a,x)_i = \sum_{k=1}^{n} CD(a,x)_k$$

Aggregate time connected to the interest x in a similar daily sample continuously is used in estimating the average contacts' duration towards x for the given daily sample. Therefore, form node A's perspective, average total time connected to x (ATCTI) in a daily sample ΔTi, in day j is shown by the cumulative moving average of the TCTI such that the daily sample (TCTI(a,x)ji), and the ATCTI in same sample in previous day (ATCTI(a,x)(j-1)i) is shown in the equation below:

$$ATCTI(a,x)_{ji} = \frac{TCTI(a,x)_{ji} + (j-1)ATCTI(a,x)_{(j-1)i}}{j}$$

3.2 Throw Box Placement in the Evening Activity

K-throw Box Issue

Regarding the k-throw box issue, when the k-throw boxes are chosen, the aim is to ramp up the maximize the network reliance. The algorithm is operated on random networks along-with x mobile users in addition to m throw boxes, the k ranges within 1-9. For the relatively smaller networks, an optimal solution is brute force algorithm is applied. Given that it is unable to attain a similar plane of reliability by incorporating reliability changes, a trade-off exists among the time complexity and network reliability [6].

Min-throw Box Issue

In the case of the min-throw box issue, it makes use of the similar set of arbitrary networks, whereas the constraint

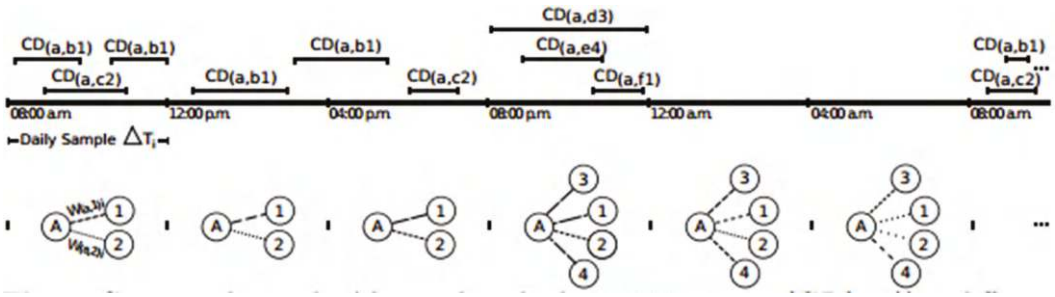

Fig. 10.1 Node a contacts with nodes with interests x (CD(a,x)) in various daily samples ΔTi

reliability g ranges from 0:40 to 0:60. It means that as the throw boxes are increased, the contact opportunities are also increased in the network. The primary intention of the OPT is to take in consideration the least number of throw boxes, in any case, the operating time is the highest when other algorithms are paralleled, and it increases likewise. Henceforth, it is affirmed that throw boxes can enable maximum amount of contact probabilities in a network, however, the OPT also needs a minimum amount of throw boxes to be deployed [6].

Adding up the Throw Boxes

As the live throw boxes are used, the transmitting opportunities among the device and node also ramps up, resulting in keeping of additionally active throw boxes also raises the bankability of a network. For maintenance of the throw boxes at a specific cost and threshold of minimum active throw boxes, the decision would involve the amount of throw boxes would be needed to be activated along-with the amount of throw boxes needed to be activated [7].

Scrapping of Throw Boxes

The particular algorithm commences with an original space-time graph as the throw boxes are initialised, as the throw boxes active are depleted gradually until and unless just the k active throw boxes remain, resulting in the breakage of the reliability constraint in the algorithm. In this process, the method depletes every throw box one by one in every round, due to certain criteria. These are operations performed during depleting the throw boxes [7].

Selecting the Desired Throw Box

The process of the throw box selection can be undertaken using 2 diverging criteria when throw boxes are selected greedily in order of the node degrees as well reliability changes. For opting the desired throw box in every round to be removed or added from the network, certains conditions are needed to be met first [7].

4. Results and Discussions

The throw box placement is an enhancement adjustment made to the SCORP routing architecture to increase the interaction chance between the nodes. To increase the likelihood of delivery, throw boxes have been designed for usage in metropolitan areas. The issue that arises in metropolitan locations is that the toss box causes the network to get crowded, which lowers the network's performance. It may be utilized in rural areas to increase the chance for engagement, which will increase the likelihood of delivery. People with various hobbies and occupations get together during the working day's evening activity. Using this position will increase the likelihood that the message will reach the target node. The average delay and cost are more effectively analyzed as a result of the toss box in a rural area's evening activity location and the rise in delivery probability."

When a node comes into contact with another node, it first determines interest of a new node. If interest matches that of target node, the message is passed to a new node; otherwise, it determines the weight of new node for time period.

The message will be transmitted to the target node if weight of encountered node is greater than the interest of the destination node.

Chance of contact will increase and the message will spread more quickly if the nodes run into each other on a bus. If they don't already have the message, they will individually send it to the other nodes. Another enhancement is that the evening activity is also a location where individuals from other locations congregate, increasing their engagement with one another and ensuring that the message gets conveyed if they are missing it. Throw boxes are positioned at the hub of nightly activity to maximize the chance of contact by storing and forwarding messages to nodes that are missing them.

The results of further switch improvements produced to boost the contact possibility and delivery likelihood through throw box is by the night time activity place were:

Delivery probabilities are 81.85% with a day to live, 82.48% with three days to live, 82.48% with one week to live, and 82.48% with three weeks to live.

With time to live for one day, three days, one week, and three weeks, the average latency is 26.53 milliseconds, 27.02 milliseconds, and 28.03 milliseconds, respectively.

The results are shown in the Fig. 10.2, 10.3 and 10.4.

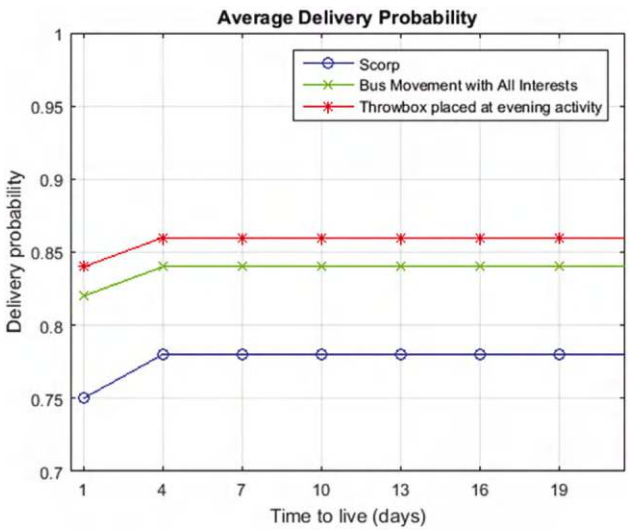

Fig. 10.2 Average delivery probability

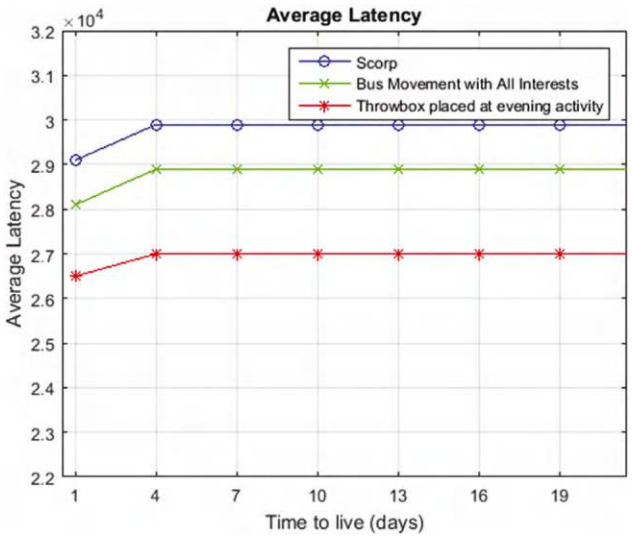

Fig. 10.3 Average latency

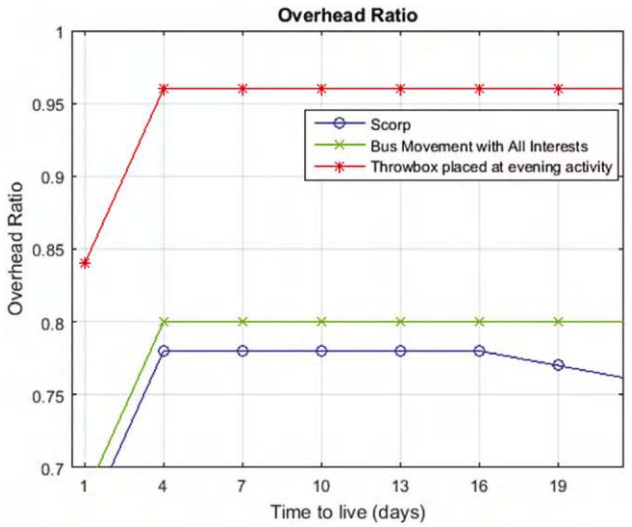

Fig. 10.4 Overhead ratio

5. Conclusion

The problem in rural locations is that because the nodes are spaced far apart, nodes have fewer opportunities are fewer opportunities for nodes to come into contact with one another. This lessens the likelihood of nodes encountering each other, which also reduces the possibility of delivery. For scenarios involving rural locations, the SCORP routing technique was developed.

In conclusion, application of the throw boxes for improvement of data delivery performance in the mobile DTNs was examined thoroughly. The throw boxes are cost-effective and small in size when they are armed with wireless interfaces. They are used for the relaying of information among the cellular nodes. The application of the throw boxes increases the network capacity by raising the opportunities of nodes to communicate amongst each other. As they are cost-effective and small, the throw boxes ensure cost-effective and flexible approach in ramping up the network capacity. The throw boxes improve the throughput. The taking in consideration of the throw box routing and deployment is imperative. The section also examined various approaches used in routing, such as epidemic routing, multi-path and single path.

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11

Thyroid Disease Identification Using Machine Learning

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Abstract: Thyroid diseases, particularly hyperthyroidism and hypothyroidism, are increasingly prevalent and pose significant health risks if not diagnosed early. This study shows the use of different ML algorithms for identification of thyroid gland issues. The research employs five classifiers—LR, DT, RF, SVC and KNN to analyse a dataset of 3772 patients. The data preparation process includes removing unwanted data, unclear data, irrelevant data, selection of features, splitting the data to optimize the performance of these models, focusing on the secretion of hormones like Thyroid stimulating Hormone (TSH), Triiodothyronine (T3), and Thyroxine (T4). When the thyroid gland malfunctions, it can lead to either hyperthyroidism, characterized by excessive hormone production, or it causes overproduction or insufficient hormone production can result in serious health problems. The DT and RF algorithm show better results compared to other algorithms they achieved to 99.73% and 99.71%.

Keywords: Logistic regression, Decision tree, Random forest, K-nearest neighbour (KNN) and Support vector machine (SVM)

1. Introduction

The thyroid gland is an important part of our body's endocrine system and has a lot of impact on metabolism, growth as well as temperature regulation. These kinds of disorders are common and affect a person's well-being [01]. Some of these are hyperthyroidism caused by the overproduction of thyroid hormones while others such as hypothyroidism come about due to under production [02]. This means that early detection and correct identification of these disorders can help in managing them well. Recently, there has been an uptake in innovative methods for enhancing diagnosis and treatment modalities for thyroid diseases through technological advancement. Utilizing such technologies increasing precision when diagnosing thyroid disorders thus lowering the risk of complications besides improving patient outcomes [03]. In this study, we will apply advanced machine learning techniques on a dataset from patients with thyroid problems to identify the best model that can be used to predict thyroid disease. The application of modern analytical approaches aimed at informing public health decision-makers about early

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detection and management of thyroid disorders will ultimately lead to improved public health outcomes. [04]

2. Literature Review

Maintaining the Integrity of the Specifications

Ebru Turanoglu Bekar et al. [05] study DM techniques and ML methods to categorize thyroid diseases. The research is fundamentally aimed at distinguishing different decision tree algorithms that would help the capture of thyroid correctly.

R. Chandan et al. [06] the authors explore various ML models to increase performance. The paper details the application of algorithms such svm, rf, and Neural Networks in analysing thyroid-related data.

N. Chandra et al. [07] signifies a fact that model performance can be improved through the selection of relevant features. Their view shows their technique is a main step towards the faster and more accurate detection of hypothyroidism. As such, it is bound to influence positively on the use of machine learning technologies in medical diagnoses, so its utilization may bring about better patient results.

Tyagi, et al. [08] the investigation concentrates on creating an engaging instrument using different types of machine learning approaches to forecast thyroid afflictions chances. The writers show how their system can deliver real-time predictions

Bhende, et al. [09] Identifying and assessing the risk factors responsible for thyroid diseases is the focus of this study. Some models are used to increase the performance. The essence here lies in detecting important risk factors then inputting them into prediction models so that diagnostic precision is improved.

Gozde Ulutagay et al. [10] this paper assesses the efficiency of several decision tree algorithms in diagnosing thyroid illnesses. The research presents an explicit comparative analysis on various decision tree models including CART (Classification and Regression Trees), C4.5 and ID3.

Palanichamy et al. [11] the investigation concentrates on the creation of a DT to optimize detection of thyroid disease through the fusion of different diagnostic criteria and expert knowledge. The authors go on to describe the architecture of the system which contains rule-based algorithms and inference mechanisms that process patient data to provide diagnostic suggestions.

Mir, Yasir [12] This paper introduces a much-enhanced model, featuring advanced dm, which improves the accuracy of a prediction. Another contribution made is that of considering outlier detection mechanisms that can help solve anomalies in the model, thus improving its robustness.

3. Proposed Work

The initial phase involves gathering relevant patient data and medical history to build a comprehensive dataset. The collected data undergoes various preprocessing steps to ensure it is clean, consistent, relevant and suitable for further analysis. Figure 11.1

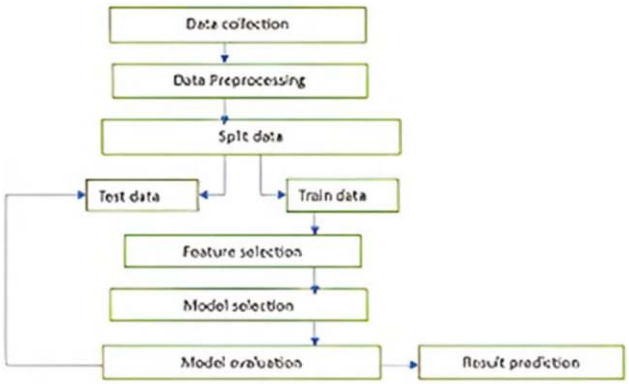


Fig. 11.1 Block diagram

Source: Author

3.1 Data Visualization

This analysis is gathered from the Kaggle website [13]. It includes various patient details which involves age, gender, and blood sample information. The dataset contains 3,758 rows and 24 columns, with a single binary class indicating whether the thyroid test result is positive or negative, as illustrated in Fig. 11.2.

	age	sex	on thyroxine	query on thyroxine	on antithyroid medication
0	41	F	f	f	f
1	23	F	f	f	f
2	46	M	f	f	f
3	70	F	t	f	f
4	70	F	f	f	f

Fig. 11.2 Dataset [13]

To enhance the model's accuracy, attributes most associated with thyroid illness were prioritized, while less relevant features were excluded. The dataset pre-dominantly features Boolean values (e.g., 'T' for True, 'F' for False) and categorical data (e.g., 'M' for Male, 'F' for Female), with a mix of object and numeric types. It is illustrated from below Fig. 11.3.

Through system application, the most significant features influencing thyroid diagnosis were identified as: Age, Gender, T3, T3 Measured, Referral Source, and FTI. Here

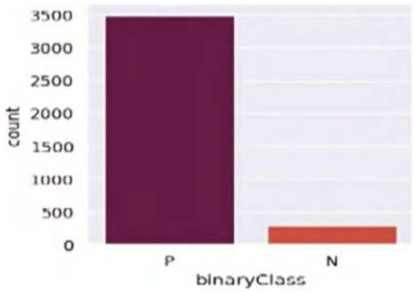


Fig. 11.3 Class distribution [13]

the Table 11.1 shows a selection of attributes based on data used for prediction. The attributes include:

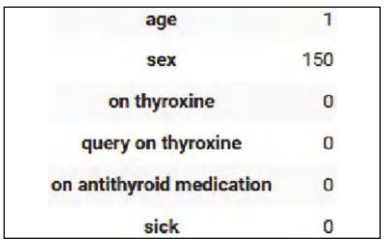
- AGE: A continuous variable representing the patient's age.
- GENDER: A categorical attribute with Boolean values where 'F' stands for female and 'M' stands for male.
- T3: A continuous variable indicating the level of T3 hormone.
- T3 MEASURED: A Boolean feature where 'T' denotes that T3 levels were measured, and 'F' indicates they were not.
- FTI: A continuous variable representing the Free Thyroxine Index.
- REFERRAL SOURCE: A categorical attribute with values such as SVI, SHVC, STWC, and others, representing different sources from which referred in Table 11.1.

Table 11.1 Major features of dataset

S. No	Attribute	Type
1	Age	Continuous
2	Gender	F,M
3	T3	Continuous
4	T3 Measured	F,T
5	FTI	Continuous
6	Referral Source	SHVC, Others, SVI, STMW

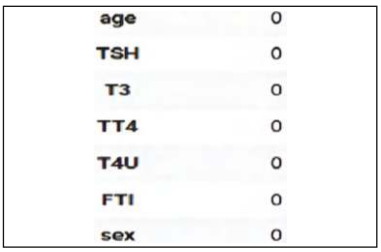
3.2 Preprocessing Techniques

The dataset has been loaded into memory, and preliminary cleaning procedures have been undertaken. Primarily, Missing data is addressed using suitable imputation methods. Unnecessary columns that do not contribute to the analysis are discarded. Those are identified and removed from the dataset, as depicted in Fig. 11.4. Categorical attributes are converted into numerical format to facilitate further analysis. In Fig. 11.5 These initial cleaning steps prepare the dataset for more accurate and effective analysis. [14]



age	1
sex	150
on thyroxine	0
query on thyroxine	0
on antithyroid medication	0
sick	0

Fig. 11.4 Missing values [13]



age	0
TSH	0
T3	0
TT4	0
T4U	0
FTI	0
sex	0

Fig. 11.5 After removal of missing value [13]

3.3 Outliers Removal

1. Before Outliers Removal: Fig. 11.6 illustrates a heatmap that effectively evaluates the distribution of missing values within a DataFrame. A heatmap is generated to represent null values (1) and non-missing values (0). Each cell in the heatmap is clearly show whether a value is missing or not.

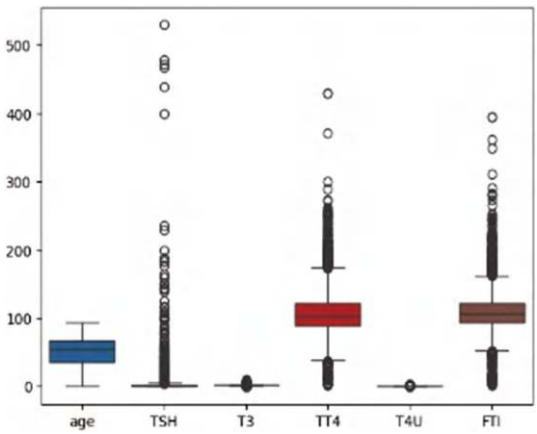


Fig. 11.6 Before removal of missing values [13]

2. After Outliers Removal: The outliers removal function identifies the data points in the numerical columns of a DataFrame as shown in the analysis results of Fig. 11.7, then the analysis obtains performed on the numerical column. The sorting function will sort the values of the respective column in ascending order. The limits are obtained by calculating the floor limit from the minimum value (0^{th} percentile) and the upper limit based on the 95th percentile value.

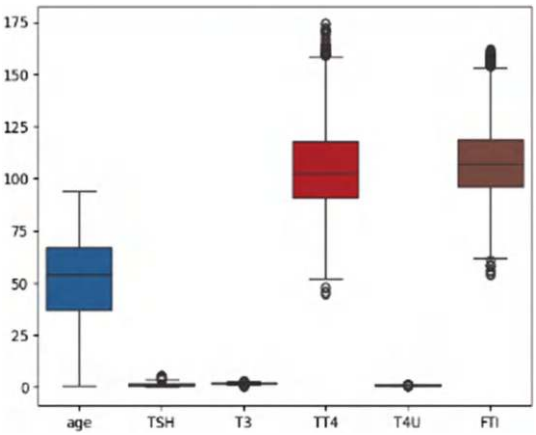


Fig. 11.7 After removal of missing values [13]

3. Correlation Matrix: This matrix indicates the strength and direction of the relationship of dependent and independent variables, being forwarded to assess whether those relations are positive or negative. By examining the correlation matrix, features with weak correlations can be removed to mitigate overfitting. The goal with reducing the features is to keep the topmost important variables and discard features that provide very little value. The values on the diagonals will indicate each of the variables self-correlation, which is [15] normally a perfect correlation of 1. If any two features show a correlation greater than 1 (a perfect correlation), it means we are likely working with two redundant features. In the case of redundancy, we would have a measure known as TBG, we may want to select one over the other such as removing the attribute TBG so there is not redundancy or duplication occurring in our dataset. All these steps are helping us to keep the data tidy by only retaining the most salient features of the dataset and continually working toward reducing redundancy based on correlation.

3.4 Selection Feature

Each time a feature is added or removed; the model will be evaluated using a specified metric to observe the impact of the changed feature shown in Fig. 11.8. To implement effective feature selection, we use the Sequential Feature Selector (SFS) from the mlxtend library. We will start with an empty set of features.

Categorization reports, include recall, precision, and F1-score.[19].

3.5 Model Selection

Classification in machine learning frameworks for predicting texts is designed to classify the texts into classes. Classification models can be conventionally divided into several types: [17]

- Binary Classification: The model predicts a label that can be characterized by one of two classes or outcomes" yes" or" no"," true" or "false", "positive" or "negative".
- Multi-Label Classification: is slightly different from binary classification. The model predicts multiples labels or categories for a single input in the labelling process adding additional complexity.
- Imbalanced Classification: This model specifically addresses instances where outcomes for the classes are not related evenly - this is inherent in real data to be considered for classification.
- Hierarchical Classification: could be used for a more complex outcome, for when the text to be classified

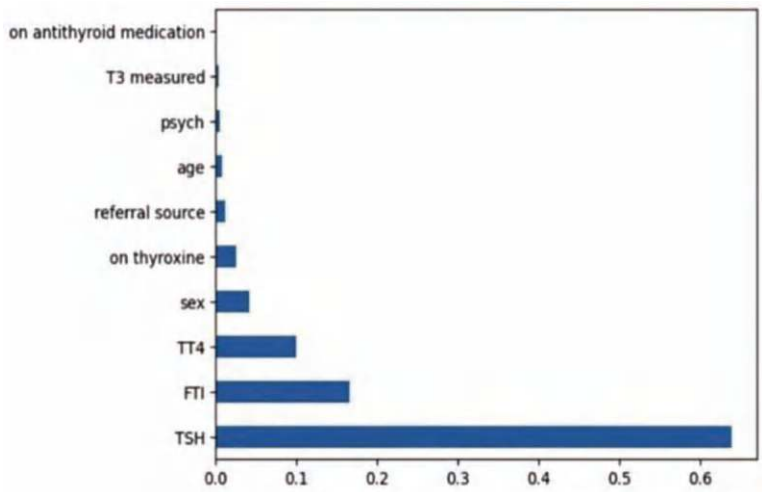


Fig. 11.8 Feature framework

has categories classified into classes of categories in a hierarchical structure.[18]

In this prediction context, the Binary Classification model will be used.

Using classification approaches, methodologies are broadly and conventionally known, are commonly presented as Classification Models; hence, approaches include LR, DT, RF, SVC and KNN.

3.6 Evaluation of Model

The methods involved are RF, SVC, LR, KNN, and DT. Key Evaluation Metrics and Tools include the Confusion Matrix, which gives an in-depth view of the model's output versus the actual class labels, providing insight into TP, TN, FP, and FN. thereby giving a high-level metric reflecting the model's accuracy.

4. Machine Learning Algorithms

- Logistic Regression: A supervised machine learning methodology that is straightforward to implement, is applied to resolve problems that involve estimating the probability that an individual case will or will not belong to a group.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

- Decision Tree: The choice tree is a specific kind of algorithmic learning system that can address both classification and regression problems. Nodes in the tree represent decisions or tests on the feature values, while leaf nodes in the tree represent answers. Information gain IG (D, A) for an attribute A is given by:

$$IG(D, A) = H(D) - \sum_{j=1}^{n} \frac{|Dj|}{|D|} H(Dj) \tag{2}$$

- Forest Randomization: Forest Randomization is a well-known sl approach that can be applied to regression tasks. The advantage Random Forest has over other techniques is its capability of handling complicated data and producing consistent predictions.

$$xstd = \frac{x - \mu}{\sigma} \tag{3}$$

- K-NEAREST NEIGHBOR: KNN is a classification and regression SML method. KNN is a robust way to classify and perform regression on a wide variety of dataset types. It finds knn to a specific data point

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (xi - yi)^2} \tag{4}$$

- SUPPORT VECTOR CLASSIFIER: SVM is a popular ML problem. The procedure of SVM involves the identification of the best possible hyper plane that segments the classes of the dataset.

$$Minimize \frac{1}{2} ||w||^2 + c \sum_{i=1}^{n} e \tag{5}$$

5. Result and Analysis

There are four trials in this examination.

Experiment 1: In this experiment, forty-two percent of the specimens were chosen randomly without any specific qualities like feature selection which is given in the Table 11.2.

Table 11.2 Accuracy rate for experiment

Algorithm	Test-Train Data			
	15-85	20-80	30-70	40-60
LR	98.11	98.09	98.04	97.96
DT	99.72	99.68	99.65	99.57
RF	99.72	99.70	99.59	90.57
KNN	99.59	90.57	97.26	97.00
SVC	97.99	98.00	97.80	97.68

Experiment 2: For this experiment, a random state forty four percent with the exclusive of feature selection was selected. These were determined as given in Table 11.3.

Table 11.3 Accuracy rate for experiment

Algorithm	Test-Train Data			
	15-85	20-80	30-70	40-60
LR	98.06	98.09	98.25	98.21
DT	99.70	99.66	989.74	99.70
RF	99.68	99.66	99.68	99.57
KNN	97.46	97.37	97.06	97.08
SVC	98.03	98.08	97.78	97.73

Experiment 3: For this experiment, a random state forty two percent with the inclusion of the feature selection criterion. This were determined as given in Table 11.4.

Table 11.4 Accuracy rate for experiment

Algorithm	Test-Train Data			
	15-85	20-80	30-70	40-60
LR	98.67	98.62	98.47	98.36
DT	99.47	99.24	99.27	99.29
RF	99.29	99.66	99.61	99.55
KNN	97.94	97.86	99.86	97.78
SVC	98.04	98.07	97.95	98.01

Experiment 4: In this instance, the random rate is forty four percent, due to the inclusion of the feature selection criterion report can be generated based on the split in Table 11.5.

Table 11.5 Accuracy rate for experiment

Algorithm	Test-Train Data			
	15-85	20-80	30-70	40-60
LR	98.63	98.64	98.73	98.66
DT	98.66	99.52	99.55	99.42
RF	99.66	99.68	99.65	99.60
KNN	97.74	97.77	97.78	97.58
SVC	98.15	98.17	98.06	97.93

Experiment 5: In this experiment, a new data division was used (22:78). It is showing the highest accuracy as 0.9966 as shown in Table 11.6. The division ratios (15:85, 20:80, 30:70, 40:60).

Table 11.6 Accuracy rate for experiment

Algorithm	Test-Train Data (22-78)
LR	98.14
DT	99.73
RF	99.71
KNN	97.42
SVC	97.98

The accuracy that are shown in the above are higher when compared with [20]. The accuracy of the referred paper is shown as LR is 97.10, DT is 99.27, RF is 99.15, KNN is 95.18 and SVC is 96.38.

6. Conclusion

Prediction of thyroid disease requires several processes, such as blood tests and sample analysis, all of which can be managed effectively for accurate results. Most ML models are greatly dependent on their success upon the quality and quantity of the data with which they get trained. A clean, well-organized dataset normally results in good accuracy and reliable performance. The diversity in healthcare has made ML an indispensable tool, helping reduce human errors and enabling detailed checks on medical data. Many predictive modelling techniques were explored in this domain, such as DT, RF, KNN, LR, and SVC. The accuracy is higher in DT.

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Polycystic Kidney Disease Identification: Harnessing Deep Neural Networks for Accurate Diagnosis

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Abstract: The renal cystic diseases are commonly occurred due to genetic factors or some environment factors and life style. A genetic condition known as polycystic kidney disease (PKD) affects the kidneys and is characterized by clusters of cysts that are filled with a watery fluid. 5-10% of end-stage renal failure treated with dialysis or transplantation is caused by PKD. In this paper a deep learning network constructed using LSTM model which is used to identify PKD disease by applying back propagation learning rule also we analyzed the optimization with gradient descent. The data collected from Kaggle chronic kidney disease data set which contains 400 records with 25 features. The data is segmented as 70% for training and 30% for testing which result the patient condition as normal or abnormal. The chronic kidney disease (CKD) results help doctors to identify the PKD disease, as one of the major causes of CKD.

Keywords: Polycystic, Chronic kidney disease, Gradient descent, Deep learning

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1. Introduction

Chronic kidney disease is a progressive kidney disease which effects the kidney functioning. The main work of kidneys is cleaning wastes from our blood with nephrons. If nephrons are damaged then it is difficult to filter our blood and then begins the symptoms of CKD in human. In fact, it is difficult to identify the CKD in early stage. In addition, without any symptoms a human may be defeated with loss of kidney function so most of us completely unaware of it in early stage.

PKD is a genetic disease; it results from a mutation in genetic. Many cysts filled with fluid will grow inside of the kidney because of PKD. Individuals who possess the cyst gene may not be aware that they are at risk for developing PKD because the environment, diet, lifestyle, and way of life all affect how quickly cysts grow in different people. These cysts get larger and harm the kidneys. Thousands of cysts can form on the kidneys, making them weigh up to 30 pounds more than they normally would. This causes renal failure, at which point the patient needs dialysis or a kidney transplant. Although there is absolutely no cure, the illness can be controlled, and research towards alternative therapies is continuing. Figure 12.1a & Fig. 12.1b shows the healthy kidney and kidney with PKD respectively.

Fig. 12.1 (a) Healthy kidney, (b) Kidney with PKD

PKD is a kind of CKD that decreases renal function and can result in kidney failure. PKD can effects various health issues like high BP, damaging blood vessels of heart and brain, also it effects the liver functioning. Kashyap et al., use machine learning techniques to diagnose CKD, improving accuracy through data preprocessing and reducing the need for costly and time-consuming treatments like dialysis or transplantation. Busi et al., highlight the potential of machine learning and deep learning in predicting CKD, a global disease affecting 4.902-7.083 million people, and improving product productivity and quality. Vyas et al., The study presents a machine learning-based method for predicting CKD using demographic, clinical, and lab data, achieving an 89% accuracy rate, demonstrating potential for intelligent diagnostics. Maurya et al., CKD is a significant medical issue, and an automated tool using machine learning techniques can help doctors predict and treat it. The system extracts CKD-related features and classifies disease stages based on severity. The goal is to suggest suitable diet plans based on medical test records, utilizing potassium zones to slow CKD progression. Asha et al., CKD is understudied, with current recommendations based on small trials. This study uses support vector machine and artificial neural network to predict CKD, but more research is needed. Choudhary et al., A machine learning model for predicting CKD using Kaggle-based data achieved 96.5% accuracy, making it a valuable tool for early detection and management, reducing healthcare costs. Rani et al., the study uses machine learning techniques to detect and treat chronic kidney disease, achieving high accuracy and precision with the XGBoost algorithm, highlighting the importance of these innovative strategies in clinical practice. Rajeshwari et al., The system uses machine learning techniques to predict chronic kidney disease, with Random Forest outperforming other methods with high accuracy scores. Pareek et al., The research proposes an AI-based smart expert system to detect early-stage CKD using patient clinical data. The system uses machine learning algorithms to predict CKD stages, potentially improving patient outcomes and reducing healthcare costs. Makaraju et al., A machine learning model predicts CKD risk based on health measurements, medication usage, medical history, and demographic data, simplifying risk assessment and aiding proactive management and informed decision-making. Jeyalakshmi et al., A Deep Learning application enhances early diagnosis and prediction of chronic kidney disease using advanced neural network designs, achieving higher sensitivity, specificity, accuracy, and AVC-ROC.

2. Material and Methods

2.1 Data Source

The data collected from kaggel chronic kidney disease data set which contains 400 records with 25 features shown in Table 12.1. Data from 70% of these samples was used for training purposes and data from 30% were used for testing purposes.

2.2 Proposed Method

Information persistence is possible with an advanced RNN, also referred to as a sequential network or long short term memory network. It has the capacity to address the vanishing gradient problem of the RNN. Bokka et al., A RNN is used to implement persistent memory. LSTM performs at a high level very similarly to an RNN cell. The

Table 12.1 Features of CKD dataset

age	ane	pe	appet	cad	dm	htn	rc	wc	pcv	hemo	pot	sod	sc	.....	su	al	sg	bp	Class_ Label
53	yes	no	poor	no	yes	yes	4	12100	29	9.5	3.7	114	7		0	2	1.02	90	ckd
61	yes	yes	poor	yes	yes	yes	3	9200	24	7.7	5.2	135	4		0	2	1.02	80	ckd
48	yes	no	good	no	no	yes	3	6900	32	9.8	3.8	136	8		0	4	1.03	80	ckd
45	no	no	good	no	no	no	5	9100	46	15.9	4.4	147	1		0	0	1.03	80	notckd
57	no	no	good	no	no	no	6	6200	42	15.4	4.7	135	1		0	0	1.03	80	notckd

internal operation of the LSTM network is as follows. The LSTM is made up of three sections, each of which serves a different purpose, as can be seen in Fig. 12.2. The forget gate, input gate, and output gate are the three parts of an LSTM cell that are referred to as gates.

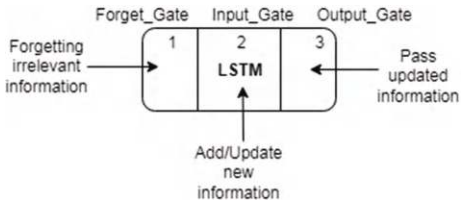

Fig. 12.2 LSTM model

The first step is forget gate which is used to decide whether to keep the information or discard. Input gate is used to assess the importance of the new information carried by the input. The output gate finds the value of the next hidden state which contains information on previous inputs.

2.3 Evaluation Metrics

Punuri et al., A classification problem's prediction outcomes are compiled in a confusion matrix. Count values are used to describe the correct and incorrect predictions for each class.

Table 12.2 Confusion matrix for classification

		Actual_Class	
		Positive	**Negative**
Predicted _Class	Positive	TP	FP
	Negative	FN	TN

Accuracy is the percentage of all samples that were correctly predicted to the total number of samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Recall also known as True positive Rate, is the measure of True Positives Vs Sum of Predicted True Positives and Predicted False Negatives.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

Specificity or the true negative rate is the measure of the proportion of True Negatives Vs Sum of Predicted False Positives and Predicted True Negatives.

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

3. Results and Discussion

The data required for this system is taken from chronic kidney disease data set which is collected from kaggel, which contains 400 records with 25 features. The segment of data is 70% for training data and 30% is for testing data. We proposed LSTM model to train the system using training data. The Table 12.2 shows the summary of LSTM model with 4 layers.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 13, 13)            780
dropout_4 (Dropout)          (None, 13, 13)            0
lstm_5 (LSTM)                (None, 13, 13)            1404
dropout_5 (Dropout)          (None, 13, 13)            0
lstm_6 (LSTM)                (None, 13, 13)            1404
dropout_6 (Dropout)          (None, 13, 13)            0
lstm_7 (LSTM)                (None, 13)                1404
dropout_7 (Dropout)          (None, 13)                0
dense_1 (Dense)              (None, 1)                 14
=================================================================
Total params: 5,006
Trainable params: 5,006
Non-trainable params: 0
```

Table 12.3 Confusion matrix for test data

47	1
2	70

The 4-layer Long Short-Term Memory (LSTM) model achieved notable performance metrics in classifying the chronic kidney disease dataset. Key evaluation metrics, including accuracy, precision, recall, and F1-score, were employed to assess model effectiveness. The LSTM model demonstrated an accuracy of 97.5% in predicting CKD outcomes, surpassing baseline benchmarks and alternative machine learning models tested (e.g., Random Forest, SVM). The model's performance in distinguishing between CKD and non-CKD cases was particularly strong, with an recall of 95.9% and specificity of 98.5%, indicating its reliability in identifying true positive CKD cases. The model's sequential layers contributed significantly to capturing temporal dependencies, especially for patients with a history of fluctuating lab results and vitals, which are pivotal in tracking CKD progression. The choice of four layers balanced model complexity and training efficiency, minimizing overfitting while capturing the necessary data dynamics.

The confusion matrix shown below was obtained with the trained model for the chronic kidney diseases dataset from kaggel.

The proposed model is best fit by considering these three-evaluation metrics. We also plot the accuracy along with training loss and validation loss shown in Fig. 12.3(a) & Fig. 12.3(b) respectively. In this plot, observed that the model is best fit since both training and validation loss is still decreasing also accuracy is above 90%.

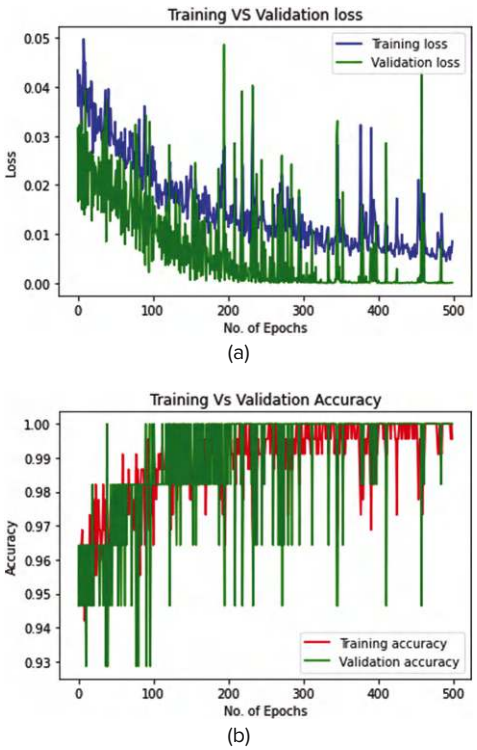

Fig. 12.3 (a) Training vs validation loss, (b) Training and validation accuracy

4. Conclusion

The LSTM model is an adaptable clinical decision support system for doctors to diagnose chronic kidney disorders. This model demonstrates potential for early-stage detection, which is critical for identifying conditions like polycystic kidney disease (PKD). Early detection of PKD allows for proactive management, as treatment options are limited for advanced stages, where patients may require dialysis or a kidney transplant. Future research could enhance this framework by exploring various deep neural network architectures, potentially yielding even greater diagnostic accuracy for PKD and other kidney diseases. Expanding the model to incorporate other neural networks could further improve predictive performance and help develop a comprehensive tool for early diagnosis and treatment planning. Additionally, model interpretability remains a challenge; while LSTMs provide powerful predictions, further exploration into explainable AI techniques could enhance clinical utility by elucidating the decision-making process of the model.

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Secure Private Cloud Storage and Sharing Services with Jetson Orin Nano

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Abstract: This proposed work focused on developing a secure private cloud storage and sharing services for organizational use. By utilizing the advanced capabilities of the Jetson Orin Nano and the user friendly Nextcloud platform, this work provides a reliable and efficient services for storing, accessing and sharing data within an

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organization. The Jetson Orin Nano is used to create a decentralized, secure, efficient, reliable data storage solution and also eliminates dependency on third party providers, enhancing control overall data, ensuring that only authorized personnel have access, ensures trust among users and protecting the system against cyber threats. In addition to the core storage functionalities, the work incorporates an Intrusion Detection System (IDS) to enhance security by monitoring and analyzing network traffic for potential threats and intrusions, particularly from internal users. The IDS is implemented to detect unusual activities such as Brute-force attacks, DoS attacks and unauthorized access attempts, to ensure the integrity and confidentiality of the stored data. By integrating Nextcloud, the proposed work offers a user friendly interface and different collaborative tools to provide efficient data management and data sharing. The implementation of the IDS system further strengthens the security services, making this proposed work as an ideal choice for organizations to protect their sensitive information from internal and external threats. This approach aims to provide a secure, scalable and private cloud solution by addressing the growing need for data security and privacy in the digital era.

KEYWORDS: Cloud storage, Jetson orin nano, Intrusion detection system, Security, Cyber attacks

1. INTRODUCTION

In today's digital landscape, the increasing data and dependence on digital storage solutions have been crucial need for secure and effective data management systems. Organizations handles massive amount of sensitive information of personal employees and organization needs dependable storage solutions. Cloud storage has emerged as an essential technology in this regard that offers scalable and flexible storage solutions for the dynamic needs of organizations. However, protecting data from increasing cyber threats, data breaches, and unauthorized access incidents has the demand for secure private cloud storage solutions that can ensure data integrity and confidentiality. As discussed above, by developing a secure private cloud storage and sharing services specifically for organizational use helps in protecting personal and organization sensitive information. Also, it provides file sharing services for the employees in the organization. This work utilizes the advanced capabilities of the Jetson Orin Nano and the user- friendly Nextcloud platform to create a decentralized, efficient, and secure data storage system. The Jetson Orin Nano, known for its high performance and energy efficiency, serves as the base of this project, providing the computational power necessary to handle intensive data processing tasks while maintaining a low latency. Its architecture and advanced security features make it an ideal choice for developing a secure private cloud infrastructure. The open-source cloud platform Nextcloud provides an extensive toolkit for effective data management and communication, which enhances the hardware capabilities of the Jetson Orin Nano. The installation of an Intrusion Detection System (IDS) to improve the security of the cloud storage solution is a crucial component of this work. In order to identify potential threats and intrusions, especially those coming from internal sources, the intrusion detection system (IDS) is made to monitor and analyze network traffic in real- time. By identifying unusual activities such as brute force attacks, denial-of-service (DoS) attacks, and unauthorized access attempts, the IDS ensures the integrity and confidentiality of the stored data. In conclusion, a major advancement in the field of data management has been made with the creation of a secure private cloud storage and sharing service utilizing Jetson Orin Nano and Nextcloud. This research lays the groundwork for upcoming advancements in secure cloud storage technologies in addition to addressing the focusing issues of data security and privacy.

2. LITERATURE REVIEW

Nishant Kumar [1] introduces a new method for securing cloud data and sharing services. This approach uses advanced encryption techniques, hash functions, access control measures, and user authentication to effectively address common security vulnerabilities. Arief Arfriandi et al. [2] focus on Hierarchical-authority Attribute-Based Encryption (HABE) for secure cloud storage, highlighting its access control advantages, weaknesses, and future research trends in information security. Akila Rahini R. et al. [3] provide a detailed review of methods for secure data storage and sharing techniques in cloud environments, examining existing solutions, their successes, and future advancements. Ishu Gupta et al. [4] offer a detailed review and analysis of techniques for secure data storage and sharing in cloud environments, highlighting their functions, achievements, gaps, and future directions for researchers.

Ms. Srilakshmi U. et al. [5] review protocols for secure cloud storage of both static and dynamic data, comparing their efficiency and emphasizing the importance of

authenticity, data freshness, and user-server interactions in maintaining data integrity and security. Maha A. et al. [6] discuss private storage cloud services that can be used for official file sharing, with faculty members sharing files using encryption. They note the challenges faced by cloud computing tasks regarding security, including data protection and uncertainty, which urgently require solutions. Blikov et al. [7] review best practices for private cloud storage, explaining what makes it more advantageous by providing high security at a low cost. A. O. Blikov's research [8] focuses on enhancing data security in private cloud storage using Hadoop technology, addressing concerns such as data leakage and storage instability, offering a secure and cost-effective solution. The authors of paper [9] introduce a Secure Organizational Cloud Storage System with advanced security measures, including message digest algorithms to protect sensitive data from cyber threats, ensuring secure data management for organizations. Security challenges in cloud computing, such as data protection and uncertainty, call for immediate security solutions. The research paper [10] provides a vision for SSL VPN and secure mobile banking, offering an ECC-based confidential private cloud storage and services model that covers secured data transfer and user actions.

3. Proposed Methodology

The proposed system architecture consists of three main components: Jetson Orin Nano, the Nextcloud platform, and an Intrusion Detection System (IDS). The Jetson Orin Nano serves as the core computational unit responsible for managing data storage, processing, and network traffic analysis. The Nextcloud platform provides a user-friendly interface for data management and sharing. The IDS monitors and responds to potential security threat

3.1 Hardware Setup Jetson Orin Nano Configurtion

The primary hardware Jetson Orin Nano for hosting the private cloud environment will be configured in this stage. The Jetson Orin Nano is configured to handle the processing, storage and networking requirements of the system. It includes installing the operating system (Ubuntu) and ensuring the hardware is optimized for hosting cloud services and security functionalities. Network Adapter Setup: A network adapter which supports packet injection and monitor mode is configured to enable connectivity between the Jetson Orin Nano and the organizational network. This setup ensures that the hardware can handle data transfers securely, support cloud services and also communicate with other network devices. The network adapter is an important device for monitoring and detecting intrusions through packet capturing and traffic analysis.

3.2 Software Setup LAMP Setup

This stage involves setting up the LAMP (Linux, Apache, MySQL, PHP) stack, which is essential for hosting web-based services like Nextcloud. This installation allows the system to act as a web server, database handler and application server. Apache is used to manage web services; the MySQL manages data storage and PHP handles backend functionalities for the cloud platform. Nextcloud Configuration: Once the LAMP stack is operational the Nextcloud is installed and configured. Nextcloud provides the interface and core functionalities for file storage, sharing and access control. This step ensures that users can securely upload, download and manage files within the private cloud environment. IDS Installation: An Intrusion Detection System (IDS) such as Suricata is installed to monitor network traffic for any suspicious activities. The IDS continuously analyses data packets and identifies potential threats such as brute-force attacks, unauthorized access attempts or denial-of service attacks. This step includes configuring the IDS to integrate with the cloud infrastructure that ensures real time detection. Rules Development: To enhance the Suricata (IDS) effectiveness, specific rules are developed and customized based on the organizational needs. These rules define the parameters for detecting potential threats, setting thresholds for triggering alerts and identifying known patterns of malicious activities. Rule development is critical to minimizing false positives and ensuring that genuine threats are identified accurately.

3.3 Monitoring Testing

In this stage the entire system undergoes testing to validate its performance, functionality and security. Different test cases, such as file uploads, downloads and simulated attacks are performed to ensure that both the cloud services and the IDS are functioning as expected. The testing also assesses how well the system handles user requests and identifies potential attacks. Evaluation: After testing, the results are evaluated to identify any areas that needs improvement. It includes reviewing system logs, analyzing IDS alerts and ensuring that all security features are working effectively. Performance Metrics: At last, the performance metrics are calculated to measure the effectiveness of the proposed work. These metrics may include response time, data transfer, detection accuracy and system resources utilization. Performance metrics are used to optimize the system and ensure it meets the organization's operational needs which provides a balance between security and efficiency.

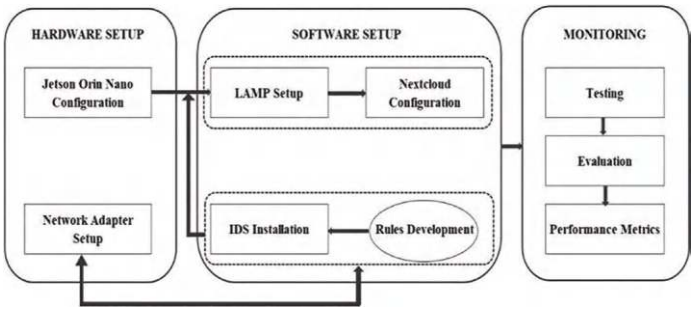

Fig. 13.1 System architecture of proposed methodology

4. Experimental Setup

Step 1: Install Ubuntu OS on Jetson Orin Nano and configure with the storage device such as memory card orany external hard drive. Then, connect the Jetson board to the local network using Ethernet or Wi-Fi.

Step 2: Install Apache in Jetson Orin Nano to act as the web server, MySQL for database management, and PHP as the server-side scripting language.

Step 3: Install and Configure Nextcloud on the LAMP stack. Also Create admin and user accounts and Configure storage allocations, user management and file sharing options within Nextcloud.

Step 4: Connect and Configure a Network adapter to the Jetson Orin Nano that supports Monitor mode for packet capturing and analysis of network traffic.

Fig. 13.2 Experimental setup

Step 5: Install Suricata IDS in the Jetson board and configure the IDS to analyze traffic captured by the network adapter. Also enable real time traffic monitoring and rule-based approach for network traffic passing through the Nextcloud server.

Step 6: Develop customized rules for the IDS to detect security threats specific to the private cloud environment and implement thresholds for network traffic that trigger alerts when suspicious behavior is detected.

Step 7: Perform file management operations from multiple users by uploading/ accessing various files to test the efficiency and response times of the Nextcloud environment.

Step 8: From another computer (Kali Linux), simulate network attacks such as DoS or brute force login attempts on the Jetson board using its IP address to test the IDS's ability to detect and respond to threats.

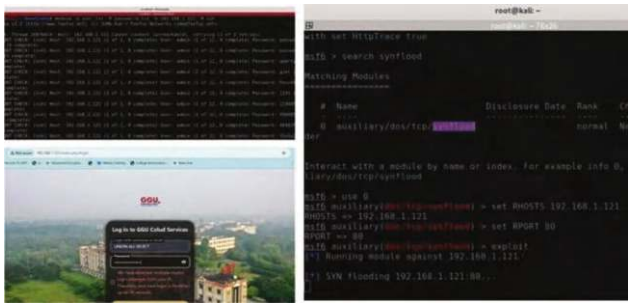

Fig. 13.3 Attacks simulation on the server

Step 9: Capture and evaluate the performance metrics of the proposed work by measuring the detection accuracy, evaluating system throughput, Resource consumption and response time etc.

5. Results and Discussion

5.1 System Configuration and Setup

The system was successfully configured with Nextcloud services running on the Jetson Orin Nano board that ensures secure private cloud storage for organizational needs. Suricata IDS was deployed and integrated with the Nextcloud platform to monitor and detect network-based intrusions and threats.

Fig. 13.4 Accessing cloud services

5.2 Detection of Attacks

Various cyber-attacks were simulated such as DoS attacks, Brute force and SQL Injection attacks. Suricata IDS rules were customized to detect these specific types of attacks. The average response time for identifying and logging an attack was within 500 milliseconds. The IDS system successfully identified:

1. **Brute Force Attacks:** Detected login attempts with multiple failed password entries in a short time span.
2. **DoS Attacks:** The system detected a high number of request packets, overwhelming the network packets and sent alerts to prevent further damage.
3. **SQL Injection Attacks:** The IDS system detected multiple SQL injection attacks such as Union based, Error based, Time-based attacks.

Fig. 13.5 Attacks detection

5.3 Resources Consumption

The resource consumption analysis across the three stages - before initialization, after initialization and during attack simulation demonstrates the system's efficiency. CPU usage increases moderately from 2.2% to 3.7% during attack simulation which shows effective management of processing tasks. Memory usage rises significantly after system initialization but remains stable during attack simulation that indicates consistent memory handling. Network activity increases during attack simulations with expected traffic changes. Overall, the system maintains efficient resource usage while effectively detecting and handling attacks.

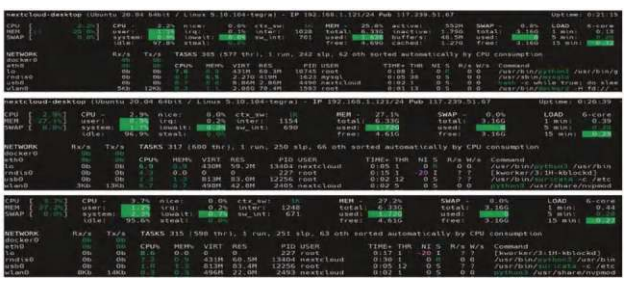

Fig. 13.6 Resources consumption analysis across the three stages

6. Conclusion

In conclusion, the secure private cloud storage and sharing services with the Jetson Orin Nano and the Nextcloud platform not only addresses the need for reliable data management solutions in organizations but also enhances security through the implementation of an Intrusion Detection System (IDS). Our findings conclude that the proposed system protects sensitive organizational data from various cyber threats such as brute-force attacks, denial-of- service (DoS) attacks and SQL injection attempts. The real time monitoring capabilities of the IDS ensured timely detection and response to potential security incidents that maintains the integrity and confidentiality of stored information. The performance metrics indicate that the system operates efficiently with moderate resource consumption, even under attack simulations

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14

Web-Based Early Stroke Detection: A Machine Learning Approach with Explainable Insights

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Abstract: Stroke is a leading cause of disability and mortality worldwide, underscoring the need for effective early detection methods. This study introduces a web-based predictive system leveraging machine learning to assess individual stroke risk. Employing models such as XGBoost, Random Forest, and k-Nearest Neighbors (KNN), we trained on a balanced dataset incorporating crucial health features, including age, hypertension, and glucose levels. Hyperparameter tuning was implemented to optimize model performance, leading to the selection of an XGBoost model that achieved an accuracy of 93.2%, surpassing other tested algorithms. To enhance model interpretability, we applied SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), which provide valuable insights into feature importance and transparency in predictions. This enables healthcare providers to identify key factors in stroke risk assessment, such as age and blood pressure, with greater confidence and clarity. Data imbalance, a common issue in stroke prediction, was addressed using Synthetic Minority Over-Sampling Technique (SMOTE) to ensure that the model trained fairly on both stroke and non-stroke cases. This research not only highlights the feasibility of machine learning in predictive healthcare but also prioritizes model interpretability to support healthcare professionals in making

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informed decisions for timely intervention. With its robust accuracy and transparency, the system presents a promising step forward in stroke prediction, laying groundwork for future integrations into clinical practice to improve patient outcomes.

KEYWORDS: Stroke prediction, Machine learning, Web application, Data imbalance, Early detection

1. INTRODUCTION

OStroke remains one of the leading causes of disability and mortality globally, creating a pressing need for early detection methods. Despite advancements in medical science, the early identification of stroke risk is challenging, leaving many high-risk individuals undiagnosed until intervention is no longer effective. Current stroke prediction models often lack sufficient accuracy or interpretability, limiting their clinical utility. This project aims to bridge this gap by developing a robust, interpretable machine learning model that not only predicts stroke risk but also provides clear insights into the factors contributing to each prediction. The primary research gap addressed is the need for a predictive model that combines accuracy with interpretability, making it feasible for use in clinical decision-making [1]. Our work leverages various healthrelated features, such as age, blood pressure, and lifestyle factors, to predict stroke risk effectively. To address the common issue of data imbalance between stroke and non-stroke cases, we applied Synthetic Minority Over-sampling Technique (SMOTE), enhancing the model's training fairness [2]. Multiple machine learning algorithms were evaluated, including XGBoost, Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (kNN), with model performance optimized through hyperparameter tuning [3]. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) were integrated to provide a transparent view of feature contributions, enabling healthcare providers to better understand stroke risk factors and build trust in the model's predictions. The unique contributions of this research include the application of advanced machine learning techniques combined with interpretability tools to create a clinically viable stroke prediction model, the use of SMOTE to balance the dataset for fair model training, and a comparative analysis of different ML models, with XGBoost showing the highest accuracy. Ultimately, this study presents an interpretable, data-driven approach to improving early stroke detection, advancing the use of machine learning in predictive healthcare.

2. LITERATURE REVIEW

Stroke causes massive death and disabilities, implying the necessity of accurate predictive models. Machine learning proved to work well with large datasets and find even complex patterns in the risk of stroke. This review of recent studies describes how they were conducted, their results, and their limitations. Paikaray and Mehta [4] had developed an integrated classifier to increase the accuracy of predictions, but did not face the clinical challenges of understanding outcomes or computation costs. Adding SHAP or LIME could help to support clinical implementation. Mahesh et al. [5] got up to 91.1% accuracy using Random Forest and Gradient Boosting methods; however, they were constrained by a single dataset, limiting generalizability. Rajora et al. [6] got up to 0.94 ROC score using Apache Spark together with Gradient Boosting; however, it has a steep computational requirement which would not be feasible in resource-limited settings. Das et al. [7] compared SVM, KNN, and XGBoost with the results showing that XGBoost works pretty well but doesn't have any techniques like SMOTE for data balancing. Sharma et al. [8] suggested lifestyle intervention with ML-based models; however, lack of longitudinal data lessens potential toward prediction over time. Gupta and Raheja [9] found that XGBoost and AdaBoost can work very effectively among so many models, while there's a lack for interpretability tools. Jalaja Jayalakshmi and others [10] showed that AdaBoost is the best performer, but it suffers with different groups as it lacks varied datasets. Azam and others [11] highlighted factors like blood pressure, but they didn't consider any outside the scopes of socioeconomic status, which may improve stroke prediction.

3. PROPOSED WORK

The proposed work outlines the model-building process, including data collection, preparation, optimization techniques, and algorithm selection, as illustrated in Fig. 14.1.

3.1 Dataset

This study uses a publicly available Kaggle dataset with features related to heart stroke, including gender, age,

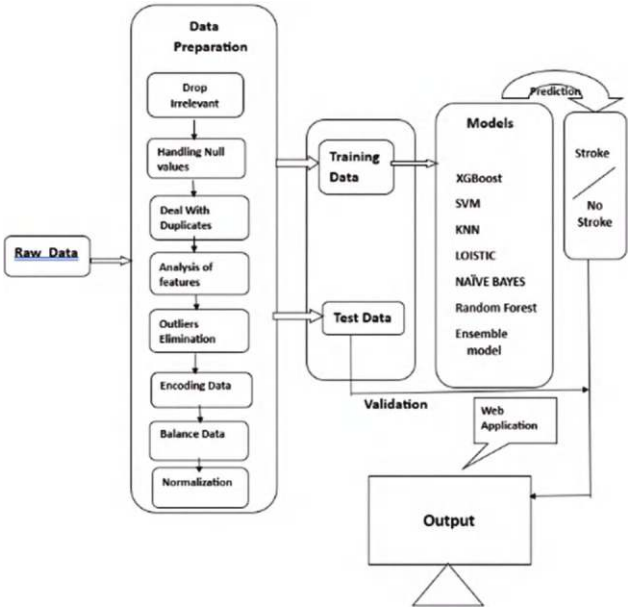

Fig. 14.1 End-to-end process for stroke risk

hypertension, heart disease, marital status, work type, residence type, average glucose level, BMI, smoking status, and stroke occurrence (1 for stroke, 0 for no stroke). The dataset contains 5110 records and 12 features, with 249 stroke cases and 4861 non-stroke cases, highlighting a significant class imbalance. To address this, techniques like SMOTE and GAN were applied to balance the dataset. SMOTE generates synthetic samples, ensuring better model performance and avoiding overfitting, ultimately improving prediction accuracy.

3.2 Data Preprocessing

In the data preprocessing phase, we carefully ensured data integrity, managed inconsistencies, and justified feature inclusion to enhance model accuracy. Each feature was selected based on its relevance to stroke prediction, rooted in medical research. For instance, age, hypertension, heart disease, BMI, glucose levels, and smoking status are all established stroke risk factors, while socio-demographic factors like gender, marital status, work type, and residence type offer additional context as represented in Fig. 14.2 & 14.3.

Addressing missing values was critical, applied mean imputation to handle 201 missing entries in the BMI column, preserving data consistency. Outliers, especially in BMI, were detected using box plots and managed with a capping technique to limit extreme values as shown in Fig. 14.4, maintaining a balanced dataset while reducing potential distortions.

We converted categorical variables into numeric data using Label Encoding, enabling the model to interpret these distinctions. A notable challenge was the significant class imbalance, with only 249 stroke cases compared to 4861 non-stroke cases. To address this, we employed SMOTE

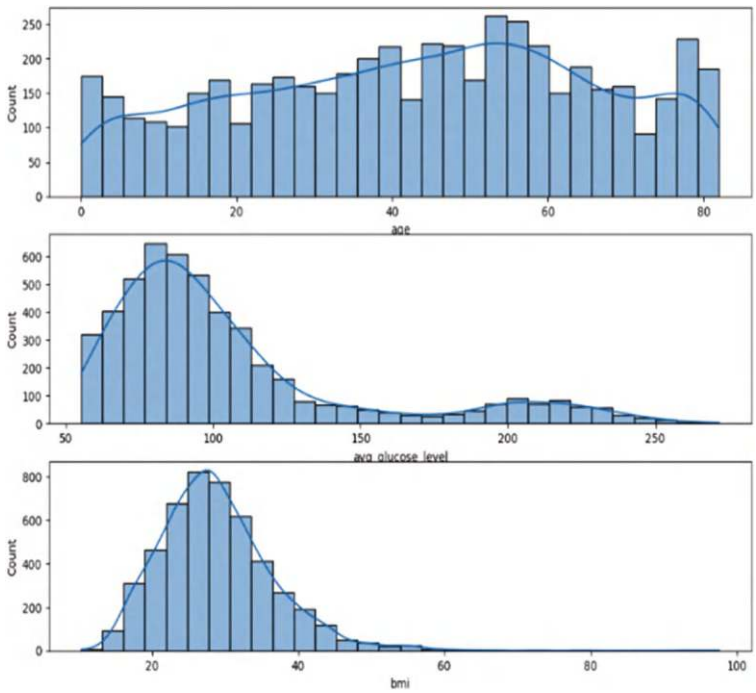

Fig. 14.2 Analysis of numerical features

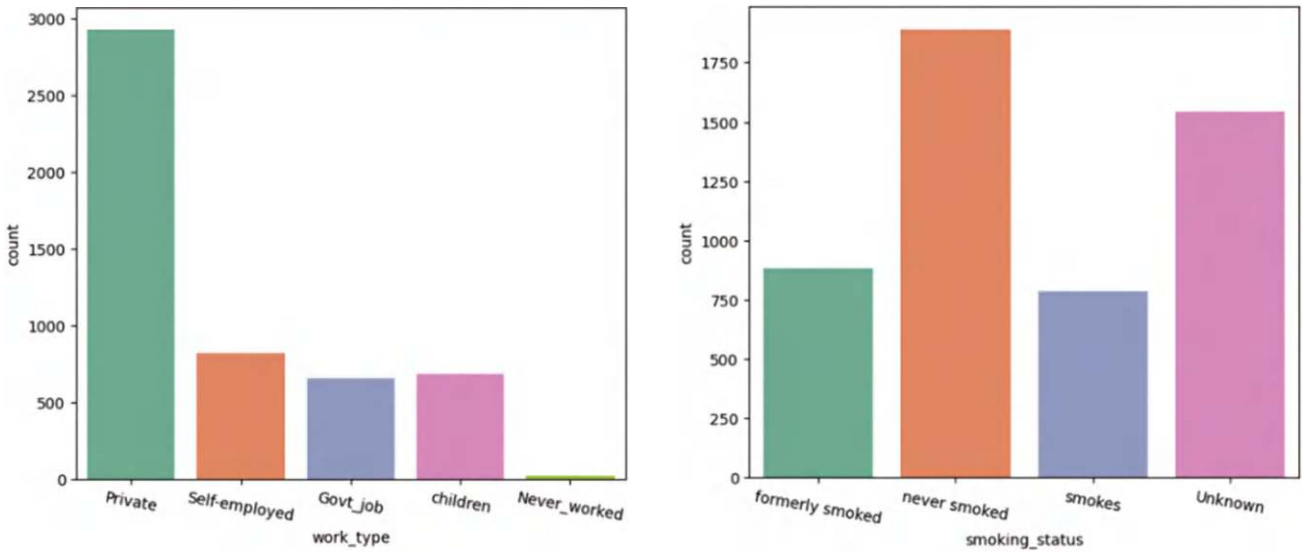

Fig. 14.3 Analyzing categorical features

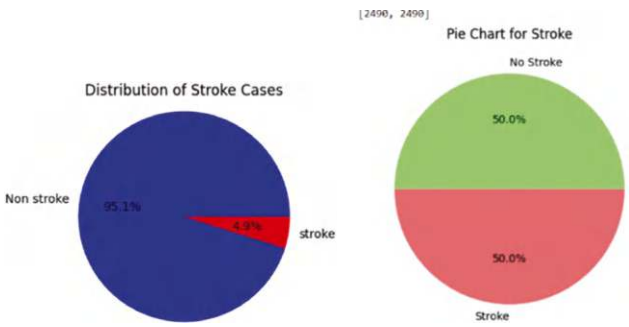

Fig. 14.4 Imbalance in data, data balanced

Fig. 14.5 illustrates, it generates synthetic data points for the minority class, thus reducing bias and improving the model's ability to identify strokes.

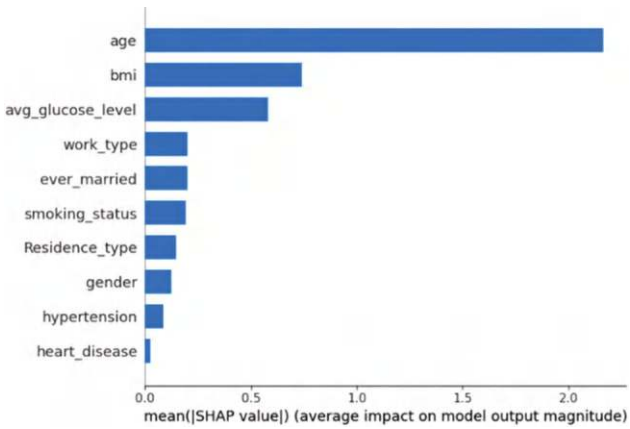

Fig. 14.5 SHAP value summary for feature importance in stroke prediction

To further refine data quality, we confirmed the absence of duplicate entries and removed irrelevant columns like ID, optimizing memory and model performance. Categorical features were analyzed using frequency counts, while numerical features such as age, BMI, and glucose levels were visualized with histograms and box plots to understand their distributions and identify central trends Lastly, by applying correlation analysis and visualizations, we assessed the relationship between each feature and the target variable, focusing on features with strong predictive value. This thorough preprocessing approach lays a solid foundation for accurate and interpretable stroke predictions.

3.3 Modeling Techniques

In this project, utilized several machine learning algorithms to develop models for stroke prediction. Each algorithm was selected for its strengths in handling classification problems. Below is an overview of each algorithm used and the results obtained:

3.4 Hyperparameter Tuning

Hyperparameter tuning was chosen as a core technique to optimize model performance and align each algorithm with the specific characteristics of the dataset. This process directly improves accuracy by adjusting critical parameters, such as learning rate and estimator count in XGBoost, and tree depth in Random Forest, enabling each model to detect complex patterns more effectively. Tuning also addresses the balance between overfitting and underfitting; for example, setting lower learning rates in XGBoost reduces overfitting, while limiting tree depth in Random Forest prevents excessive model complexity. Additionally, tuning

promotes model efficiency and generalization, ensuring consistent performance across diverse patient data essential in healthcare contexts. Techniques like GridSearchCV and RandomizedSearchCV systematically identify optimal parameter values, streamlining the tuning process and enhancing model reliability. In summary, hyperparameter tuning was essential to ensure high-performing models suited to real-world applications in stroke prediction, achieving a balanced and effective approach to model building. Here's a brief summary of the process and results. XGBoost GridSearchCV identified optimal parameters: colsample bytree=0.8, learning rate=0.1, max depth=9, n estimators=400, subsample=0.8. This resulted in an accuracy of 0.93 with precision, recall, and F1-scores of 0.91, 0.95, and 0.93, respectively. Support Vector Machine (SVM) Tuning parameters C=100, gamma='scale', and kernel='rbf' improved accuracy to 0.88, with precision, recall, and F1- scores of 0.85, 0.93, and 0.88. Logistic Regression The best parameters were C=1, penalty='l2', solver='liblinear', max iter=5000, achieving an accuracy of 0.80 with precision, recall, and F1-scores of 0.79, 0.81, and 0.80. Random Forest With n estimators=150, max depth=None, min samples split=2, and criterion='gini', accuracy reached 0.92, with precision, recall, and F1-scores of 0.90, 0.94, and 0.92. k-Nearest Neighbors (KNN) Tuning n neighbors=3, p=1, weights='distance', and leaf size=10 improved accuracy to 0.88, with precision, recall, and F1-scores of 0.84, 0.94, and 0.88. Gaussian Naive Bayes Using var smoothing=1e-09, accuracy reached 0.78, with precision, recall, and F1-scores of 0.74, 0.83, and 0.79, though tuning had limited effect. In summary, hyperparameter tuning enhanced model performance across multiple metrics, demonstrating its value in refining predictive models.

3.5 Ensemble Learning with Voting Classifier

Ensemble learning was applied using a Voting Classifier to combine the strengths of Random Forest and XGBoost, leveraging hard voting for majority class selection. The Voting Classifier achieved an accuracy of 0.92, with precision, recall, and F1- scores of 0.93 for class 0 and 0.92 for class 1, outperforming individual models and providing more reliable predictions. In the case of data leakage, it occurs when the data preparation process is not correctly separated between training and test sets, allowing the model to "see" data it shouldn't, resulting in inflated accuracy. To avoid data leakage, splitting the data into train and test before preprocessing and handling missing values separately for each set ensures more accurate results. Without data leakage, accuracies for models were KNN 87.32, XGBoost 91.0, Random Forest 89.46, Logistic Regression 80.40, SVM 80.4, and Naiıve Bayes 80.4.

3.6 Model Explainability with SHAP and LIME

It's very important to understand how the model makes decisions. This us be sure about how reliable its predictions are. To this, used LIME and SHAP. These methods explain how individual features add to the model's predictions. They give us a peek into our Random Forest and XGBoost models' strengths and weaknesses Fig. 14.5 provides a visual representation of explainability.

SHAP (Shapley Additive Explanations) values, derived from cooperative game theory, measure feature importance by showing each feature's role in model predictions. In the stroke prediction model, age was the most influential feature, followed by BMI and average glucose level. Other features like work type, marital status, and smoking status had some impact, while residence type, gender, hypertension, and heart disease had little effect. For the Random Forest model, SHAP analysis revealed that age, BMI, and glucose levels were highly influential, though the model struggled with stroke cases, indicating a need for improved sensitivity. The XGBoost model also showed similar patterns, with age and BMI playing key roles but facing challenges in distinguishing between stroke and non-stroke cases. Further tuning could improve performance. Interaction plots of age and gender demonstrated how these features jointly influence stroke prediction decisions.

LIME and SHAP enhance model interpretability by highlighting key features like glucose level and BMI in stroke prediction. For Random Forest (94% accuracy), LIME emphasized these features in non-stroke predictions but struggled with stroke cases, identifying potential improvement areas. Similarly, LIME showed that XGBoost's stroke predictions varied, with lower feature influence on stroke outcomes. SHAP provides fair feature impact distribution using game theory, while LIME offers localized explanations through input perturbations. Together, these tools improve model transparency, uncover biases, and support effective stroke prediction, benefiting healthcare practices, as illustrated in Fig. 14.6.

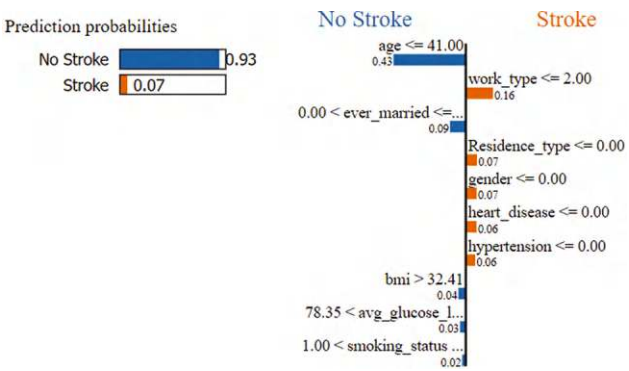

Fig. 14.6 LIME contribution in prediction

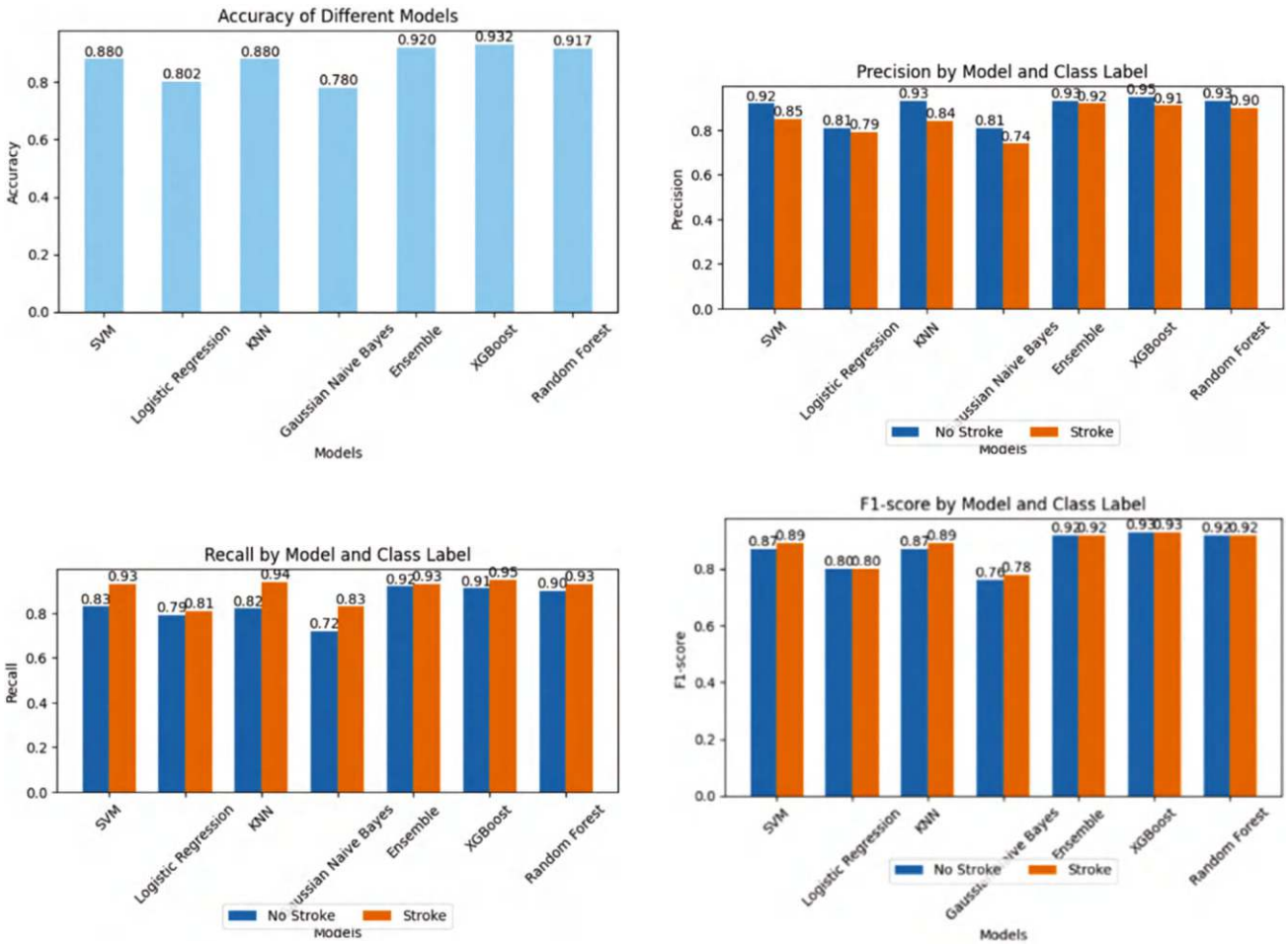

Fig. 14.7 Accuracy, precision, recall, F1-score curves of model's class wise

4. Results and Discusion

This section evaluates the performance and robustness of machine learning models for stroke prediction using patient data attributes such as age, BMI, glucose levels, and lifestyle factors. The models were assessed based on metrics like accuracy, precision, recall, F1-score, and interpretability as depicted in Fig. 14.7, with SHAP values identifying feature importance to test model stability, minor data variations were introduced, and XGBoost along with ensemble methods consistently maintained high accuracy, demonstrating resilience to data distribution changes.

XGBoost confusion matrix with low false positives and negatives as shown in Fig. 14.9, it means the model is reliable in real life. The highest accuracy gained was in XGBoost with 93.2%, ensemble methods 92%, and Random Forest at 91.7%. SVM and KNN reached 88%. Logistic Regression got 80.2%, and Gaussian Naive Bayes fetched 78% (Table, Fig. 14.8). By SHAP and LIME, the features glucose, age, and BMI were the important one.

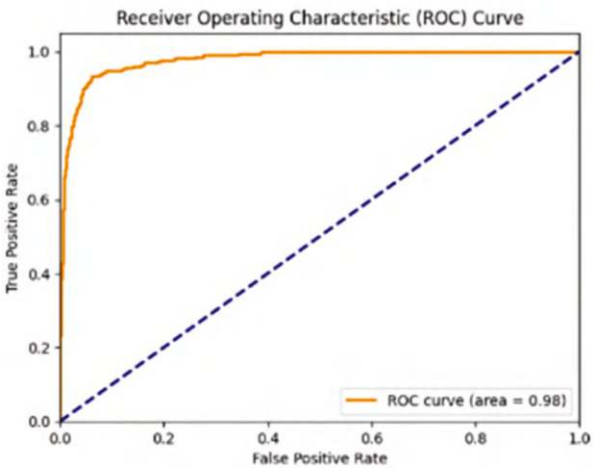

Fig. 14.8 Performance assessment via ROC curve

High accuracy and good interpretability of XGBoost and ensemble models helped healthcare providers understand how the features influence predictions.

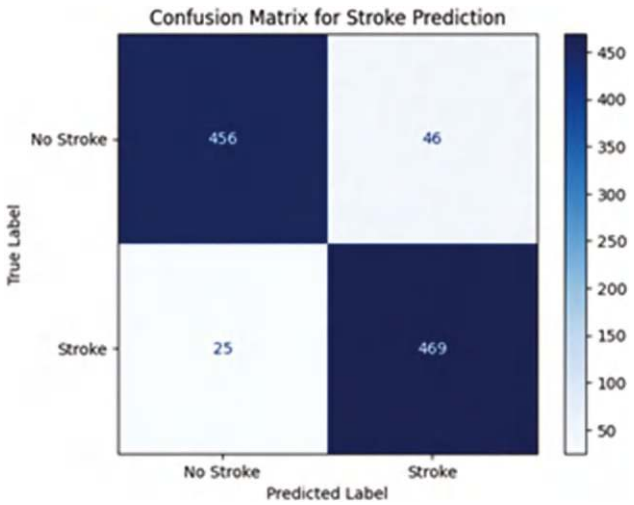

Fig. 14.9 Confusion matrix for XGB model

While precision in XGBoost, ensemble methods, and Random Forest is high, which reduces the number of false positives, the recall metrics and the balanced F1-scores proved them to be reliable for stroke prediction. The good performance and clarity of XGBoost and ensemble methods make them highly suitable for clinical use.

SMOTE balancing further improved model robustness by enhancing accuracy on an imbalanced dataset. This combination of accuracy and transparency positions the model as a reliable tool for healthcare, where understanding prediction factors is as crucial as accuracy itself. In summary, the use of advanced ML techniques and interpretability tools, visualized through classification reports, ROC curve can find in Fig. 14.9, confusion matrices as depicted in Fig. 14.10, and SHAP values, contributed to a reliable stroke prediction model that supports early detection and proactive healthcare strategies. Table 14.1 describes the accuracy of a different models.

Table 14.1 Model accuracies

Models	Accuracy
XGB Classifies	93.2
Support Vector Machine	88.0
Logistic Regression	80.2
K-Nearest Neighbors	88.0
Random Forest	91.7
Naïve Bayes	78.0

5. Stroke Prediction Web Application Integration

Application uses both frontend and backend technologies, as depicted in Fig. 14.10.

This makes it super easy for anyone to check their stroke risk. Frontend Development: First off, the frontend made with HTML, CSS, JavaScript and Bootstraps to make it look nice and work well on any device, Fig. 14.10 provides a visual representation of UI. Users can fill in their health infousing forms. These forms are really neat because they react and change thanks to CSS and JavaScript. Machine Learning Model Integration: Model was trained in Python using libraries like scikit-learn. This model gets saved as a special object (like joblib or pickle). When someone submits their info, it's sent to the backend, where it gets prepared. Then it goes to the model for a prediction! Finally, the result pops up on the frontend for users. Workflow: Clients provide their inputs, which are swiftly sent to the server. The model then estimates the stroke risk, and users receive their results immediately. Technologies Used: The project utilizes HTML, CSS, JavaScript, and Bootstrap for the frontend, Python with Flask or Django for the backend, and Python libraries such as scikitlearn and XGBoost for machine learning.

Fig. 14.10 Block diagram of application working

6. Conclusion and Future Research Direction

This study created a good machine learning model to predict strokes early. XGBoost showed high accuracy and was easy to understand using SHAP and LIME. SMOTE helped fix the data imbalance, and tuning the parameters improved performance. The XGBoost model worked well with complex patient data, helping healthcare providers find people at risk. However, the size and limited variety of the dataset might impact how widely it can be used. SMOTE helps with class imbalance but might not reflect the true nature of the stroke cases and fixed health attributes could drop accuracy over time. Even with the clarity SHAP and LIME offer, more clinical testing is necessary. Future studies could make the model better by including real-time health data, such as lifestyle changes and wearable metrics that increase its adaptability and accuracy. An expanded dataset of a more diverse population may make this dataset stronger. Better balancing methods than SMOTE could be explored to fix the problem of imbalanced data well. Further adjustments and clinical trials are very important for performance improvement to build a foundation in predictive health and possible utility in systems used for stroke prevention.

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Optimizing Real Time Intrusion Detection for Enhanced Network Security

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Abstract: This addresses the growing threats of computer viruses, malware, and cyberattacks on networks, emphasizing the importance of intrusion detection as a proactive defense mechanism. Existing solutions primarily rely on DNN, which, while effective, face challenges in accuracy and false positive rates. To enhance cybersecurity, we propose innovative algorithms, including CNN, RNN with LSTM, DNN, RBM combined with BILGRU, and a hybrid CNN+LSTM model. Our hybrid approach achieved an impressive 99% accuracy on the KDD-Cup dataset, significantly improving detection effectiveness and reducing false positives. Utilizing a generative adversarial network and contrasting unaided and DL-based discriminative techniques, we offer a total methodology that further develops ID in digital actual frameworks controlled by the IoT. This work addresses a significant accomplishment nearby and adds to more vigorous protection against changing digital assaults by featuring the capability of complex DL procedures in handling network safety shortcomings..

Keywords: 'Cybersecurity, Internet of things, Intrusion detection system (IDS), Anomaly detection, Security attacks, Deep learning'

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1. Introduction

Three layers — info, yield, and secret layers — make artificial neural networks (ANNs) [25] the establishment for deep learning (DL) approaches. Working in a nonlinear way, each layer answers information inputs subsequently permitting the organization to learn perplexing examples. In a few disciplines, including visual acknowledgment, picture handling, signal handling, and sound acknowledgment [23], DL [1] procedures have become extremely famous. Particularly for genomics and ailment diagnostics, DL [24] has been exceptionally normal in medication as it shows its capacity to oversee complex information structures, similar to pictures and text, utilizing forward and in reverse proliferation strategies [20]. The trouble is augmenting values and hyperparameters north of a few aspects to appropriately control enormous example numbers and decrease contrasts among preparing and testing results [2].

One of the main lines of assurance against cyberattacks is intrusion detection systems (IDs). Working with security frameworks including encryption and confirmation, IDS [3] safeguard against digital assaults. Through the examination of harmless traffic examples and use of assault explicit rules, IDS can isolate among unlawful and approved conduct. [4] Information mining further develops IDS ability, consequently empowering more exactness in spotting complex cyberthreats [22], especially in key framework frameworks as Internet Industrial Control Systems (IICs) [27].

This study presents an effective IDS for IIoT-fueled IICs utilizing a profound autoencoder-based LSTM [5] model to tackle these issues. [30] Great IDS need to keep mystery to ensure that hidden information is protected all through information move in testing and preparing stages. [021] Ordinarily, IDS might be isolated into 'host-based intrusion detection systems' (HIDS) [7] and 'network intrusion detection systems' (NIDS), the two of which utilize various ways to deal with screen and handle any dangers without jeopardizing network execution [8].

2. Literature Review

Recent advancements in deep learning (DL) have significantly enhanced intrusion detection systems (IDS), leveraging architectures such as bidirectional LSTM networks. For instance, Imrana et al. [9] introduced a bidirectional approach that effectively captures both past and future context in network traffic, improving detection rates of anomalies.

Additionally, Salih et al. [10] reviewed various DL approaches for IDS, highlighting the versatility of neural networks in adapting to different types of data inputs and environments.

The integration of convolutional neural networks (CNNs) into intrusion detection has also shown promise. Azevedo and Portela [11] discussed practical applications of CNNs in identifying patterns in network traffic, illustrating their ability to process multidimensional data effectively. Furthermore, the use of residual networks has been explored for improving image recognition tasks, demonstrating the potential of deep residual learning frameworks in handling intricate datasets [12]. The transferability of features across different tasks has also been analyzed, indicating that robust feature extraction can lead to improved model performance [13].

3. Proposed Methodology

3.1 Proposed Work

The proposed system utilizes deep learning with a generative adversarial network to significantly enhance cybersecurity detection in IoT-enabled cyber-physical systems, achieving high accuracy, maintaining data privacy, and ensuring ease of deployment. The proposed system markedly enhances cybersecurity threat detection accuracy. It leverages deep learning, improving intrusion detection in complex settings. And also preserves critical data privacy and integrity for security. In our project, we successfully implemented an ensemble method to boost predictive accuracy by integrating multiple individual models. Particularly noteworthy is the inclusion of a hybrid architecture, combining CNN and LSTM, denoted as CNN+LSTM. This hybrid model achieved an impressive accuracy of 99% when applied to the KDD-Cup dataset, underscoring the efficacy of our ensemble technique for intrusion detection in IoT-based cybersecurity infrastructures (as shown in Fig. 15.1).

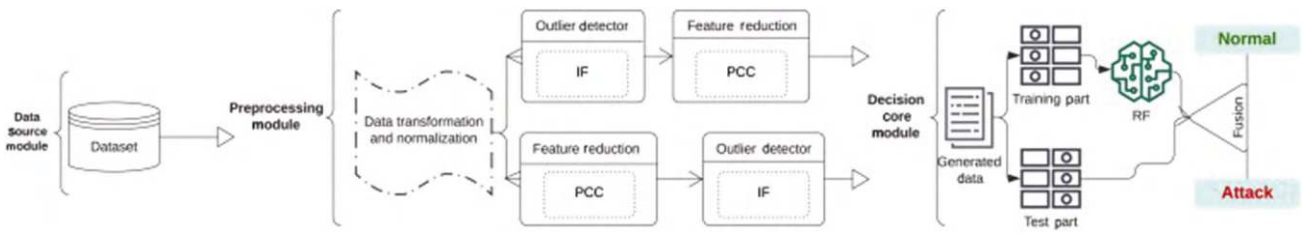

Fig. 15.1 Proposed architecture

3.2 System Architecture

The system architecture for the project "Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered CyberSecurity Infrastructures" follows a structured approach. It begins with dataset exploration to handle and track down significant qualities, continues on with information readiness to prepare the dataset for model preparation, and afterward isolates the information into training and testing sets. Building AI models — including a hybrid CNN+LSTM model and an independent CNN model to learn examples and portrayals for intrusion detection — is the quintessence of the plan. Model evaluation is performed using the testing set, assessing metrics like accuracy and precision, followed by a comprehensive analysis of model performance. The integration of CNN+LSTM showcases a commitment to leveraging both spatial and temporal information for enhanced intrusion detection in real time within IoT-driven cybersecurity environments.

3.3 Dataset Collection

The study examines KDDCup99, NSL-KDD, and UNSW-NB15 as important IDS training and evaluation datasets. With 42 traffic, content, and content feature properties, the NSLKDD dataset enhances KDD99 by removing duplicate data and improving record counts in training and testing [14]. From the DARPA98 IDS assessment, KDDCup99 provides labeled and unlabeled IoT cybersecurity data. The UNSW Cyber Range Lab's UNSW-NB15 dataset contains 47 characteristics across 10 attack categories to assess malicious activity (as shown in Fig. 15.2). In online protection research, regularly utilized datasets survey antagonistic movement and recognize assaults. By bringing down copy information and adjusting record includes in preparing and testing sets, NSL-KDD improves upon KDD99. It has 42 traffic, content, and host-based capabilities in addition to other things. Famous for IoT network safety research, KDDCup99 comes from DARPA98 IDS and offers marked and unlabeled information. Planned by IXIA and UNSW Digital Reach Lab, UNSW-NB15 has 47 qualities and models 10 sorts of assaults, including DoS, Exploits, Observation, and Worms, so helping current attack detection.

3.4 Data Processing

Crude information is transformed into important information by data processing, in this manner directing organizations in their choices. Information is assembled, organized, cleaned, checked, broke down, and changed over into structures like diagrams, charts, or reports in various cycles. Information handling raises its worth for chiefs through better information quality and openness. Contingent upon the amount and intricacy of the data, there are a few methodologies for information handling: manual, mechanical, and electronic ones. In contemporary conditions, particularly for overseeing tremendous measures of information like enormous information, robotized arrangements including specific programming are basic. Through these instruments, the handling stream is improved and significant bits of knowledge are delivered that help quality administration, functional upgrades, and key preparation, so assisting organizations with obtaining a strategic advantage by information driven approaches.

3.5 Feature Selection

By isolating out the most relevant, non-excess data for model structure, highlight choice upgrades prescient execution while eliminating computational costs. This methodology supports the expulsion of unnecessary factors as datasets extend, working on model effectiveness. By focusing on the main qualities, it further develops ML by changing information factors and delivering predominant results.

3.6 Algorithms

Used in image and video recognition tasks.

Convolutional Neural Networks (CNNs) are intended to analyze input that resembles a grid, especially photographs. [15] They use convolutional layers to automatically learn feature spatial hierarchies, which is why they work so well on image and video identification tasks.

Step 1: Data Collection: Gather and preprocess labeled datasets, including images or signals relevant to intrusion detection.

Step 2: Model Architecture: Design a CNN with multiple layers for feature extraction and classification.

Step 3: Training: Train the CNN using the prepared dataset, optimizing hyperparameters to improve detection accuracy.

Step 4: Evaluation: Assess model performance on test data, focusing on metrics.

RNNs [16] are designed to work with sequential data by maintaining an internal state or memory. They process inputs in a way that information cycles through a loop, allowing the network to consider previous context. This makes them suitable for tasks involving sequences or time-series data.

Step 1: Data Preparation: Collect and preprocess sequential data, ensuring proper labeling for intrusion detection tasks.

Step 2: Model Design: Construct a RNN architecture to capture temporal dependencies in data.

Step 3: Training Process: Train the RNN using the prepared dataset, adjusting parameters to enhance performance.

Step 4: Performance Evaluation: Evaluate the model on test data, measuring accuracy, recall, and false positive rates.

Combining **CNN and LSTM** leverages CNN's ability to capture spatial features from data (e.g., images) and LSTM's [17] capability to understand and retain temporal dependencies. This hybrid approach is effective for tasks involving both spatial and sequential data.

Step 1: Data Acquisition: Collect and preprocess both spatial and temporal data for intrusion detection analysis.

Step 2: Model Integration: Design a hybrid architecture combining CNN for feature extraction and LSTM for sequence processing.

Step 3: Training Phase: Train the combined CNN-LSTM model on the dataset, optimizing for accuracy and efficiency.

Step 4: Model Assessment: Evaluate performance on test data, focusing on metrics such as accuracy and precision.

RBM is a generative stochastic ANN used for unsupervised learning. Combining CNN with BiGRU[18] suggests using a mix of convolutional layers for feature extraction (CNN) and bidirectional gated recurrent layers (BiGRU) to capture sequential patterns, potentially for complex pattern recognition tasks.

Step 1: Data Preparation: Gather and preprocess data, ensuring proper normalization for effective Restricted Boltzmann Machine (RBM) training.

Step 2: Model Configuration: Set up the RBM architecture, defining visible and hidden layer sizes and parameters.

Step 3: Training Process: Train the RBM using contrastive divergence to learn feature representations from the input data.

Step 4: Feature Extraction: Utilize the trained RBM to extract features, feeding them into classifiers for intrusion detection.

When arranged in a multi-layer perceptron architecture, **DNNs** can learn complex data patterns and characteristics [19]. They are utilized in many ML classification and regression problems.

Step 1: Data Collection: Gather and preprocess datasets, ensuring proper labeling for effective deep neural network training.

Step 2: Architecture Design: Construct a deep neural network (DNN) with multiple hidden layers for complex feature learning.

Step 3: Training Phase: Train the DNN on the dataset, adjusting weights using backpropagation to minimize loss.

Step 4: Performance Evaluation: Evaluate model accuracy and performance metrics on test data, ensuring effective intrusion detection.

4. Experimental Result

4.1 Performance Evaluation

Precision: Precision evaluates the percentage of correctly identified cases among the positive-labeled cases. It is based on a formula that determines the accuracy of positive predictions (see Fig. 15.1).

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

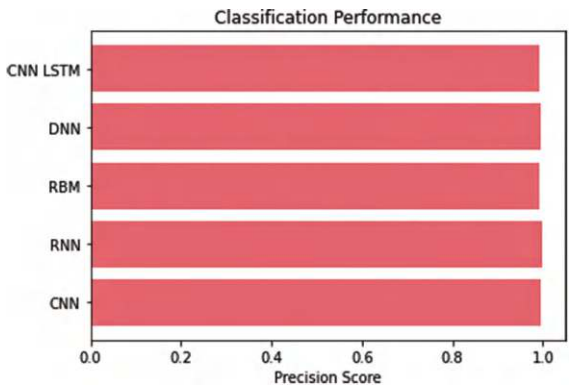

Fig. 15.2 Precision comparison graph

Recall: The recall of a model quantifies its capacity to locate all pertinent instances of a given class. It provides information about how well the model detects a certain class and is expressed as the ratio of properly predicted positives to all actual positives (see Fig. 15.3).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

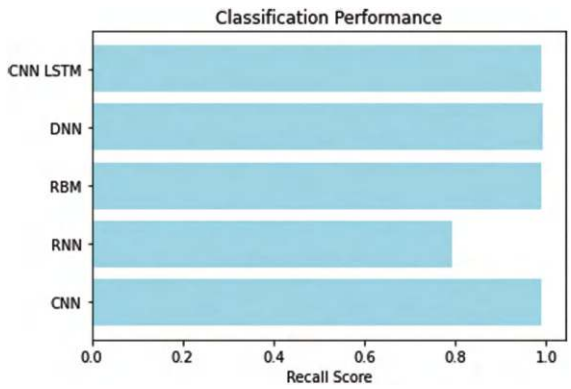

Fig. 15.3 Recall comparison graph

Accuracy: The percentage of accurate predictions is known as accuracy, and it indicates how well a model performs overall in classification tasks (see Fig. 15.4).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

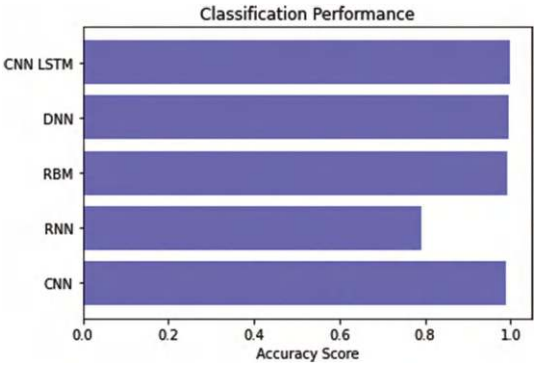

Fig. 15.4 Accuracy graph

F1 Score: For assessing unbalanced datasets, the F1 Score— which is the harmonic mean of accuracy and recall—is perfect since it balances false positives and negatives (see Fig. 15.5).

$$F1\,\text{Score} = 2 * \frac{\text{Recall X Precision}}{\text{Recall + Precision}} * 100$$

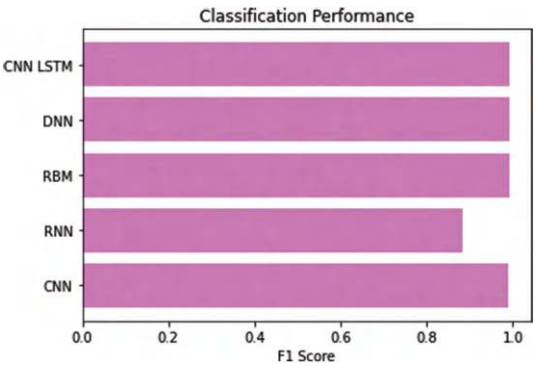

Fig. 15.5 F1Score

Table 15.1 Performance evaluation

Algorithms used	Accuracy	Precision	Recall	F1 - Score
CNN	0.989	0.994	0.989	0.991
RNN	0.793	1.000	0.793	0.885
RBM	0.991	0.993	0.991	0.992
DNN	0.994	0.994	0.994	0.994
Extension CNN+LSTM	1.000	0.993	0.990	0.992

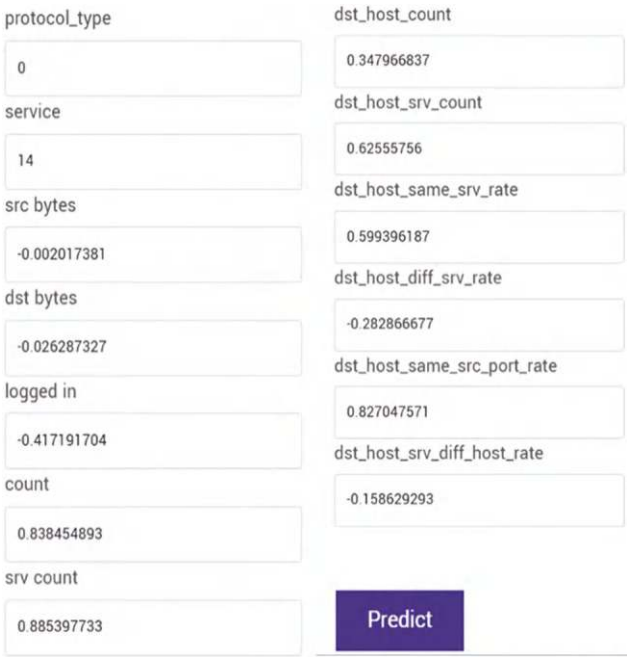

Fig. 15.7 User input

Fig. 15.8 Predict result for given

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	...	dst_host_srv_count
0	0	tcp	http	SF	181	5450	0	0	0	0	...	9
1	0	tcp	http	SF	239	486	0	0	0	0	...	19
2	0	tcp	http	SF	235	1337	0	0	0	0	...	29
3	0	tcp	http	SF	219	1337	0	0	0	0	...	39
4	0	tcp	http	SF	217	2032	0	0	0	0	...	49
...	...	...	...	...	...	...	...	...	...	...	...	...
494016	0	tcp	http	SF	310	1881	0	0	0	0	...	255
494017	0	tcp	http	SF	282	2286	0	0	0	0	...	255
494018	0	tcp	http	SF	203	1200	0	0	0	0	...	255
494019	0	tcp	http	SF	291	1200	0	0	0	0	...	255
494020	0	tcp	http	SF	219	1234	0	0	0	0	...	255

494021 rows × 42 columns

Fig. 15.6 KDDCUP dataset

5. Conclusion

The effectiveness of using DL techniques like RNN, CNN, and DNN for early cyberattack detection and malware identification is emphasized heavily in this research. By leveraging the capabilities of deep learning, the project showcases its potential to significantly enhance cybersecurity measures, providing a proactive approach to identifying and mitigating threats.

The Flask framework provides a streamlined and intuitive interface, making it easier for users to deploy and interact with the cybersecurity system. The venture's ground breaking approach is underlined by its emphasis on constant recognition and arrangement of unfriendly activities, which makes ready for continuous headways in reinforcing network protection estimates utilizing state of the art innovation.

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Enhancing Cybersecurity with AI: A Deepfake Detection Framework Using InceptionResNetV2 and LSTM

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Abstract: In the era of advanced digital manipulation, the phrase "seeing is believing" no longer holds true, especially with the rise of deepfakes. As technology advances, creating deepfakes has become increasingly accessible, even through mobile applications. This development has made it challenging for the human eye to detect such fabrications. Researchers are actively developing techniques to identify these falsifications. Deepfakes involve media generated through artificial intelligence (AI) algorithms, which learn and merge attributes from both target and source images to create convincingly altered content. This paper presents a method for detecting deepfake videos using deep learning, specifically employing Long Short-Term Memory (LSTM) networks in combination with InceptionResNetV2. Using transfer learning, our method uses a pretrained InceptionResNetV2 convolutional neural network (CNN) is used to generate feature vectors from video frames. These vectors are processed by an LSTM layer to capture temporal dependencies. The model's performance is validated using a confusion matrix, demonstrating a 91.48% accuracy rate. The final output classifies video content as "real" or "fake," providing a reliable indicator for detecting deepfakes.

Keywords: Deepfake detection, InceptionResNetV2, LSTM networks, Video analysis, AI manipulation, Transfer learning

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1. Introduction

Recent advancements in digital technology have revolutionized the manipulation of online content, making it possible to significantly alter appearances in videos. Unlike basic Photoshop edits, these alterations involve intricate processes where artificial intelligence (AI) is employed to train machines to replicate human voices and facial expressions. This is accomplished by providing the AI system with a dataset containing real images, audio samples, and videos of an individual, allowing the machine to learn and generate entirely fabricated videos.

Deepfakes may be produced in two main ways. The first one entails using a stand-in actor for the original person. The machine encodes data from both the original person and the actor's videos, identifying similarities, compressing the data, and then decoding it to swap the content between the two videos. This results in viewers seeing and hearing what appears to be the original person, even though the content is derived from the actor. The second approach uses generative adversarial networks (GANs) [1].

In this method, random noise is used to create artificial images through deep learning algorithms, which are subsequently combined with real photos. Repeated processing of this data eventually leads to the creation of highly realistic depictions of non-existent individuals. Essentially, deep learning now enables the production of convincing videos of individuals performing actions they never actually engaged in. Deepfakes is divided into three categories: facial expression alterations, face swaps, and face synthetics.

Face synthetics often employ techniques like StyleGAN, where the generator model is trained to separate high-level features from other attributes. A common method for detecting these synthetic faces is to identify manipulated regions, typically producing a binary output to determine if the picture is real or fake. Face swapping, an additional kind of deepfake, involves replacing the target's face with a real one. This process uses technologies such as image blending, face alignment, and cropping. Detection methods for face swaps often rely on training CNN and RNN to identify residual traces left during the generation process. Finally, face expression manipulation refers to altering attributes such as gender, facial color, skin tone, age, or expressions, thereby changing a person's appearance or mood [2].

2. Literature Review

In recent years, the proliferation of deepfakes has grown exponentially, fueled by the availability of software that simplifies their creation. These deepfakes pose significant threats to privacy, democracy, and public trust, creating an increased demand for effective detection methods. Below, we review several notable approaches to deepfake detection.

Jadhav et al. [3] created a web-based tool that enables users to upload videos and quickly determine their authenticity. Their model utilized LSTM for sequential data processing and ResNeXt for feature extraction from video frames. The approach involved splitting the videos into frames, cropping them around the facial region, and combining selected frames to form a new dataset. This method proved highly reliable and user-friendly, with performance evaluated through a confusion matrix.

Y. Li and S. Lyu [4] proposed an innovative method using Convolutional Neural Networks (CNNs) to compare facial regions with adjacent areas. Their approach aimed to detect deepfake-generated images, especially those created with limited resources, by analyzing discrepancies between facial regions and neighboring areas.

L. Yin, U. A. Ciftci, and I. Demir [5] focused on feature extraction and computed temporal consistency and coherence from biological signals retrieved from face areas in both real and synthetic video pairs. The study used a combination of Support Vector Networks (SVNs) and CNNs to assess the probability of video authenticity.

D. Guera and J. Delp [6] developed a two-stage analytical method for automated deepfake detection. In the first stage, a CNN was used to extract frame-level features, and in the second stage, a Recurrent Neural Network (RNN) captured inconsistencies arising from face-swapping processes. Their model, tested on a dataset of 600 videos from various online sources, achieved an accuracy of 94%.

S. Lyu, Y. Li, and M. Chang [7] introduced a system that identifies deepfakes by analyzing eye-blinking patterns, often poorly replicated in synthetic media. Their method utilized a LRCN to detect temporal anomalies in blinking behaviour. They first identified the face region in each frame and then analyzed the blinking behaviour to expose inconsistencies.

3. Existing Systems

Existing deepfake detection systems have utilized various techniques, each with distinct strengths and limitations. Earlier systems predominantly relied on basic Convolutional Neural Networks (CNNs), which focused on capturing spatial features from images. These CNN-based models achieved moderate accuracy rates, typically between 75% and 85%. While they could detect certain visible artifacts, they frequently missed subtle manipulations introduced during the deepfake creation process. This shortfall was

largely due to their emphasis on spatial features, neglecting temporal elements, which are critical in identifying more complex alterations.

To address these shortcomings, Recurrent Neural Networks (RNNs) were introduced to analyze video sequences. These models demonstrated improved performance, with accuracy rates between 80% and 88%. RNNs, including their variant LSTM networks, are better equipped to capture temporal dependencies and changes over time. However, despite this enhancement, these models still struggled to detect complex patterns and subtle inconsistencies common in advanced deepfakes. Their limited feature extraction capabilities and failure to adequately identify temporal inconsistencies across video frames remained significant challenges.

Additionally, these systems faced high false-positive rates and scalability issues, which compromised their effectiveness in real-world applications. High false positives meant that legitimate content was often misclassified as fake, undermining the system's reliability. Scalability problems further limited their practical application, making them unsuitable for large-scale deployments. As a result, despite advancements, these early systems were not fully capable of addressing the growing sophistication of deepfake technologies.

4. Proposed Methodology

The generation of deepfakes primarily relies on an encoder-decoder architecture. In this architecture, the encoder captures key features from both the target and source faces, while the decoder utilizes these features to generate a manipulated video. Although advanced techniques are applied to enhance the video quality and remove most visible artifacts, subtle imperfections often remain, which are difficult to detect with the naked eye. These residual artifacts are critical for our detection model.

Our proposed approach incorporates Inception ResNetV2 for feature extraction. Using the extracted features, a Training a RNN to find out if a video has been edited. As deepfakes typically involve alterations in short segments of a video, the detection model processes smaller video frames for better accuracy.

4.1 Dataset and Preprocessing

The dataset used in this study includes approximately 6,458 video samples, sourced from the Deepfake Detection Challenge dataset on Kaggle, along with the FaceForensics and Celeb-Deepfake Forensics datasets. This dataset comprises both real and manipulated videos created using various deepfake generation techniques, providing diverse samples for robust training and evaluation 30% of the dataset was used for testing, while 70% was used for training. During preprocessing, each video was labelled as either "real" or "fake" to indicate its authenticity. To manage computational constraints, key frames (approximately 147 frames per video) were extracted, focusing on segments likely to contain transitions between real and manipulated content. This selection ensures that the model receives relevant data for both training and testing phases.

Figure 16.1 shows the dataset containing videos used for deepfake detection. The collection includes both manipulated and authentic videos, illustrating the diversity essential for training and evaluating the model's accuracy.

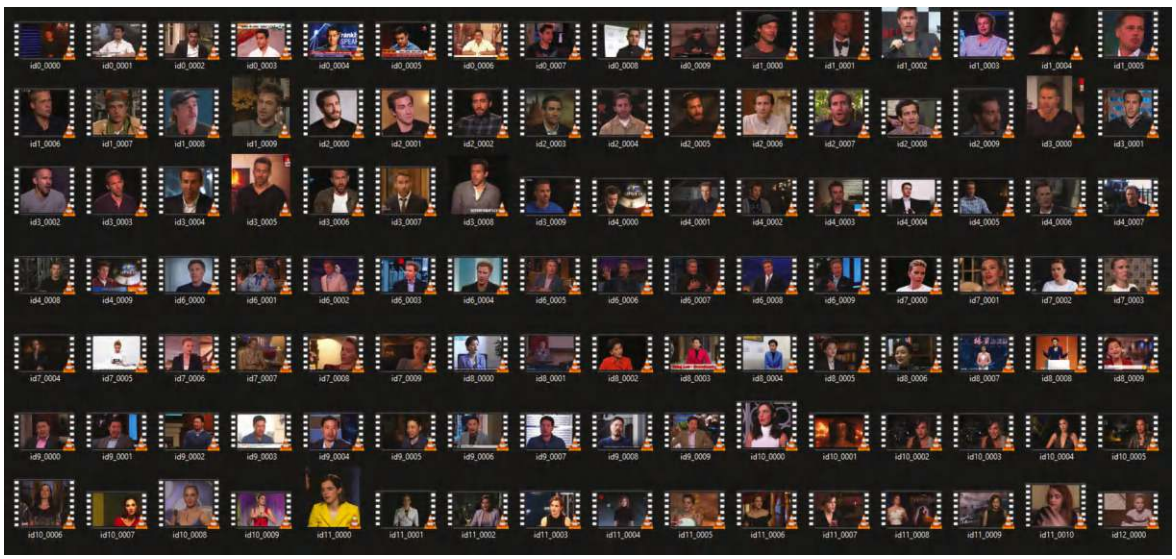

Fig. 16.1 Dataset of video files used for training and testing in deepfake detection

During preprocessing, labels were assigned to indicate whether a video was real or fake. Key frames, particularly where the transition from an authentic video to a deepfake occurs, were identified and analyzed. On average, 147 frames were extracted from each video. Due to computational limitations, a subset of frames was used for training, while the remainder was utilized for testing.

4.2 Modeling

Our approach performs categorization of images for every frame taken from the videos. The model architecture integrates a RNN, specifically LSTM, and a pretrained CNN model (InceptionResNetV2). During the training process, key components such as loss functions, optimizers, and hyperparameters were fine-tuned, with the learning rate adjusted to minimize loss and improve accuracy.

InceptionResNetV2 is a deep CNN with a 164-layer architecture, combining the strengths of residual and inception modules to capture intricate spatial features from images. This model generates high-dimensional feature vectors (2048-dimensional) from each input frame, enabling it to extract nuanced details from facial features. The architecture's deep layers are particularly beneficial in distinguishing subtle manipulations present in deepfakes. In our framework, InceptionResNetV2 is used as the primary feature extractor, generating robust spatial features from each frame.

The LSTM network is an advanced RNN was created to solve the issue of disappearing gradients, making it well-suited for learning long-term dependencies in sequential data. The LSTM layer processes the sequence of frame-based features generated by InceptionResNetV2, capturing temporal inconsistencies that are characteristic of deepfake manipulations. This combination of CNN and RNN architectures leverages both spatial and temporal analysis, improving the model's detection of modifications.

4.3 Feature Visualization and Classification using InceptionResNetV2

Object detection and feature extraction from images are accomplished using InceptionResNetV2, combining the ResNet and Inception architectures with 164 layers. The model was fine-tuned by modifying only the final layer to adapt to the deepfake detection task. During preprocessing, artifacts such as resolution discrepancies in affine face warping, commonly introduced during video editing, were replicated to train the model effectively.

Figure 16.2 illustrates the integration of InceptionResNetV2 for LSTM and feature extraction for sequential analysis, highlighting the enhanced detection of deepfake manipulations by capturing both spatial and temporal attributes.

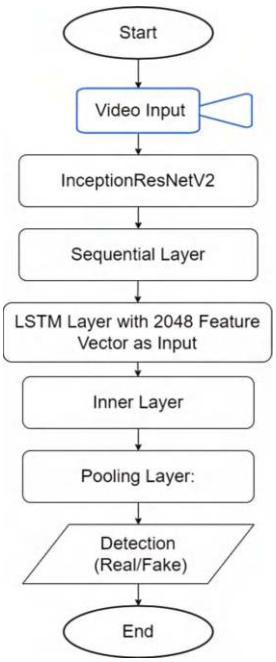

Fig. 16.2 Proposed model architecture

Using this approach, InceptionResNetV2 generates 2048-dimensional feature vectors from each frame. These vectors are then passed to the LSTM layer for further analysis, enabling the model to capture both spatial and temporal features. While CNNs are proficient at facial feature extraction, they lack the ability to account for temporal inconsistencies, which is where LSTM networks come into play.

4.4 LSTM for Sequential Processing

The vanishing gradient problem that traditional RNNs encounter was addressed by the development of a specific type of RNN known as Long Short-Term Memory (LSTM), enabling the model to identify enduring relationships in sequential data. The 2048-dimensional feature vectors produced by the CNN are fed into the LSTM layer, which processes the frames sequentially, analyzing the characteristics across time points. By comparing features at different time steps, the model identifies any inconsistencies that may suggest the presence of deepfake manipulations.

Once trained, the model can determine if a given input video is authentic or manipulated, using the combined power of InceptionResNetV2 and LSTM for robust detection.

5. Results and Discussions

The performance of the proposed deepfake detection model was evaluated over 20 and 40 epochs. Due to runtime limitations, the accuracy achieved was 84.75% at

20 epochs and 91.48% at 40 epochs. The results indicate a significant improvement in accuracy as the number of epochs increases. During testing, the accuracy of the model was evaluated using the confusion matrix, providing insights into the system's ability to distinguish between actual and manipulated videos.

The training and validation accuracy curves are displayed in Fig. 16.3 for the deepfake detection model across 20 and 40 epochs. As illustrated, both training and validation accuracy improve with more epochs, with significant accuracy gains observed from 20 to 40 epochs. The model's performance on the training data is represented by training accuracy, whereas validation accuracy shows how well the model generalizes to unseen data. The upward trend in both curves highlights the model's increasing ability to detect deepfakes as training continues.

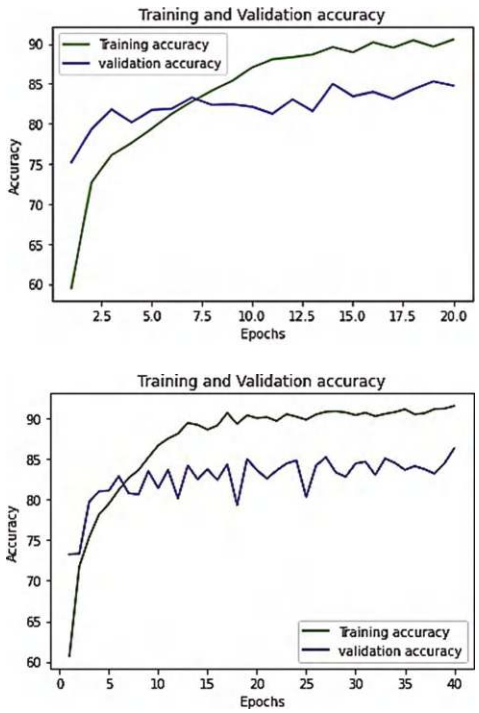

Fig. 16.3 Accuracy graphs for training and validation at 20 and 40 epochs

Figure 16.4 shows the output from the deepfake detection model, classifying the uploaded video as 'Fake,' suggesting manipulations are present.

Figure 16.5 displays the output from the deepfake detection model, confirming that the uploaded video is classified as 'Real,' indicating its authenticity.

Table 16.1 highlights the advantages of our proposed method over others, especially in terms of accuracy, making it a highly effective deepfake detection model.

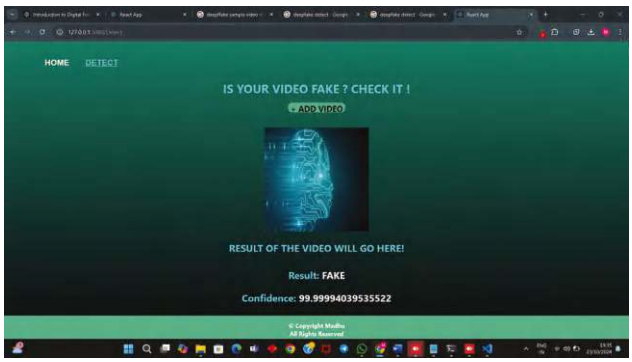

Fig. 16.4 Results of deepfake detection indicating the video is classified as fake

Fig. 16.5 Results of deepfake detection indicating the video is classified as real

Table 16.1 Comparative analysis of deepfake detection models

References	Accuracy (%)	Features/Approach
A. Jadhav et al. (2021) [3]	89.7	LSTM with ResNeXt for sequential processing and feature extraction
Y. Li & S. Lyu (2020) [4]	85.3	Comparison of generated face areas with surrounding regions using CNN
U. A. Ciftci et al. (2020) [14]	88.9	Feature extraction of biological signals from facial regions
Y. Li, M.C. Chang & S. Lyu [20]	88.1	Eye blinking analysis using LRCN
Proposed Method	91.48	InceptionResNetV2 for feature extraction, LSTM for sequential analysis

The comparative analysis of various deepfake detection methods is provided in Table 16.1, showcasing the accuracy rates and techniques used. The proposed method, which employs InceptionResNetV2 for feature extraction and LSTM for sequential analysis, achieved the highest accuracy at 91.48%, outperforming other approaches.

Precision: Precision is a metric for positive forecast accuracy.

$$\textbf{Precision} = \frac{TP}{(TP + FP)}$$

Accuracy: The ratio of correct predictions to the total number of predictions.

$$\textbf{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Recall: Recall quantifies the model's accuracy in identifying positive cases.

$$\textbf{Recall} = \frac{TP}{(TP + FN)}$$

F1 Score: To create a balance between recall and accuracy, the F1 Score computes the harmonic mean of the two measures.

$$\textbf{F1 Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Where:

- True Positives (TP): Correctly predicted deepfake videos.
- False Positives (FP): Incorrectly predicted real videos as deepfakes.
- True Negatives (TN): Correctly predicted real videos.
- False Negatives (FN): Incorrectly predicted deepfake videos as real.

Table 16.2 shows that the High F1-score, recall, and accuracy are attained by the suggested model., indicating a well-balanced performance in detecting deepfake videos with minimal misclassifications.

Table 16.2 Model evaluation metrics for deepfake detection

Metric	Value (%)
Precision	90.32
Recall	88.75
F1-Score	89.52
Accuracy	91.48

6. Conclusion

The rapid rise of deepfakes has significantly impacted public trust, with increasingly deceptive media content appearing across various platforms. In response to this challenge, the method presented This research uses a deep learning technique to identify deepfakes automatically. By dividing videos into individual frames and applying advanced preprocessing techniques using LSTM for feature extraction and InceptionResNetV2 for sequential analysis, the proposed model has demonstrated both high accuracy and reliability.

The convolutional LSTM framework enables precise detection of manipulated faces within videos, which can help mitigate the spread of harmful content, such as defamatory deepfakes. While the current results are promising, further experimentation—such as training the model with more epochs and optimizing the learning rate—could potentially improve accuracy even further.

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Enhancing Industrial Internet Security with Blockchain-Based Equipment ID

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Abstract: The venture makes a blockchain-based industrial equipment traceability system. Blockchain's internal traceability arrangement chiefly catches modern industrial equipment's recognizability data and A digital overview of all the traceability information. Specific industrial equipment traceability information and virtual describes are typically recorded by the traceability arrangement that is not developed on blockchain technology. This paper presents a traceability framework that confirms every single discernible datum and forestalls blockchain information blast. An inner blockchain traceability arrangement records basic data and computerized outlines straightforwardly onto the blockchain, while an outer traceability arrangement assembles thorough data outside the organization.

Keywords: Blockchain platform, Equipment ID, Traceability, IOT, Smart contracts, Digital summaries, Governance model, Dual system'

1. Introduction

The Industrial Internet is changing assembling by blending IoT and distributed computing. Secure and solid information taking care of is fundamental for ongoing equipment monitoring using Industrial Wireless Networks (IWN) and cloud stages. A solid blockchain stage with equipment IDs further develops industrial environment traceability, data respectability, and security [1-3]. This methodology utilizes blockchain's decentralization to give straightforward correspondence between arranged gadgets, decreasing dangers of unlawful access, altering, and information breaks and working on modern insight and functional effectiveness.

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Online protection is fundamental for shield touchy data and industrial systems from arising dangers as firms use IoT, cloud computing, and remote organizations. Industrial Wireless Networks (IWN) make modern conditions defenseless against undesirable access, information breaks, and control [4-5]. Modern cycles major areas of strength for require insurances including encryption, verification, and continuous checking. Keeping up with trust and strength in the creating modern environment requires handling security worries as information sharing and cloud-based advances become more normal [9].

Blockchain innovation is changing information the board by giving a decentralized and secure stage for exchanges and information trade across areas. Blockchain empowers straightforwardness, traceability, and security by creating permanent records of information spread all through an organization, decreasing information altering and unlawful access [7-8].

2. Literature Review

Blockchain technology has excited interest and theory in banking and supply chain management lately. This writing audit sums up blockchain agreement cycle, application, and results research [10].A total investigation of blockchain agreement techniques and mining system the executives [12]. The paper inspects blockchain biological systems' agreement calculations, from PoW to PoS, and organization players' mining strategies. The creators enlighten blockchain agreement instrument improvements and issues by integrating writing[22].

A seminal exploration of blockchain technology's potential to reshape the global economy in his work, "Blockchain: Blueprint for a New Economy." [13]. Drawing upon real-world examples and case studies, the author articulates a compelling vision for a decentralized future underpinned by blockchain technology, thereby laying the groundwork for further research and exploration in this burgeoning field [14-16].

Explore the performance of blockchain technology in the supply chain management, focusing specifically on soybean traceability within agricultural supply chains [17]. The potential for transformative impact within the agricultural sector, paving the way for enhanced supply chain resilience and efficiency [20]. By leveraging blockchain's cryptographic features and decentralized architecture, a robust framework for ensuring data integrity and trust within food supply ecosystems, underscoring the transformative potential of blockchain technology in safeguarding critical infrastructure [18].

In summary, the literature survey presented herein offers a multifaceted exploration of blockchain technology's transformative potential across diverse domains. From consensus mechanisms to real-world applications, the studies surveyed herein underscore the profound [4].

3. Existing System

As indicated by an examination, the blockchain system includes data, network, agreement, and different layers. Data layer guarantees information security and protection. The information layer depends on encryption, Merkle tree, chain structure, and timestamp. P2P networks, data distribution, and confirmation strategies structure the organization layer of decentralized stockpiling. The agreement layer runs the blockchain circulated network without a hitch. PBFT, Kafka, Pontoon, PoW, PoS, and DPoS are normal agreement calculations [11].

4. Proposed Methodology

The industrial equipment traceability system that is being proposed uses blockchain technology and presents a unique solution to address the drawbacks of existing system. The system is made to take advantage of blockchain technology's advantages while resolving the issues with traditional traceability methods.

It utilizes blockchain technology to establish a secure and tamper-resistant identification system for industrial equipment. Blockchain ensures the integrity and authenticity of traceability information through its decentralized and cryptographic features [2].

In Fig. 17.1 Shows the system architecture encompasses four main components: Production, Circulation, Supervision, and Distribution, all underpinned by blockchain technology for secure data storage [21].

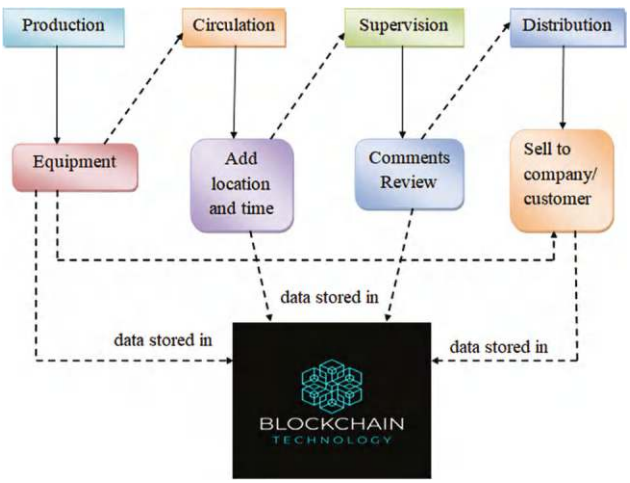


Fig. 17.1 System architecture of proposed system

4.1 The Blockchain-Based Traceability Technique

In the beginning into, the blockchain-based device traceability system's traceability organization must conduct identity verification and key distribution.. Upon fulfillment of the procedure, unique permissions have been granted to every individual within the system. Smart contracts will be implemented by traceability companies and the government to track equipment information regarding traceability as it moves through the manufacturing process.

The working principle of the proposed method is as follow:

Step 1 : The "Production Login" module serves as a gateway for authorized users overseeing the production phase of industrial equipment.

1. The production employee determines in using true credentials.
2. They enter data such the unique code, production date, and equipment batch number.
3. Once verified, the information is sent in.
4. To ensure traceability, a new block including the equipment details is created in the blockchain.

Step 2 : The "Circulation Login" module is tailored for users engaged in the movement and circulation of industrial equipment. With specialized access privileges, these users can efficiently input and manage logistics-related information.

1. A circulation employee logs in.
2. They provided the date and the works of the delivery.
3. During verification, data is added to the blockchain.
4. The blockchain gets modified with a new block that safely records the circulation data.

Step 3: The "Distribution Login" module is specifically designed for users overseeing the distribution phase of industrial equipment.

1. The distribution employee logs in.
2. The circulation data is safely recorded in a new block that is appended to the blockchain.
3. The distribution data has been evaluated and reported.
4. The blockchain receives a new block that contains distribution information.

Step 4: The "Supervision Login" module is tailored for users overseeing the industrial equipment production process. The supervision employee logs in.

1. They examine the equipment and record any errors or problems.
2. Once validated, the defect information is provided.
3. For storing the fault data for later use, the blockchain creates a new block.

Step 5: The Tracking Data Traces the data which is stored in the Equipment details.

1. The system is accessed by authorized users.
2. They have access to all the information that is safely kept in the blockchain, including manufacturing, delivery, sales, and equipment faults.

Step 6: The Blockchain Security technology to securely store industrial equipment data, including unique IDs, production details, logistics, distribution records, and defect reports .

1. Every action and piece of data is safely saved as an unchangeable block to avoid unwanted modifications.
2. Data integrity is ensured by the system's ability to detect tampering and modify data.

Step 7: The "Smart Contracts" is an Ethereum blockchain-based software.

1. Information can only be modified or changed by authorized individuals.
2. Only verified users can execute updates, and all other users can only view the data, thanks to smart contracts that automatically enforce access permissions.

Each step of the equipment data tracking process from production to distribution is clear, safe, and real-time according to this unique algorithm.

4.2 Traceability Technique Without Utilizing Blockchain

The paper represents a traceability solution that doesn't depend on blockchain technology ensure the traceability of special information throughout the entire equipment supply chain. To gain equipment traceability, the equipment traceability system is applied by the solution, which also stores the information about equipment traceability in the traceability enterprise identification management server with the object ID information for identification registration mechanism. Based on the object ID identification analysis method Information, the solution obtains detailed information about equipment traceability. Information that cannot be processed by the blockchain is the solution to the traceability of capacity equipment blockchain data explosion difficulty.

5. Experimental Result

Through the Production phase, items can be produced using equipment, and necessary data is captured and stored in the blockchain. The Fig. 17.2 Equipment Blockchain folder to start python server. In order to provide transparency and traceability across the supply chain, the place and time of products movement are added to the blockchain during Circulation. In Fig. 17.3 Adding all product equipment details.

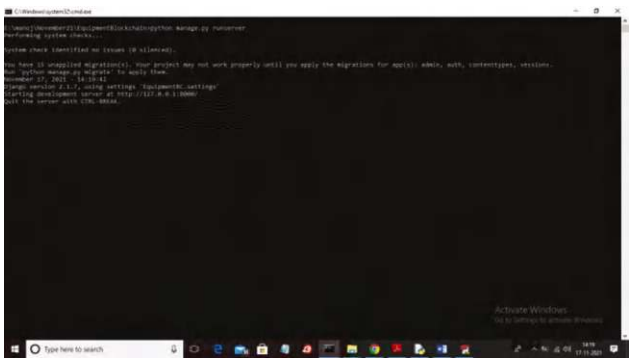
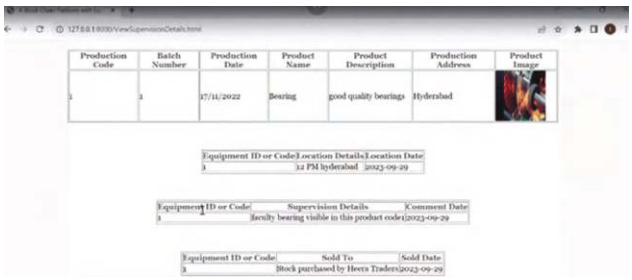


Fig. 17.2 Python server



Production Code	Batch Number	Production Date	Product Name	Product Description	Production Address	Product Image
1	1	17/11/2022	Bearing	good quality bearings	Hyderabad	

Equipment ID or Code	Location Details	Location Date
1	12 PM hyderabad	2023-09-29

Equipment ID or Code	Supervision Details	Comment Date
1	faculty bearing visible in this product code	2023-09-29

Equipment ID or Code	Sold To	Sold Date
1	Stock purchased by Heera Traders	2023-09-29

Fig. 17.3 Details from block chain

In Fig. 17.3 shows user can fetch all details from Blockchain and view and similarly you can add any number of product details

5.1 Performance Evaluation

The project integrates blockchain to enhance security in the authentication and access control processes. Utilizing block chain , the system ensures secure user authentication by employing cryptographic techniques.

$$B = f(T, C, S, E, A) \quad (1)$$

here B represents the system's security or blockchain efficiency as a function of:

1. T: Traceability
2. C: Cost
3. S: Security level
4. E: Efficiency
5. A: Accuracy

Equation 2:

$$B = k_1 * (T * S/C) + k_2 * E + k_3 * A$$

which quantifies the system's security, where:

k_1: A constant that scales the effect of the transaction volume and security relative to the computational cost.

k_2: A constant scaling the effect of efficiency or energy consumption.

k_3: A constant scaling the effect of access control.

Accuracy:

$$Accurracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Where:

1. TP- True Positives.
2. TN- True Negative.
3. FP- False Positives.
4. FN- False Negatives.

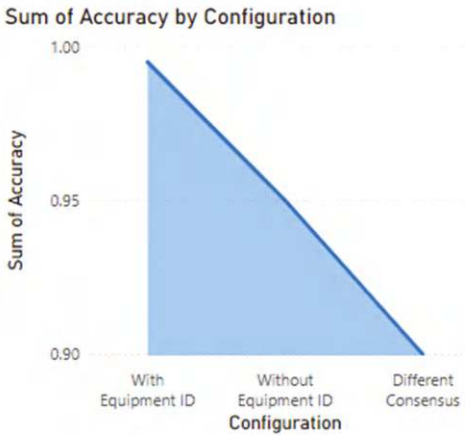


Fig. 17.4 Accuracy comparison graph

Precision - Precision measures how many of the predicted positive values were actually correct.

$$Precision = \frac{TP}{TP + FP}$$

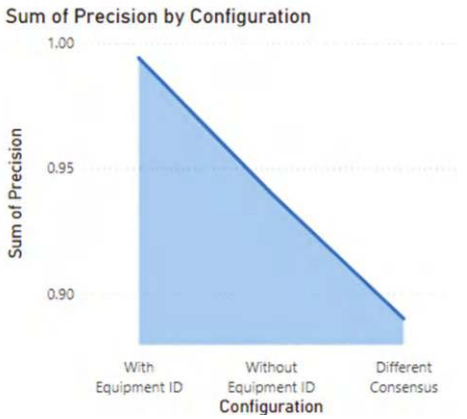


Fig. 17.5 Precision comparison graph

Recall - Recall captures the ability to locate all crucial occurrences (TP (True Positive))

$$Recall = \frac{TP}{TP + FN}$$

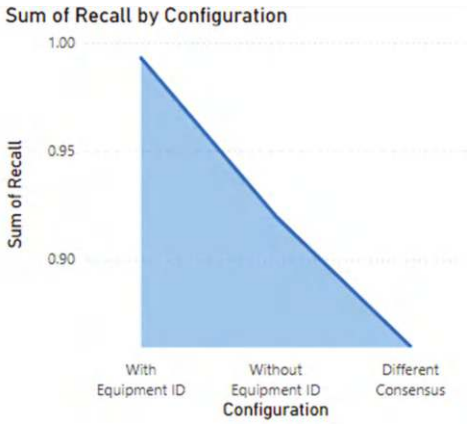


Fig. 17.6 'Recall comparison graph'

F1-SCORE - By obtaining Precision and Recall's harmonic mean.

$$F1\ Score = \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

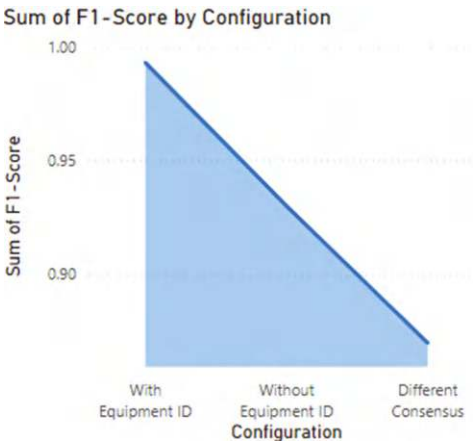


Fig. 17.7 F1-Score comparison graph

Table 17.1 shows Evaluation of performance is related to proposal requirements such as Accuracy, Precision proposal requirements such as Accuracy, Precision, Recall and F1-Score

Table 17.1 Performance evaluation of proposed system

Configuration	Accuracy	Precision	Recall	F1-score
With Equipment ID	0.995	0.994	0.993	0.993
Without Equipment ID	0.950	0.940	0.920	0.930
Different Consensus	0.900	0.890	0.860	0.870

Table 17.2 shows Enhanced Execution Performance for Query for the provided proposal. The system throughput growing gradually from 350 to 400 while the proposal request raised from 1000 to 4000.

Table 17.2 Evaluation of performance is related to proposal requirements

Propose Requests & operations	Average runtime(s)	System fall (ms)	T Execution Rate
500	2.76	2.74	364.26
1000	2.76	2.74	364.26
1500	4.00	2.78	360.65
2000	5.24	2.82	357.04
2500	6.75	2.83	377.24
3000	8.26	2.84	397.43
3500	8.82	2.68	375.81
4000	9.38	2.51	354.81
4500	9.95	2.65	356.35
5000	10.51	2.79	358.51

Table 17.3 shows, Enhanced Execution Performance for Query. By increasing the query request from 500 to 5000, the system throughput reached a stable level of approximately 350.

Table 17.3 Enhanced execution performance for query

Propose requests & operations	Average Run time(s)	System fall (ms)	Execution Rate
500	2.84	2.86	350.06
1000	2.84	2.86	350.06
1500	3.96	2.70	372.53
2000	5.07	2.53	395.00
2500	6.14	2.47	404.30
3000	7.20	2.42	413.60
3500	8.29	2.37	422.24
4000	9.38	2.32	430.88
4500	10.44	2.36	423.83
5000	11.50	2.40	416.78

6. Conclusion

The analysis showed that blockchain technology might change industrial equipment data security and traceability. The stage's cryptographic ideas and decentralized plan have settled earlier security issues and made an unchanging record of equipment data. This has assembled certainty and receptiveness in the modern climate, further developing

responsibility and unwavering quality. The recommended framework's advantages go past its execution. The stage lays out the foundation for industrial traceability and data management with continuous updates, easy to use connection points, and savvy strategies.

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18

Performance Evaluation of Different Machine Learning Models in Predicting Stock Prices Assisted by Volume Data

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Abstract: This study presents an approach to forecast stock closing prices by using various machine learning models, including Linear Regression, Random Forest, and XGB Regressor. In the view of complexity of fluctuating prices, key indicator in the form of the delivery percentage of volume traded is considered for accurate prediction of the closing prices in the daily time frame. To validate the performance of the trained models a randomly chosen dataset of companies ABB India Limited, KRBL, Ajantha Pharma of National Stock Exchange (NSE) are chosen. The dataset ranges from 1st November 2021 to 28th April 2023. In this for training the dataset ranges from 1st November, 2021 to 28th February, 2023 and for testing the dataset ranges from 1st March, 2023 to 28th April, 2023. Further metrics including Mean Square Error (MSE), Accuracy (Acc.), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) are evaluated to determine the performance. The findings from the current work can offer valuable insights in utilizing Machine Learning for accurate decisions related to Stock Market investments.

Keywords: Machine learning, Stock market, Linear regression, Random forest, XGB regressor

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1. Introduction

Stock Market is essentially a giant Marketplace where people buy and sells stocks of the companies.A Stock trader must be aware of some important things at the time of purchasing a stock like what kind of stock he was buying,the fluctations in the prices of the stocks,is that stock really worth buying ?. To be fondly aware of these things so much scrutiny of data and the ability to forecast an outcome is essential. Because of the fluctuations in the stock prices it is quite difficult to get a fortunate forecast through the traditional knowledge.Exactly this is the place where Machine learning plays a crucial role in the prediction of the stock prices by scrutinizing a large amounts of data and becoming competent in forecasting predictions [1]. The Corner stone of a Well predicted model is the selection of some crucial factors. They are: The data you provide, the model that you selected for the prediction, the instructions you had given to the model on how to predict the data and testing the model performance on new data. Given the amount of data generated in the domain of stock market trading, the prominence for applying Machine Learning (ML) models has increased. [2]. While predicting the exact ups and downs of the market is still a tricky business, ML can be a powerful tool for investors. Large volumes of historical data, such as previous stock prices, trade volume, and economic indicators, can be analyzed by them [3]. This makes it easier to recognize trends and patterns that people might find challenging. When compared to more conventional approaches, machine learning algorithms have a significant advantage in identifying correlations between stock prices. Deep learning models such as Multilayer Perceptron , Long Short-Term Memory , and Gated Recurrent Unit are used to anticipate stock price fluctuations, with LSTM showing greater predictive skills because to its management of long-term dependencies. [4]. By comparing different deep learning architectures, the study found that LSTM excelled in capturing intricate patterns in stock price data, providing valuable insights. Wenjie Lu et al. focussed on predicting the next day's close price using CNN-BiLSTM-AM method [5]. The proposed CNN-BiLSTM-AM method outperformed seven other methods in predicting stock closing prices, showing the smallest MAE and RMSE values and the largest R2 value. Aparna Nayak et al. [6] aimed to predict stock market trends using supervised machine learning algorithms. They developed models for daily and monthly predictions, incorporating historical prices and sentiments. The daily prediction model achieved an accuracy of up to 70%, while the monthly prediction model highlighted the differences in trends between different months. Stock trading involves a plethora of indicators to assist the movement which can help improve prediction when applied in combination with models such as ANN and Random Forest [7]. The models were developed taking into account of volume profile apart from closing prices. Stock price prediction using a hybrid model that combines machine learning and deep learning techniques, specifically targeting the NIFTY 50 index in India from 2015 to 2018 are also explored [8]. It is found that a Convolutional Neural Network (CNN) model significantly outperforms traditional methods in forecasting the index's weekly movements. The study underscores the CNN's effectiveness in capturing complex patterns in stock price behavior, leading to high prediction accuracy. Fundamental and technical analysis methods for stock market prediction, highlighting the significance of factors like Price to Earnings ratio and Moving Average Convergence-Divergence indicator have a significant relevance [9]. The systematic analysis involved critically assessing insights spanning the last decade, compiled from various online digital libraries and databases. Using distinctive regression models for stock forecasting has yielded surprising results [10]. Analysis shows that both the OLS and Ridge models deliver strong predictive accuracy, particularly effective in lower and middle price brackets. In contrast, the XGBoost model, though powerful in some contexts, exhibits reduced accuracy and a noticeable bias in high-price predictions. These insights offer valuable guidance for researchers and analysts in choosing appropriate models, especially when working with datasets that present varied price characteristics. By leveraging regression algorithms and machine learning techniques, investors can potentially maximize profits by predicting stock price movements and trends effectively [11]. The study focused on dataset preprocessing, sentiment analysis methods, and the use of Linear Regression models (Simple and Multiple) for prediction. Further the effect of fundamental ratios on short term price movements can also be capture through regression analysis [12]. A more unique approaches in the context of identifying sectorial trends have also been explored using regression models [13]. In a study [14], which compared several machine learning and deep learning architectures, it was discovered that LSTM performed exceptionally well in identifying subtle patterns in stock price data. This discovery offers vital insights for financial practitioners, allowing them to improve their ability to anticipate stock prices and make more informed investment choices.

2. Methodology

This paper investigates the application of using Machine learning algorithms to forecast the stock prices. For that three different kinds of algorithms were employed to

analyse the data that had been provided and to predict the close prices as shown in Fig. 18.1. Initially the fundamental step to proceed further is Data collection, and the data had been taken data from Y finance from date 1st Nov 2021 to 28th Apr 2023. The collected delivery data is in the form of colour coding and historical data was collected using a python code. The raw data incorporated various trading percentages categorized by colours. To facilitate analysis, these coloured data points converted into probability values. This involves assigning a specific decimal value to each colour. This process made all the trading percentages look the same way, which made the analysis and comparison easier. The revised datasets comprise of details like the opening price, closing price (what should be predicted), highest price of the day, lowest price, and how many shares were bought and sold and the probability of buying that stock at the end of the day (Delivery data). For the prediction purpose the three machine learning algorithms that had been used are Random Forest, Linear Regression, XGB Regressor.

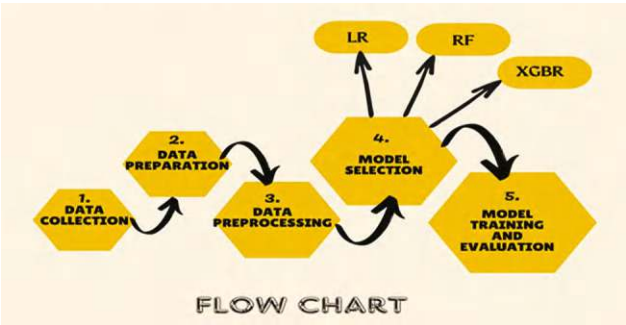

Fig. 18.1 Flow chart of the proposed model

2.1 Step 1: Data Collection

The data is collected from the yfinance website where the delivery data which is in the form of colour coding, and this historical data collected from the yfinance using a python code. Historical Data starts from 1 November 2021-28 April 2023. Figure 18.2 represents the delivery volume of a stock. Figure 18.3 depicts other parameters: Open price, Close prise, High Price, Low Price of a stock on a daily time frame.

Fig. 18.2 Delivery data

Date	Symbol	Open	High	Low	Close	Adj Close
01-11-2021	AARTIIND	970.0	992.75	960.299988	988.150024	979.427368
02-11-2021	AARTIIND	981.5	996.0	952.450012	958.200012	949.74176
03-11-2021	AARTIIND	962.0	971.549988	936.650024	947.650024	939.284851
08-11-2021	AARTIIND	960.0	964.950012	945.0	953.299988	944.884949
09-11-2021	AARTIIND	953.049988	966.650024	951.200012	953.849976	945.430176
10-11-2021	AARTIIND	955.75	966.5	950.0	957.799988	950.341553
11-11-2021	AARTIIND	960.0	961.450012	923.299988	939.900024	932.580994
12-11-2021	AARTIIND	950.099976	951.200012	932.049988	948.299988	940.915588
15-11-2021	AARTIIND	948.299988	968.25	945.0	963.849976	956.344421

Fig. 18.3 Historical prices

2.2 Step 2: Data Preparation

For the delivery data which had been considered from the initial data, raw data was converted into numerical data through App script code in google sheets, every coloured value had replaced with the mean of the percentage ranges and non-repeated stocks in each month had been deleted. Finally, delivery data had combined with historical collected from yfinance website using python and a different sheet made for a different company. For the delivery data which is considered our initial data represents various trading percentages classified by colours:

Violet: 80% and above
Dark Green: 60%-80%
Light Green: 50%-60%
Blue: 40%-50%
White: 30%

To facilitate analysis, these colored data points are converted into probability values:

Violet: 0.8
Dark Green: 0.7
Light Green: 0.55
Blue: 0.45
White: 0.25

This transformation allows for a standardized representation, simplifying subsequent analysis and comparison of trading percentages.

2.3 Step 3: Data Processing

In this data preprocessing, all the null values in each company thoroughly verified cleared and replaced with mean values and the time stamp had been changed in date column of every company dataset and final dataset is mentioned in Fig. 18.4.

Date	Symbol	Open	High	Low	Close	Adj Close	Volume	Delivery
01-11-2021	ABB	2105.0	2170.0	2032.099976	2079.699951	2063.378662	485302	0.45
02-11-2021	ABB	2090.0	2115.0	2041.300049	2062.449951	2046.263794	118552	0.0
03-11-2021	ABB	2066.199951	2144.75	2052.199951	2068.949951	2052.712402	385323	0.55
08-11-2021	ABB	2110.0	2124.350098	2071.199951	2086.899902	2070.521729	194599	0.0
09-11-2021	ABB	2094.949951	2208.399902	2084.449951	2185.050049	2167.901611	595914	0.55
10-11-2021	ABB	2185.050049	2222.100098	2151.0	2170.699951	2153.664307	207186	0.0
11-11-2021	ABB	2181.850098	2205.0	2132.149902	2172.300049	2155.251953	123304	0.0
12-11-2021	ABB	2160.199951	2232.0	2153.5	2211.300049	2193.945557	258341	0.25
15-11-2021	ABB	2230.0	2231.0	2137.0	2148.100098	2131.241943	91793	0.0
16-11-2021	ABB	2148.100098	2189.949951	2140.199951	2176.949951	2159.86499	384464	0.85

Fig. 18.4 Final dataset

2.4 Step 4: Model Selection

Model-1: Linear Regression

A linear regression model, as illustrated in Fig. 18.5, represents the relationship between a dependent variable (or response variable) and one or more independent variables (also called predictor or explanatory variables). Because it enables the prediction of the response variable based on the values of the predictor variables, this modelling approach is frequently employed. This is the reason for its widespread use. The formula for the linear regression model is provided in equation (1):

$$\bar{Y}_n = \sum_{i=1}^{n} \theta_i X_i + b \tag{1}$$

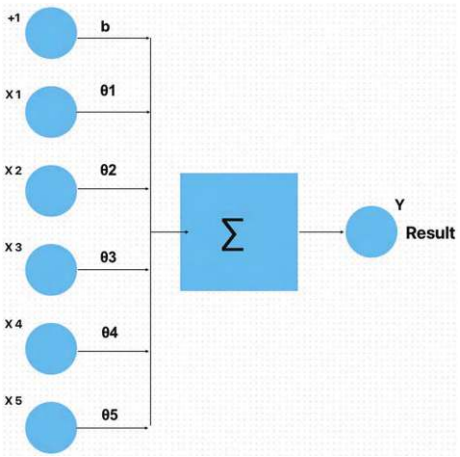

Fig. 18.5 Linear regression architecture

Model-2: Random Forest

An ensemble algorithm known as a Random Forest Regressor is one that generates predictions for the target variable by combining the results of many decision trees. The random selection of features and the splitting points during the tree building process enhance the performance of the model. Random Forest Regressor can be used to solve a plethora of problems and is commonly used in many practical applications. The architecture of this model is mentioned in Fig. 18.6.

Model-3: XGB Regressor

XGBoost is a gradient boosting framework that is based on the tree learning algorithm and is an optimized implementation that improves upon the efficiency and accuracy of traditional tree models. XGBoost uses a technique which involves iteratively adding new trees to the model to improve its performance. The resulting model is much more accurate and efficient than a simple tree model. The architecture of this model is mentioned in Fig. 18.7.

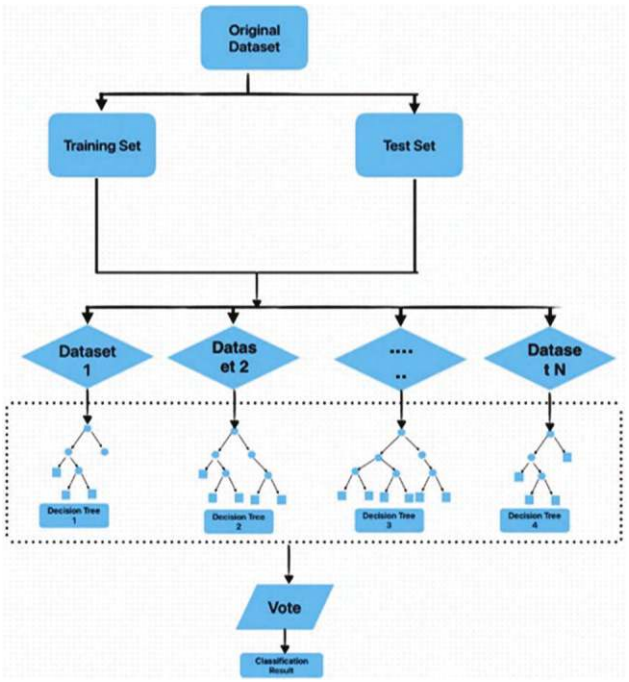

Fig. 18.6 Random forest architecture

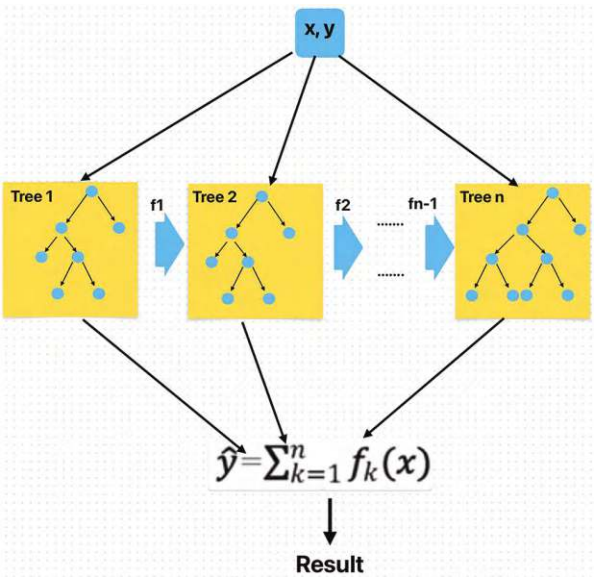

Fig. 18.7 XGB regressor architecture

3. Results and Discussion

The results and discussion on stock prediction using Linear Regression, Random Forest, XGB Regressor models can vary depending on the specific study and dataset used.

3.1 MODEL-1: Linear Regression

Figure 18.8, Fig. 18.9, Fig. 18.10 show the plot of predicted closing price (PCP) of ABB, KRBL, AJANTHA

Fig. 18.8 Predicted vs original price of ABB by linear regression model

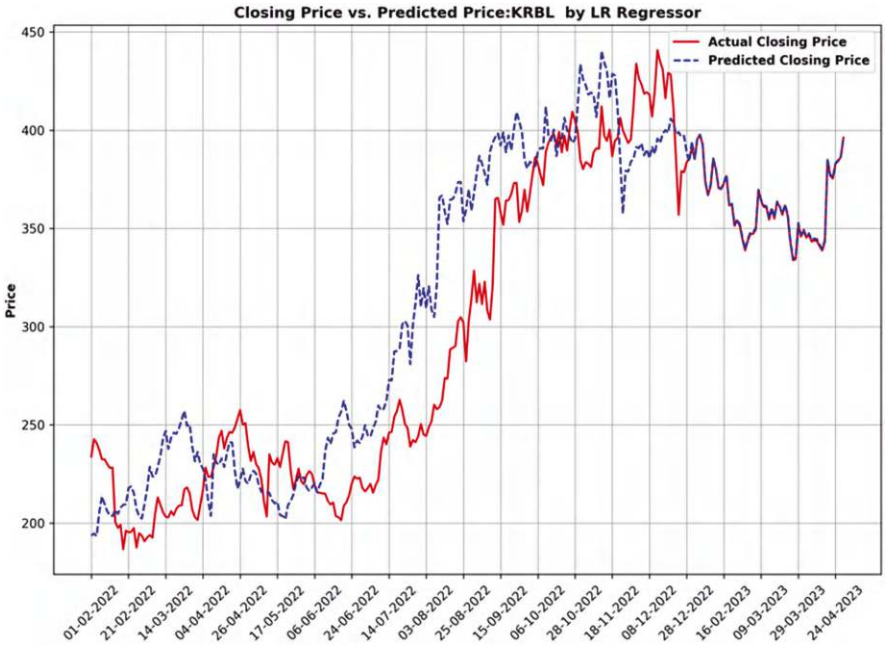

Fig. 18.9 Predicted vs original price of KRBL by linear regression model

PHARMA for Linear Regression model respectively. This model achieved the highest accuracy and lowest Mean Absolute Error (MAE) for companies ABB, KRBL, AJANTHAPHARMA, suggesting a strong linear relationship between variables for predicting its closing price. The computed parameters along with Accuracy are shown in Table 18.1. linear regression, known for its

Table 18.1 Summary of linear regression performance

Stock	Acc.	RMSE	MSE	MAE	PCP
ABB	99.94	2.89	8.38	2.68	3419.28
KRBL	99.82	9.24	85.47	7.18	388.29
AJANT PHARMA	99.65	26.77	716.67	20.14	1426.79

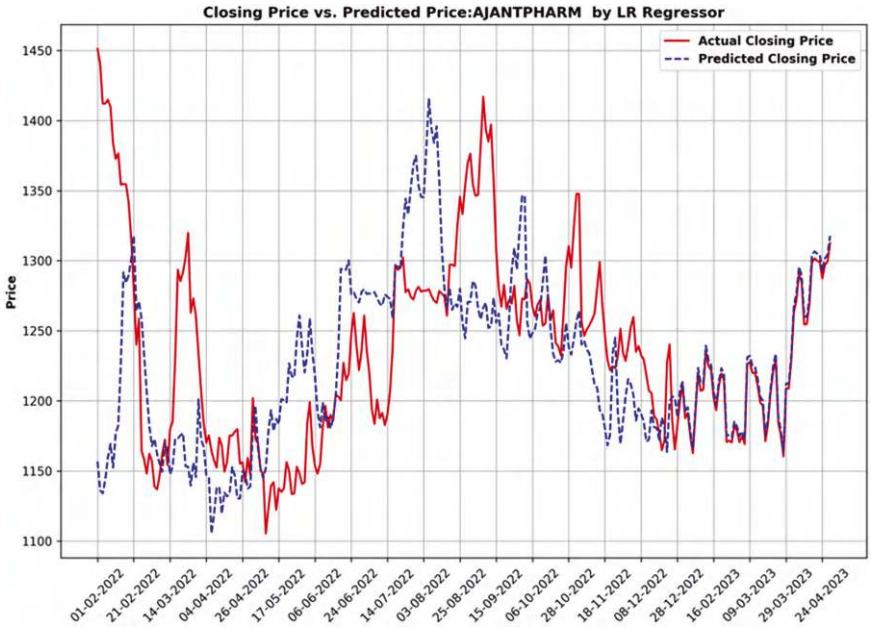

Fig. 18.10 Predicted vs original price of AJANTHA PHARMA by linear regression model

simplicity, achieved the highest accuracy in predicting stock prices within our dataset.

3.2 MODEL-2: Random Forest

In this case, three different company datasets are gathered for the purpose of predicting the closing prices. These datasets are then augmented by cross-validation and grid search for hyperparameter tuning. The Random Forest model demonstrates a strong performance in forecasting the closing prices for the following day. Figure 18.11, Fig. 18.12, Fig. 18.13 show the predicted results of ABB, KRBL, AJANTHA PHARMA by Random Forest model respectively. Evaluation metrics confirm the model's predictive accuracy and consistency whose values are mentioned in Table 18.2.

Fig. 18.11 Predicted vs original price of ABB by random forest model

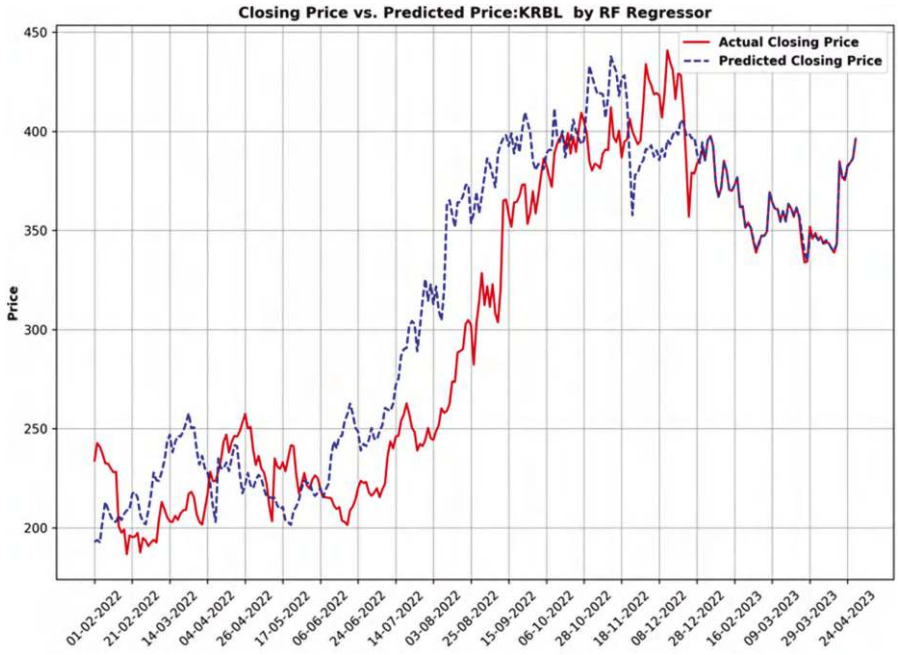

Fig. 18.12 Predicted vs original price of KRBL by random forest model

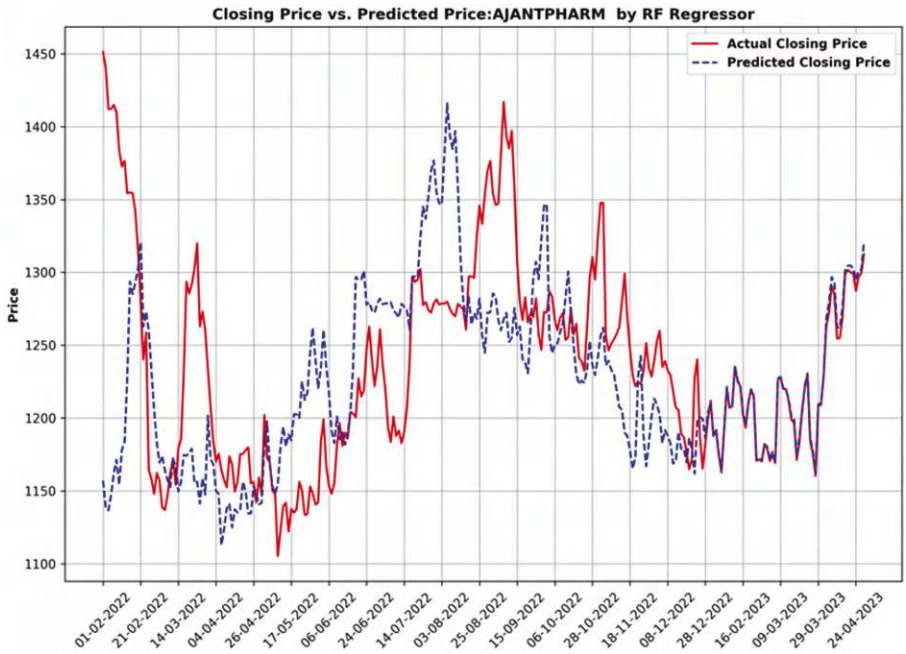

Fig. 18.13 Predicted vs original price of AJANTHA PHARMA by random forest model

Table 18.2 Summary of random forest performance

Stock	Acc.	RMSE	MSE	MAE	PCP
ABB	99.77	20.29	411.81	13.67	3362.84
KRBL	99.68	7.68	59.06	5.30	396.16
AJANT PHARMA	99.70	31.51	993.41	23.18	1269.93

3.3 MODEL – 3: XGB Regressor

Figure 18.14, Fig. 18.15, Fig. 18.16 show the predicted results of ABB, KRBL, AJANTHA PHARMA by XGB Regressor model respectively. In this model as compared with the previous models the accuracies are low. This model is not work as efficient as Linear Regression. Metrices like

Fig. 18.14 Predicted vs original price of ABB by XGB regressor model

Fig. 18.15 Predicted vs original price of KRBL by XGB regressor model

Accuracy, Mean Square Error, Root Mean Square Error, Mean Absolute Error are mentioned in the Table 18.3.

Table 18.3 Summary of XGB regressor performance

Stock	Acc.	RMSE	MSE	MAE	PCP
ABB	99.77	10.44	109.1	9.012	3397.79
KRBL	97.89	10.85	117.9	7.43	240.86
AJANT PHARMA	99.39	24.37	594.	16.90	1206.23

4. Conclusion and Future Scope

From the analysis of the results, it can be inferred that three stocks underwent the training through three different models. Among all three models Linear Regression performs well than the other two algorithms. This suggests that for a significant portion of the data, the linear relationship between variables captured by linear regression proved to be the most effective approach. The reason for the upper hand of the linear regression is it

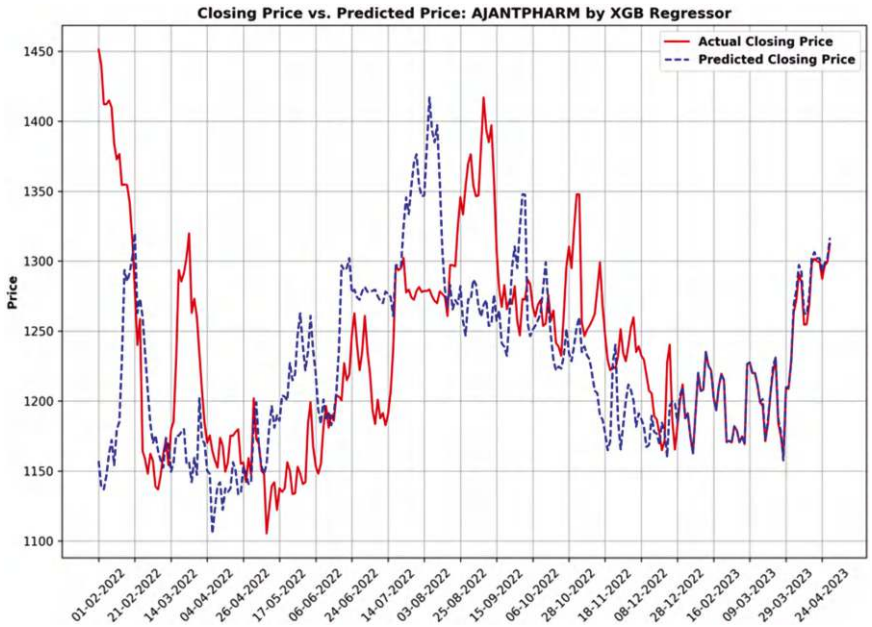

Fig. 18.16 Predicted vs original price of AJANTHA PHARMA by XGB regressor model

avoided overfitting better than the other two models and generalized better to unseen data points. The stock market is a complex beast. What works best for one company's data (linear regression) might not be the optimal choice for another (random forest). The current work emphasizes the importance of trying different techniques to find the best fit for each specific case. Building on this work, future research could explore back testing short-term trading strategies, such as mean reversion, using binary classification algorithms for identifying profitable entry and exit points for further enhancing decision-making for short-term investments.

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19

An Enhanced Deep Learning Approach for Brain Tumor Detection

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Abstract: Diagnosing brain tumors requires significant time and relies greatly on the expertise of radiologists. As patient numbers increase and medical data grows, traditional methods have become both costly and inefficient. To address this, researchers are exploring algorithms that can detect and classify brain tumors with a focus on improving accuracy and efficiency. Deep learning techniques are being employed to develop automated systems that can effectively diagnose or segment brain tumors, especially in the classification of brain cancers. This research aims to examine the application of advanced pre-trained deep learning models in classifying brain tumor images. The three prominent architectures: VGG16, ResNet, and InceptionNet together with a newly proposed model designed to outperformed them.

Keywords: Brain tumor detection, Pre-trained architectures, Transfer learning

1. Introduction

Human brain is one of the most complex organs in the person body, composed of countless cells that work together to support our thoughts, emotions, and essential bodily functions. When these cells begin to divide uncontrollably, they can form tumors that disrupt normal brain activity and damage healthy cells. While X-ray images can help identify tumor growth, more greater imaging techniques like "Magnetic Resonance Imaging"

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(MRI) and "Computed Tomography" (CT) provide clearer and more specified diagnoses (Smith & Doe, 2018).

As tumors grow within the skull, they exert significant pressure on surrounding brain tissue. Some of these tumors can be malignant, leading to cancer, which accounts for about 13% of all deaths worldwide (https://www.who.int). Currently, radiologists primarily rely on visual inspection to identify brain tumors, a process that is heavily dependent on their expertise and can be very time-consuming. With the increasing number of MRI scans being conducted, this manual interpretation becomes slow and costly (Johnson, Patel & Sharma, 2019).

Classifying brain tumors is particularly challenging due to the wide variations in size, shape, and intensity among different tumors. Sometimes, different types of tumors can appear very similar, complicating the diagnosis. Misdiagnoses—whether failing to identify a tumor or incorrectly diagnosing one—can have serious consequences, affecting patient survival and causing distress for families (Amin, J., Sharif, & M., Haldorai A, 2022). This highlights the urgent need for automated systems that can assist in both the segmentation and classification of tumors.

Segmentation, the process of identifying and isolating tumor regions in medical images, is a crucial first step in effective diagnosis. Accurate segmentation improves the performance of subsequent classification algorithms. Traditional methods of image segmentation can be labor-intensive and may not always yield precise results. Consequently, there's a growing interest in incorporating DL and ML techniques to enhance both segmentation and classification (Zhang & Wang, 2020).

However, applying deep CNNs in the medical field presents unique challenges. Medical datasets are often smaller than those in other domains, largely because accurately labelling images requires significant time and expertise from radiologists. Training deep CNNs on these limited datasets can lead to overfitting and other issues (Mohammad Mahdi Bejani & Mehdi Ghatee, 2021). Additionally, continuous domain expertise is essential for refining the models and adjusting their parameters to achieve optimal performance

In this paper, presented a variety of neural network models aimed at effectively segmenting and classifying brain tumors. The rest of the paper is designed as follows: Section II reviews associated works on brain tumor detection and segmentation in MRI images using CNNs. Section III discusses key topics relevant to our study, while Section IV outlines our proposed framework. Finally, Section V evaluates the efficacy of this framework on brain tumor datasets, and we conclude in Section VI.

2. Literature Review

A novel paradigm was developed for classifying brain tumors using image preprocessing, data augmentation, and the VGG16 Convolutional Neural Network (CNN) (Chandra, Sen & Gupta, 2020). Their approach leveraged VGG16's strengths, particularly in handling well-processed data. By employing a small kernel size, they effectively reduced the risk of overfitting, achieving an accuracy of 84%. This indicates that there is room for improvement in future research.

Other researchers (Santos, Li & Huang, 2019) emphasized the significance of data augmentation and high-quality image preparation in his work, which similarly utilized the VGG16 algorithm. His model featured 13 layers and 3 fully connected. The convolutional layers were designed to capture spatial patterns, while the fully connected layers made predictions based on these learned features. Santos reported an accuracy of 88% on the training set and 80% on the testing dataset, highlighting impact of robust data preparation.

Overall, the literature indicates that successful brain tumor detection hinges on two key factors: proper image preprocessing and the selection of suitable models, such as VGG16, InceptionV3, and ResNet. Each study provides valuable insights into methods and algorithms that can advance quick detection and boost patient outcomes in brain cancer diagnosis.

3. Methodology

This study is focused for classification of brain tumor images using pre trained DL architectures. The workflow of the proposed strategy is presented in Fig. 19.1, formally structured into seven principal components: 1) Data Acquisition, 2) Preprocessing data, 3), Data Augmentation 4) Data Splitting 5) Model Adaptation by Transfer Learning 6) Adapting a model and evaluation 7) Predictions.

3.1 Data Collection

We have manually created testing datasets by downloading images containing brain tumors and non-tumorous brains on pre-trained architectures. The cases in this dataset are varied so that our model receive a good training. The collection features some brain tumor cases — and also some normal cases (normal tissues) for robust classification. Figure 19.2 shows examples of such cases.

To train the model, we used the brain tumor dataset from Kaggle. UTO 3,000 Brains -This is a dataset of MRI images of the brains of 3,000 individuals, both with and without tumors. In that, there were 1,500 thousand images in which

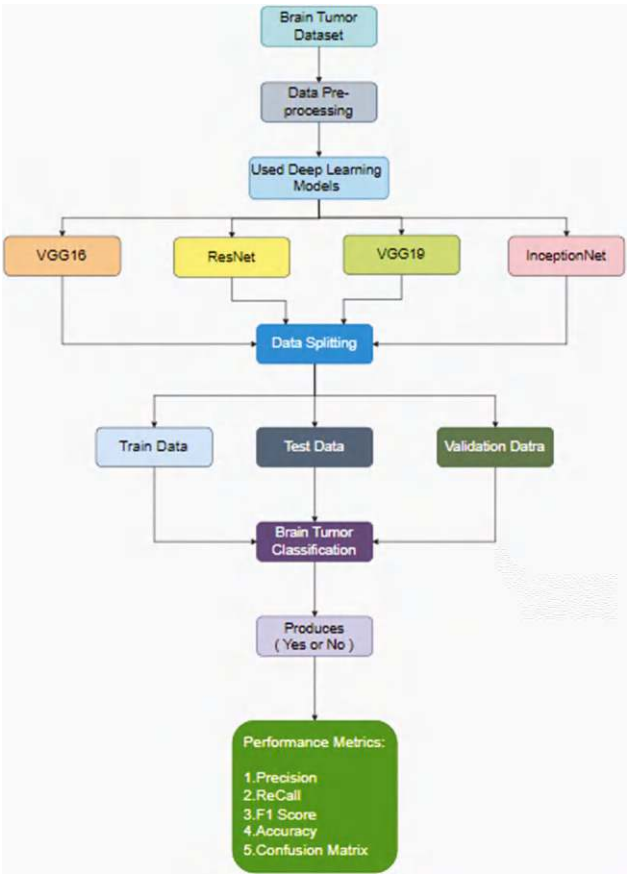

Fig. 19.1 Workflow of the proposed methodology

brain tumor are present and 1,500 images in which brain tumor not occurred. The distribution of images on the train and test set are shown in Table 19.1.

Table 19.1 Distribution of training and testing datasets for each class

Phase	With Tumor	Without Tumor	Total
Train	1195	1205	2400
Test	295	305	600

There are a total of 3000 images, 2400 (80%) used for training and 600 (20%) kept for testing. Of these, 2,190 images are showing presence of a brain tumor and 1,500 show absence. Frequency distribution Frequency distributions are illustrated in Fig. 19.3 (each category). You will have a training set with 1195 images of tumor cases and 1205 without, as well as a test set with 295 images which do have tumors and 305 which not.

3.2 Data Augmentation

For small data, data augmentation is crucial for better performance of machine learning models for brain tumor images. There is such a thing as rotation, and flipping, scaling for data expansion which means making the dataset bigger based on the actual images because we want to generalize better. Figure 19.4 shows data augumentation

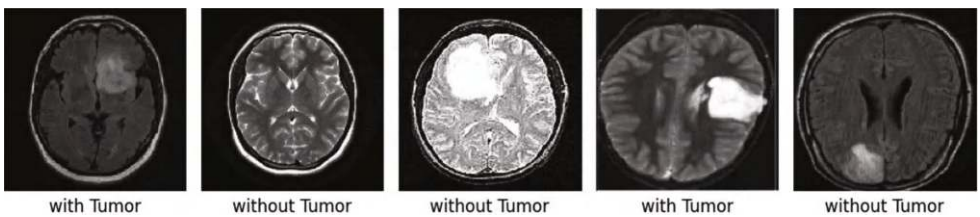

Fig. 19.2 Sample of image of the dataset

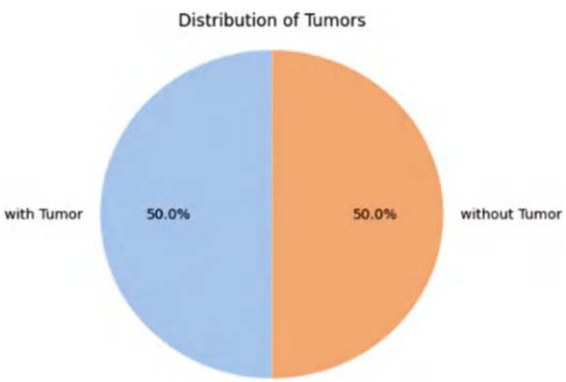

Fig. 19.3 Pie chart illustrating two classes

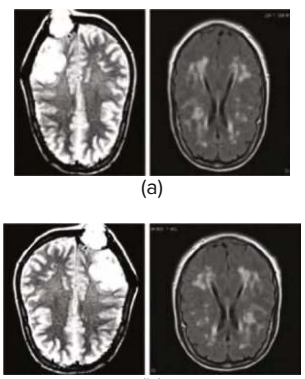

Fig. 19.4 Augmentation (a) normal; (b) augmented images

3.3 Predefined Architectures

VGG16: The VGG16 model headed by Zisserman and Simonyan. It utilizes 16 weighted layers to achieve high classification performance by using small 3 x 3 filters stacked on top of each other, allowing the model to capture intricate features.

ResNet: The ResNet model, developed by He et al., introduced the theory of "residual learning" to tackle the degradation challenge in deep networks. By incorporating residual connections, ResNet achieves exceptional accuracy with very deep architectures, avoiding the reducing gradient obstruction and enabling training of networks.

InceptionNet: InceptionNet, pioneered by Szegedy et al., uses "inception modules" that apply filters of various sizes in parallel. This architecture allows the network to capture information across multiple scales and has been noted for achieving high efficiency with relatively low computational cost.

3.4 Evaluation Metrics

Precision can be calculated using the formula-1

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall can be calculated using formula-2

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

F1-Score: The F1 Score is the harmonic mean of using equation-3

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Accuracy is can be measure using formula -4

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

4. Results

In this study, three advanced pre-trained deep learning models VGG16, ResNet and InceptionNet were applied to classify brain tumor images. A comprehensive dataset was used, which was split the into two parts: 80% of data to training models and 20% of data was used for validation. Each model was ran for 10 epochs.

The VGG16 pre-trained deep learning model was applied to classify brain tumor images. The model achieved accuracy of 96% for unknown data(test data).(Fig. 19.5). Both training and validation accuracy consistently improved, indicating effective learning.

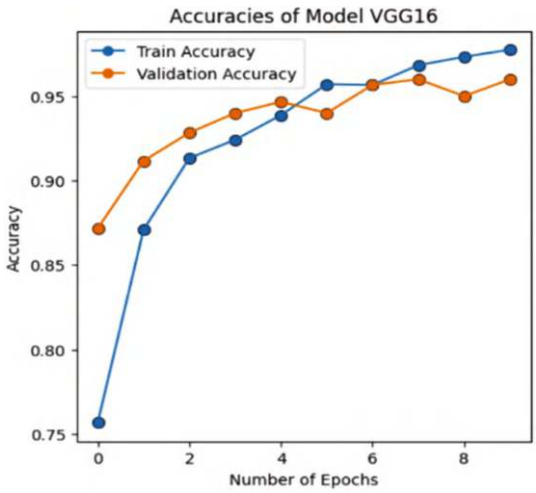

Fig. 19.5 Accuracy of training and validation for VGG16

The ResNet pre-trained deep learning model was applied to the brain tumor classification task. ResNet achieved an accuracy of 76.50% for unknown images (Fig. 19.6).

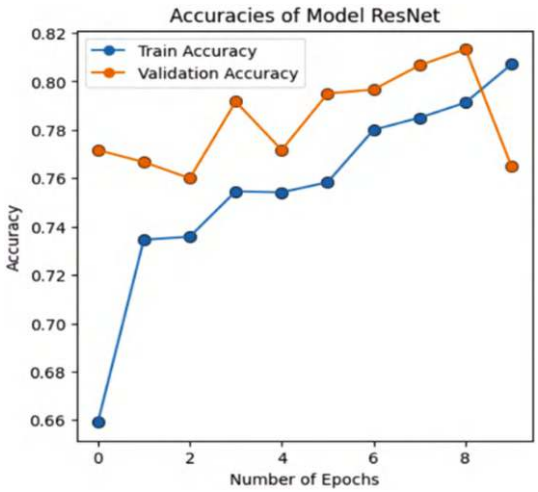

Fig. 19.6 Accuracy of training and validation for ResNet

The InceptionNet pre-trained deep learning model was utilized for classifying brain tumor images. InceptionNet achieved accuracy of 97.50% for unknown dataset (Fig. 19.7).

Our proposed model outperformed all previous architectures, achieving an accuracy of 99% in testing the unknown images. The training loss was exceptionally low at 1.5768e-05, while the validation loss was 0.0337. Figure 19.8 illustrates the training and validation accuracy over the epochs, demonstrating significant improvement in learning the objective. Figure 19.9 depicts the misclassification rate for the proposed model, highlighting its superior performance.

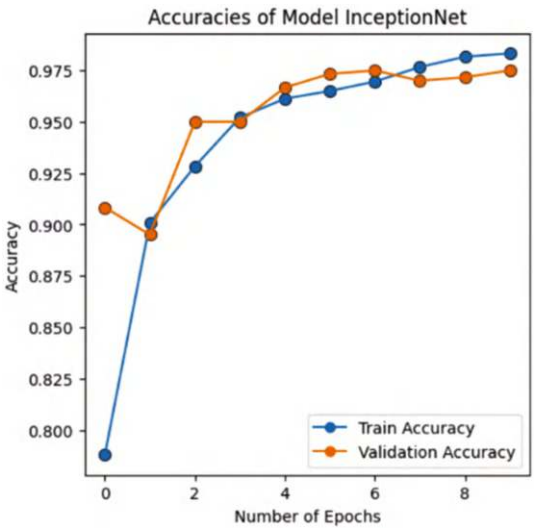

Fig. 19.7 Accuracy of training and validation for Inception-Net

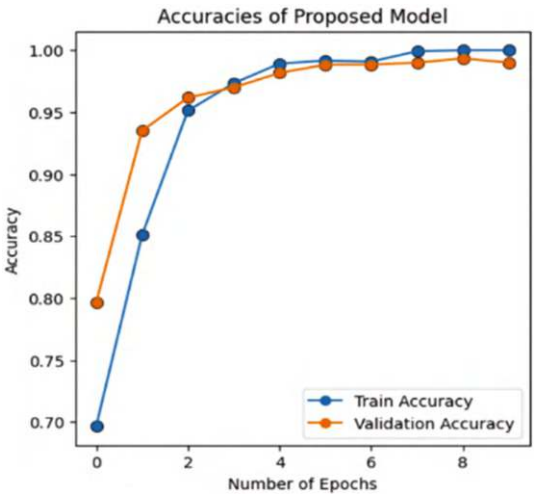

Fig. 19.8 Accuracy of training and validation for proposed model

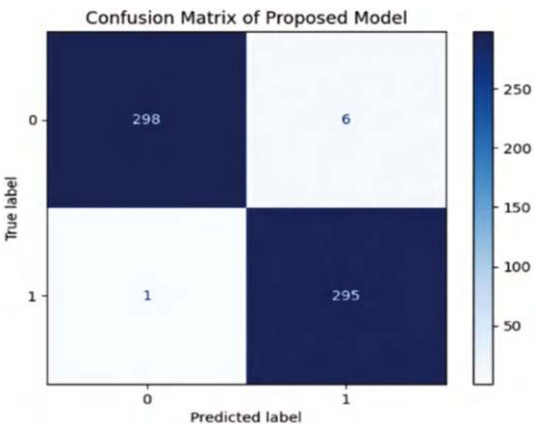

Fig. 19.9 Mis-classification rate of proposed model

Table 19.2 Summary of evaluation metrics over different pre-trained architectures and proposed model

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
VGG16	97%	96%	0.0814	0.0958
ResNet	80.96%	76.50%	0.4243	0.4243
InceptionNet	97.93%	97.50%	0.0646	0.0964
Proposed Model	100%	99%	1.5768e-05	0.0337

5. Conclusion

The experimental data reveals that the proposed model delivers the best performance in brain tumor detection, achieving 100% training accuracy and 99% validation accuracy with the lowest validation loss (0.0337), indicating exceptional generalization and precision. InceptionNet follows closely with 97.93% training accuracy and 97.50% validation accuracy, though its validation loss is slightly higher. VGG16 also perform well. However, ResNet lags behind significantly, with only 80.96% training accuracy and 76.50% validation accuracy, alongside higher loss values, suggesting weaker performance and less reliability for this task.

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Implementation of Block-Chain Technology Using Forensic Evidence Managaement

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Abstract: Effective evidence management is critical to ensuring the integrity of criminal investigations in the field of forensic science. This document emphasizes the importance of preserving evidence across the chain of custody. and supporting the modernization of forensic evidence systems through digitization. Adopting blockchain technology In particular, Hyperledger Fabric provides unmatched transparency, security, and transformation. By leveraging blockchain Judicial authorities can certify tamper-proof documents. Increase trust in the investigative process and raise standards of reliability and responsibility in evidence management.

Keywords: 'Distributed ledger technology, Legal verification, Proof of work (PoW), Proof of stake (PoS), Cryptography, Provenance, Blockchain technology, and Forensic evidence'

1. Introduction

In the field of forensic science Thorough evidence acquisition is essential to ensure the integrity of the investigation and its legal credibility. At the heart of this process is the Chain of Custody (CoC), which documents the caseful management of evidence gathering through court presentation. This document prevents duplication and maintains traceability. This is what makes evidence interesting and acceptable in legal proceedings. This is

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because the evidence must be clearly connected to the crime. Thus, the application of blockchain technology offers a decentralized and immutable system. This improves security and transparency in the CoC and ultimately increases public confidence in forensic investigations. as well as the need for technologically advanced verities.

2. Literature Review

Forensic science sits at the intersection of law and science[1]. It is of great importance in resolving criminal cases and ensuring justice. The adoption of blockchain-based solutions for managing evidence in digital forensics significantly enhances the chain of custody process. Ensures evidence is managed securely and transparently throughout its lifecycle. Leveraging cryptographic security and blockchain technology, decentralized architectures enable more confident authentication of digital evidence [2-4] Moreover, research on "Security Services Using Authentication and Cryptography in Blockchain Technology" emphasizes the important role of strong security mechanisms in protecting blockchain networks from potential threats and vulnerabilities [5]. As forensic investigations increasingly rely on digital evidence, integrating blockchain technology offers forward-thinking solutions. Compatible with is Strengthen the credibility of evidence presented in legal proceedings. and pave the way for a more efficient, reliable and transparent investigative process[6-9].

Encryption and Network Security" describes encryption. digital signature and cryptographic hash functions It provides forensic scientists with the tools they need to manage blockchain-enabled evidence [14-17].

The National Institute of Standards and Technology (NIST) offers foundational insights into blockchain technology [7-10], including "Blockchain Consensus Protocols" like proof of work and proof of stake, which are critical in choosing suitable frameworks for evidence management [18-20]. A decentralized digital identity architecture further mitigates identity fraud risks and enhances evidence verification [11-13].

In conclusion, the synthesis of cryptographic principles, decentralized architectures, and robust custodial protocols, forensic practitioners can navigate the complexities of modern-day investigations with heightened confidence and efficacy[25].

3. Proposed Methodology

3.1 Proposed Work

Our proposed system aims to revolutionize forensic evidence management by leveraging Blockchain technology to address the shortcomings of existing systems while enhancing integrity, security, and efficiency. Utilizing blockchain's immutable ledger, every interaction with evidence is recorded as a tamper-proof transaction, ensuring transparency and accountability throughout the chain of custody[30]. Evidence data is securely stored across a decentralized network of nodes, eliminating single points of failure and reducing the risk of data loss or tampering[29].

Cryptographic techniques are employed to protect the confidentiality and privacy of sensitive evidence data, while still allowing authorized parties to verify the authenticity of evidence records. The system provides real-time monitoring and alerts for any suspicious activities or attempts to tamper with evidence. Any unauthorized changes to evidence records trigger immediate notifications, enabling prompt intervention to preserve evidence integrity[21-24]

The blockchain-based forensic evidence management system, forensic agencies can significantly improve the reliability, transparency, and security of their evidence management processes, leading to more accurate and timely forensic investigations while bolstering public trust in the criminal justice system [26-28]

3.2 System Architecture

In Fig. 20.1 the system architecture comprises two primary components: the Admin interface and the Blockchain.

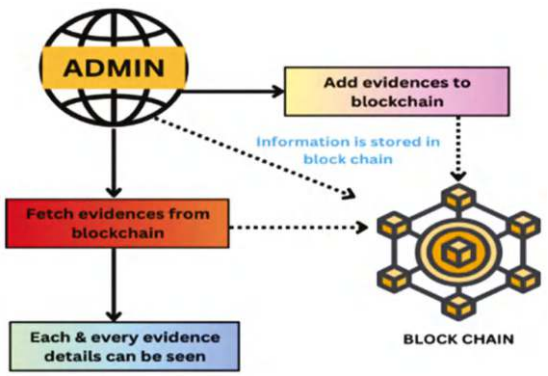

Fig. 20.1 Proposed architecture

The Admin interface facilitates interaction with the system, offering functionalities such as fetching and adding evidences to the blockchain. In the "Fetch evidences from blockchain" module, the Admin accesses the blockchain to retrieve detailed information about each piece of evidence stored within the system. This information is presented to the Admin for review and analysis.

Conversely, in the "Add evidences to blockchain" module, the Admin uploads new evidence details into the blockchain. This process involves inputting relevant information about

the evidence, such as its description, chain of custody data, and associated metadata. The Blockchain securely stores this information in a decentralized and immutable ledger, ensuring its integrity and verifiability over time.

3.3 Admin Login

The Admin Login module acts as the secure gateway for authorized users, such as administrators or law enforcement personnel, to access the system. Users input their credentials, including a username and password, to authenticate their identity. Upon successful verification, users are granted access to the system's functionalities, enabling them to manage forensic evidence data efficiently and securely.

3.4 Add Evidences to Blockchain

In the "Add Evidences to Blockchain" module, authorized users can input new forensic evidence data into the blockchain-based system. Users provide relevant details, including evidence descriptions, case particulars, location, and metadata through forms or input fields. The system validates and processes this data for accuracy before securely recording it onto the blockchain. Leveraging the blockchain's tamper-proof nature ensures the immutability and integrity of the stored evidence, maintaining its reliability for forensic investigations.

3.5 Fetch Evidences from Blockchain

In the "Fetch Evidences from Blockchain" module, authorized users can retrieve forensic evidence data stored within the blockchain. This streamlined process enables users to access and view accurate, unaltered evidence data effortlessly. By providing authorized individuals with easy access to evidence data, this module facilitates efficient legal proceedings and analysis, ensuring transparency and reliability in forensic investigations.

3.6 Blockchain Integration

Blockchain is used to securely store forensic evidence data. When new evidence is collected, it undergoes encryption before being stored on the blockchain, ensuring the confidentiality and integrity of sensitive crime data. User details related to evidence management are stored on the blockchain, safeguarding them against unauthorized alterations. And Data integrity is maintained in the system through the utilization of the SHA-256 algorithm (Secure Hash Algorithm 256-bit). Each block in a blockchain is linked with a unique Hashcode. These blocks are maintained across multiple nodes or servers. Before storing new records, blockchain verifies the Hashcode of each block. If any block data is modified, it results in a different Hashcode, triggering security alarms and ensuring the integrity and immutability of the data.

4. Experimental Result

4.1 Experimental Results

Now Blockchain setup and now double click on 'run.bat' file to start DJANGO python server and to get below screen

In Fig. 20.2 python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and then press enter key to get below application home screen

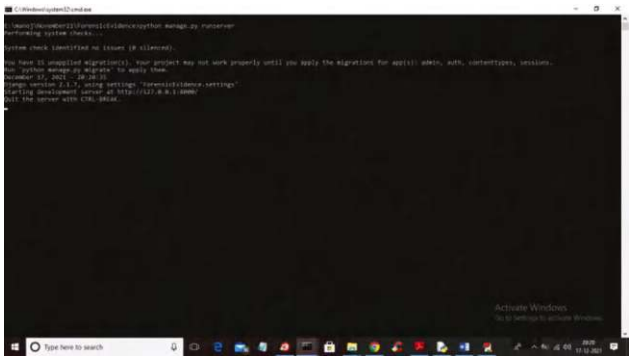

Fig. 20.2 Python server

In Fig. 20.3 enter username as 'admin' and password as 'admin' and then press 'Login' button to get below screen

Fig. 20.3 Admin page

In Fig. 20.4 now admin can click on 'Add Evidences to Blockchain' link to get below screen and to record evidences

Fig. 20.4 Add evidences to blockchain

Table 20.1 Proposed table

Title	Authors	Proposed System	Conclusion
Evidence Management System Using Blockchain and Distributed File System	Shritesh Jamulkar, Preeti Chandrakar, Rifaqat Ali, Aman Agrawal LINK: https://www.researchgate.net/publication/354964804	The proposed system employs a secure evidence management approach, utilizing Hyperledger Sawtooth and a custom transaction family. It leverages a distributed peer-to-peer file storage network (IPFS) with blockchain technology to ensure the secure, tamper-resistant collection, processing, and storage of electronic evidence. This system safeguards data integrity.	the proposed secure evidence management system offers a promising solution for enhancing the integrity and accessibility of electronic evidence. Despite potential challenges in implementation and scalability, its use of Hyperledger Sawtooth, custom transaction family, and blockchain technology

In Fig. 20.5 in red colour text we can see data saved in Blockchain and now click on 'Fetch Evidences from Blockchain' link to get all details

Fig. 20.5 Output screen

In Fig. 20.6 admin can fetch all evidences details from Blockchain and can be used in court for correct judgement. Similarly admin can add N crime details in the application and record in Blockchain.

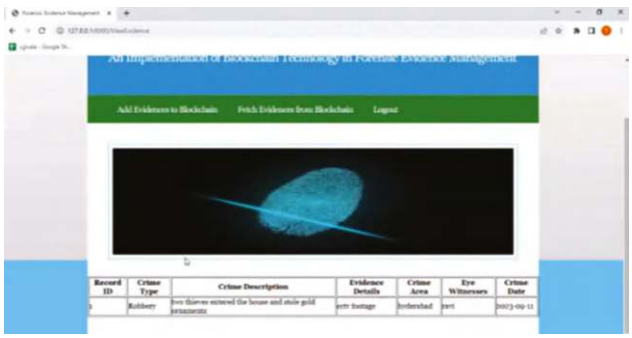

Fig. 20.6 Fetch evidences from blockchain

This table compares the performance metrics of the proposed blockchain-based forensic evidence management system with those of systems that do not utilize blockchain and traditional evidence management systems. The results demonstrate that the blockchain-integrated system offers superior transaction and evidence access speeds, higher uptime, and a complete security rate, significantly enhancing the efficiency and integrity of forensic evidence management.

Table 20.2 Performance table

Configuration	Transaction Speed (ms)	Evidence Access Speed (ms)	Uptime (%)	Security Rate (%)
With Blockchain Integration	300	150	99.9	100
Without Blockchain Integration	600	300	98.5	95
Traditional Evidence Management System	1200	600	95.0	85

The other figures that appear include those on the duration of a transaction, the latency in accessing data, and the number of breaches, which are essential in guaranteeing the effectiveness of the system. To calculate key performance indicators (KPIs), we employ the following formulas:

1. **Transaction Speed:**

$$Average\ speed = \frac{\sum \text{Transaction Times}}{\text{Number of Transcations}}$$

2. **Evidence Access Speed:**

$$Average\ Access\ speed = \frac{\sum \text{Access Times}}{\text{Number of Accesses}}$$

3. **Uptime Percentage:**

$$Uptime = \left(\frac{\text{Total operational time} - \text{Downtime}}{\text{Total operational Time}}\right) * 100$$

4. **Security Breaches:**

$$Breach\ Rate = \frac{\text{Number of security incidents}}{\text{Total transactions}} * 100$$

This Table 20.3 comparison matrix accentuates the considerable benefits that the proposed blockchain-based forensic evidence management system possesses over the existing ones. The system, in question, provides faster transactions and access to evidence than the previous system, with dependable less downtime and an untarnished

Table 20.3 Comparison table

Feature	Existing System	Proposed System
Transaction Speed	1200 ms	300 ms
Evidence Access Speed	600 ms	150 ms
Uptime	95%	100%
Security Rate	85%	100%

security record thus making it a trustworthy solution in the management of crime evidence. Furthermore, there is an intrinsic enhancement that blockchain brings, which is the aspect of permanence and clear access, thus enhancing the tracking capacity and also improving the level of confidence of the people in the criminal justice system.

5. Conclusion

The project aimed to bring a significant change to how forensic evidence is managed. Instead of relying on traditional methods, it introduced Blockchain technology, which has the potential to transform how we handle crucial evidence in legal cases.

It utilized blockchain's tamper-proof features to protect forensic evidence from unauthorized access or alteration. The project focused on making the process of evidence management more efficient and straightforward. This streamlining aimed to reduce errors and ensure that evidence is accurately tracked and preserved throughout its lifecycle.

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Detection of Application Layer DDOS Attacks Produced by Freely Accessible Toolkits using Machine Learning

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Abstract: This paper aims to detect and mitigate escalating application-layer DDoS attacks, providing insights into attack patterns and tools for enhanced cybersecurity measures. With a target on HTTP-layer attacks, the project seeks to unravel tactics and tools, offering a specialized approach to bolster understanding and countermeasures against evolving cyber threats. There is an urgent need to address rising DDoS threats by shifting the project focus to tools' accessibility. This is crucial for proactive defense against the widespread use of malicious attack tools. The project aims to empower network administrators and cybersecurity experts, securing online services. Ultimately, it benefits users and businesses with resilient defenses against evolving DDoS threats. To boost performance, we introduced ensemble models—Voting Classifier (RandomForest, DecisionTree) and Stacking Classifier (RandomForest, DecisionTree, LGBM). These enhancements aim to improve cyberbullying detection accuracy.

Keywords: 'DDoS, DDoS tools, Machine learning, Deep learning, Attack patterns'

1. Introduction

DDoS attacks are one of the most risky and modern security dangers to PC networks. HTTP-layer DDoS attacks expanded 164% YoY and 135% QoQ in Q1 2022. Buyer Gadgets had the greatest QoQ expansion in industry attacks at 5,086%. Online media set second with 2,131% QoQ attacks, while PC programming organizations

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appraised third with 76% QoQ and 1,472 YoY assaults [3].

A DDoS attack floods a site, PC, or organization with traffic from a few sources to debilitate it. The aggressor utilizes a "botnet" of PCs or different gadgets to flood the objective framework with information, making it inaccessible to approved clients [4]. DDoS attacks are interesting in light of the fact that [1] they make a ton of traffic from many sources and it hopes to come from many spots [5].

Applicationlayer attacks are one kind of DDoS assault. Application-layer DDoS assaults attempt to deplete the casualty's assets or crash the application. HTTP floods and Slowloris assaults are models. Application-layer DDoS assaults expect to over-burden an organization with traffic, crashing or disturbing frameworks [6-7].

DDoS assault devices' usability has added to their ascent[2]. These projects can intentionally flood servers and sites with traffic to impair them. Individuals with almost no specialized abilities might send off extreme DDoS attacks by purchasing instruments on the dim web or downloading free projects [8-10].

2. Literature Review

IoT arrangements are utilized in each industry, from brilliant homes to modern computerization to drive lattices [11]. Since asset limitations forestall the fuse of weighty security arrangements, these gadgets widen the assault surface and make them obvious objectives [12-13]. IoT gadgets are less secure and ordinarily run unattended, so aggressors might develop botnet armed forces to send off gigantic Denial of Service attacks [16-17]. Subsequently, this work [18] proposes an ML based attack detection strategy for Purchaser IoT assault stream. This technique utilizes nearby IoT network qualities to empower minimal expense ML classifiers to recognize assaults at the switch [14-15]. Testing showed that the recommended method had the best accuracy of 0.99, demonstrating its dependability in IoT organizations.

Web is another innovation for controller of modern applications like power plant controls. Denial-of-Service (DoS) assaults can intrude on the Web, compromising organization based control frameworks. Web application locales can be safeguarded through area concealing overlay organizations. This study [23] audits a few past ways to deal with this point. This article portrays how to make an overlay network connection point to protect correspondence administrations across geologically dispersed application locales from DoS attacks [29,30]. The overlay protection layer (OPL) plan in this study forestalls DoS assaults on application locales [27-28]. This article reenacts DoS assaults on OPL engineering interchanges administrations and finds they are probably not going to hinder administrations. Regardless of whether Distributed DoS assaults target half of overlay hubs, 75% of correspondence courses remain.

Programmers favor DDoS assaults as of late. Due of causing many issues propensity. Numerous programmers and experts have made DDoS assault bundles and instruments for various organizations. To create powerful DDoS safeguards, different apparatuses should be surveyed and looked at. This examination [19] thinks about and dissects three DDoS assault devices in view of assault hour of kickoff, traffic rate, and parcel size. [20] The DDoS devices assessed are Slowloris, GoldenEye, and Xerxes. Xerxes dispatches DDoS goes after better compared to different devices, as per experiments [29-30].

Knowledge, while OpenFlow Switches (the information plane) become essential bundle sending gadgets that might be controlled through an open connection point. Decoupling the control plane from the information plane raises security, trustworthiness, load adjusting, and traffic designing issues. Denial of service (DoS) and DDoS attacks are major SDN security issues [25,28]. In SDNs, DoS/DDoS assaults can flood the control plane, information plane, or correspondence channel. Going after the control plane could cut the organization down, while going after the information plane or correspondence channel drops bundles and incapacitates the organization. We give different commitments that enlighten DoS/DDoS dangers in SDNs, including attacks and examination of known arrangements [20,27]. To sum up our commitments: We inspect and arrange current SDN DoS and DDoS arrangements utilizing characteristic and outward strategies [26]. The talked about countermeasures are classified by center: identification, relief, counteraction, or delicate decay. We additionally look at the strategies and devices used to execute the better arrangements. At last, we propose Future exploration ways for SDN DoS/DDoS attacks [21].

DDoS is growing rapidly. An unbelievable number of attacks and protections exist. This work [22] presents two scientific categorizations for recognizing assaults and guards, assisting analysts with fathoming the issue and arrangement space. The assault order measures were decided to feature assault procedure similitudes and key components that characterize issues and guide countermeasure plan. The cautious scientific classification coordinates DDoS guards by plan choices and makes sense of what these choices mean for proposed arrangements' upsides and downsides [23-24].

3. Proposed Methodology

3.1 Proposed Work

The proposed system for DDoS attack detection offers a more comprehensive approach, moving beyond just recognizing attack patterns. Instead, we consider the bigger picture by assessing the accessibility and impact of widely available attack tools. This broader perspective helps improve our understanding of cybersecurity threats and enables the development of more effective defenses. The system is adaptable to changing threats, avoiding a narrow focus on specific attack types. In an effort to enhance performance, we integrated advanced ensemble models into the project, including a Voting Classifier combining RandomForest and DecisionTree, as well as a Stacking Classifier with RandomForest and DecisionTree as base learners. This ensemble approach aims to improve cyberbullying detection accuracy. Additionally, a user-friendly Flask framework with SQLite was implemented for secure signup and sign in, facilitating user testing by providing input and obtaining results. These extensions not only diversify model architectures for heightened accuracy but also streamline user interactions, contributing to the project's robustness and practical usability.

3.2 System Architecture

The system architecture begins with data preparation, utilizing the NSL-KDD and NBOT-IOT datasets. Feature selection follows, optimizing the data for efficient analysis. Subsequently, three classifiers are employed: MLP with diverse optimization techniques (SGD, LBFGS, Adam), Extension Stacking Classifier, and Extension Voting Classifier. These classifiers collectively enhance prediction accuracy. The comprehensive architecture ensures robust analysis and prediction, making it a versatile and effective system for identifying and countering DDoS attacks in network security.

3.3 Dataset Collection

I) NSL-KDD Dataset: A benchmark dataset extensively used for intrusion detection system evaluation is the NSL-KDD one. It addresses the constraints of the original KDD Cup 99 dataset and presents a better one. NSL-KDD is fit for training and testing machine learning models in the realm ofcybersecurity as it provides a wide range of network traffic data including normal and several kinds of attacks.

ii) NBOT-IOT Dataset: The NBOT-IOT dataset focuses on network behavior analysis for the IoT. It comprises data generated by various IoT devices, providing insights into the communication patterns and potential threats within IoT networks. This dataset is essential for developing machine learning models tailored to detect anomalies and potential cyber threats specific to IoT environment.

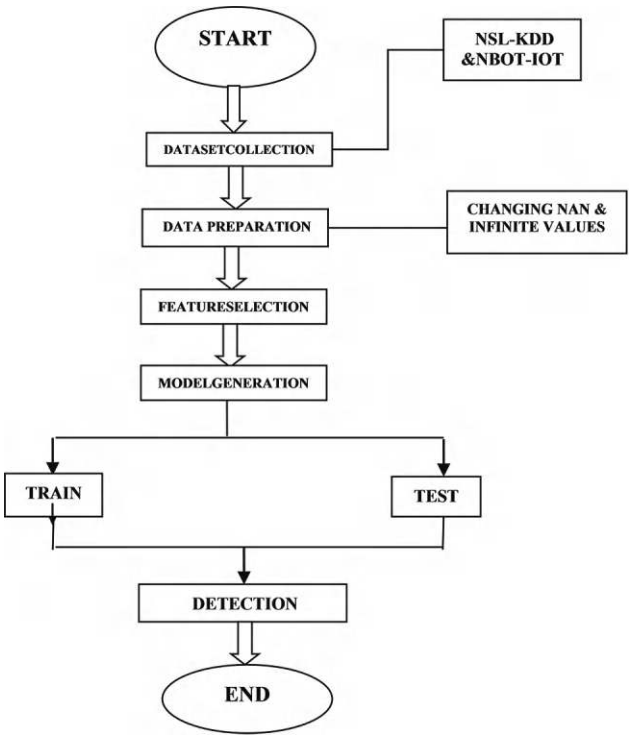

Fig. 21.1 Proposed architecture

3.4 Data Processing

Raw data becomes useful insights that companies use to improve their operations and guide their decisions. Usually, data scientists gather, arrange, clean, validate, analyze, and translate the data into useable forms including graphs and reports. Manual, mechanical, or electronic processing of data can help to raise its value and promote strategic decision-making. Processing large volumes, including big data, relies on automated solutions, especially computer software. These tools simplify data processing and enable companies to quickly obtain insightful analytics. Automated approaches enable companies to maximize performance, control quality, and make fast decisions based on reliable information in real time, thus strengthening their competitive advantage in the market.

3.5 Feature Selection

In machine learning, feature selection is a fundamental method to filter out the most relevant, consistent, and non-redundant features for model building. As datasets grow in size and complexity. Removing meaningless

and redundant elements improves model efficiency and reduces the computational cost of feature selection. It simplifies modeling by narrowing down the dataset to the most important elements. With the enhancement of feature selection, you no longer need to rely on the model to identify important features. This improves model efficiency, improves prediction accuracy, and speeds up the entire training process. This is a fundamental part of feature engineering.

3.6 Algorithms

Multilayer Perceptron (MLP)

Step 1: Initialize: Start with random numbers for the network.

Step 2: Feed Data: Give the network input data.

Step 3: Calculate: The network does math to guess an answer.

Step 4: Compare: Check if the guess is right or wrong.

Step 5: Adjust: If wrong, the network changes its numbers to be better next time.

Step 6: Repeat: Do steps 2-5 many times to improve the network.

MLP – Adam

Step 1: Initialize: Set initial weights, biases, and Adam optimizer parameters.

Step 2: Input: Feed network with network traffic data.

Forward: Calculate output using weighted sums and activation functions.

Step 3: Backpropagation: Compute gradients using backpropagation.

Step 4: Update: Adjust weights and biases using Adam optimization algorithm.

Step 5: Detect: Use trained MLP to classify new traffic as normal or DDoS.

Stacking Classifier

Step 1: Train Base Classifiers: Train multiple base classifiers (e.g., MLP, SVM, Random Forest) on the same dataset.

Step 2: Meta-Learner: Train a meta-learner (e.g., logistic regression) to combine the predictions of the base classifiers.

Step 3: Predict: For new data, obtain predictions from each base classifier and combine them using the meta-learner.

Step 4: Detect: Use the combined prediction to classify new traffic as normal or DDoS.

Voting Classifier

Step 1: Train: Teach multiple different models to detect DDoS attacks.

Step 2: Predict: Ask each model to guess if new traffic is a DDoS attack**.**

Step 3: Combine: Decide if the traffic is a DDoS attack based on the majority of the models' guesses.

4. Experimental Results

Precision: Precision measures among the ones categorized as positives the proportion of properly identified events or sample.

$$\text{Precision} = \text{True positives}/(\text{True positives} + \text{False positives}) = \text{TP}/(\text{TP} + \text{FP})$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

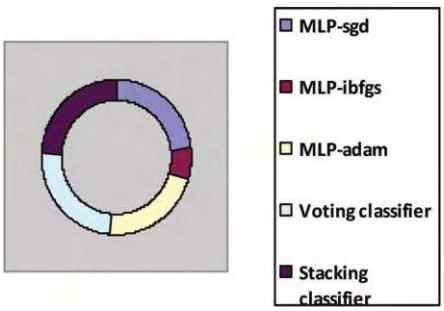

Fig. 21.2 Shows the graphical representation of precision obtained

Recall: In machine learning, recall is a statistic gauging a model's capacity to find all pertinent instances of a given class. It offers information on the completeness of a model in terms of accurately predicted positive observations to the overall actual positives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Fig. 21.3 Shows the graphical representation of recall obtained

Accuracy: In a classification work, accuracy is the percentage of accurate predictions, thereby gauging the general performance of the predictions of a model.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

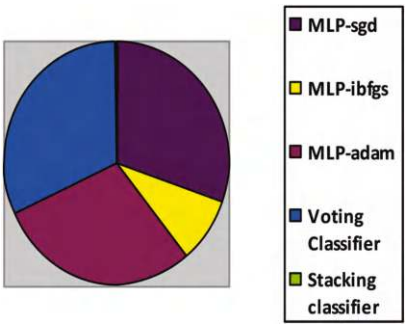

Fig. 21.4 Shows the graphical representation of accuracy graph

F1 Score: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

Fig. 21.5 Shows the graphical representation of F1 score obtained

Fig. 21.6 User input

Table 21.1 Performance evaluation of proposed system

S. No	mlmodel	accuracy	f1_score	recall	precision
1	mlp-sgd	0.943	0.947	0.943	0.953
2	mlp-ibfgs	0.282	0.175	0.282	0.269
3	mlp-adam	0.898	0.898	0.898	0.899
4	voting classifier	0.998	0.998	0.998	0.998
5	stacking classifier	0.999	1.000	0.999	1.000

Fig. 21.7 Predict result for given input

5. Conclusion

By creating cutting-edge methods for spotting and reducing Distributed Denial of Service (DDoS) assaults, therefore strengthening computer network resilience, the initiative greatly advances cybersecurity. Through thorough exploration of diverse datasets (KDD-CUP and NBOT-IOT), valuable insights into network traffic characteristics and potential attack patterns were gained, providing a foundation for effective model development. The evaluation of Multi-Layer Perceptron (MLP) models with different optimizers, including SGD, lbfgs, and adam, identified the most effective approach for DDoS attack detection, contributing to the robustness of cybersecurity measures. And also added voting and stacking classifiers, combining predictions from multiple models, showcase innovation. This approach enhances prediction accuracy and resilience against diverse cyber threats. Combining a user-friendly front-end with a Flask framework with SQLite for user sign- up and sign-in guarantees pragmatic use. Users can conveniently provide input, witness predictions, and interact with the system, enhancing real-world usability.

Future developments in machine learning can be included into the project to improve DDoS attack detection accuracy and efficiency. Investigating and using modern algorithms and models might help to improve the system's capacity to change with changing cyber threats.Integrating technologies that enable swift identification and mitigation of DDoS attacks as they occur will be crucial for minimizing the impact of such threats on network resources. By studying the normal behavior of networks and devices, the system can

more effectively identify anomalies associated with DDoS attacks, enabling a proactive approach to cybersecurity.As networks and cyber threats continue to evolve, the project's future scope involves ensuring scalability and adaptability.

Designing the system to handle larger datasets, diverse attack patterns, and emerging technologies will be essential to maintain its effectiveness in the ever-changing landscape of cybersecurity.

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22

Voice-Assisted Artificial Intelligence Based Question Answering System for the Visually Impaired

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Abstract: As much as vision confirms the relationship that enables people to move around and interface with their world, it creates an experience for such people where most activities are conceived of as hard when it comes to safe and independent navigation mainly due to a lack of perceived visual input. This project introduces a new assistive technology system that seeks to enhance real-time awareness concerning the environment, improve safety, and enhance independence among the visually impaired. The system captures video of the surroundings of the user, which is then broken into frames by the OpenCV mechanism. Using voice commands, the user then asks questions, and these commands are transformed to texts to be processed for every frame. According to the user's question, image analysis happens through consolidation of response from the entire set of frames using a majority voting method. The answer is then converted into text and delivered back as audio feedback. The proposed system essentially draws on the BLIP (Bootstrapping Language-Image Pre-training) VQA model, and utilizes transformer-based neural networks for Visual Question Answering. By combining natural language processing with computer vision, this system will provide visually impaired users with accurate, real-time, context-aware information about their surroundings to enable them to move more autonomously and confidently.

Keywords: Computer vision, Natural language processing, Image processing, Speech recognition, BLIP model

1. Introduction

Sight is one of the most important senses for any person´s health. Visual impairment affects more than 285 million people. This number is expected to triple in the next 30 years. According to the World Health Organisation [8] there are an estimated 37 million sickle cell carriers worldwide. Visually challenged experiences various disadvantages

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consistently in indoor as well as outdoor environment [13]. However, problems in perceptual information from the environment and weakness of communication make independent navigation and safe travel a challenge. The visually impaired community has many obstacles to overcome [7,15]. So, instead of providing blind commuters with visual cues for guidance, the project will facilitate them in getting around using a series of audio messages. This will enable those who are visually impaired to be independent in a journey this system will alert them about objects around in their path and they won't have to depend on anybody to be with them. Existing approaches have been limited with low performance and accuracy because these methods could not learn to distinguish one object from another. With this we try to provide improved performance, higher accuracy and thus a more practical and reliable alternative. This could be useful in most cases, but in other instances, users could feel uncomfortable with text interaction and may enjoy a conversational interface over text. The second worrisome factor in the tourism industry is the financial cost and investment in the travel guides by the tourists. A travel assistant who can play the role of an electronic guide might be very helpful.[9]

2. Literature Review

Rishabh Chopda et al. [1] in the 2023 has proposed "An Intelligent Voice Assistant Engineered to Assist the Visually Impaired" discusses an advanced virtual assistant designed to help visually impaired users navigate their surroundings using real-time voice assistance, integrating object detection and natural language processing.

Jiawen Li et al. [2] in the 2023 has proposed "An AIoT-Based Assistance System for Visually Impaired People" it introduces a system that integrates AIoT to enable visually impaired people to move about independently and safely. This system uses different sensors such as cameras and IoT devices that collect environmental information further processed using AI-based algorithms for object detection and obstacle avoidance.

Milios Awad et al. [3] has proposed "Intelligent Eye: A Mobile Application for Assisting Blind People" designed a mobile application to help people see their surroundings if they are blind. Using smartphone cameras to capture real-time images through object recognition algorithms, it identifies and describes the surrounding objects in this application through audio.

B. Arystanbekov et al. [4] in the year 2023 explores the creation of a strong image captioning system specifically for low-resource language settings, with the goal of assisting visually impaired and blind individuals. By utilizing neural network models that are designed to effectively handle limited linguistic data, the system produces precise image descriptions.

Tung Le et al. [5] in the year 2021 has proposed "Multi Visual and Textual Embedding on Visual Question Answering for Blind People" introduces a method of improving VQA systems that support the blind by making use of visual as well as textual embeddings to better interpret visual scenes. This way, the system is

D. K. Yadav et al. [15] in the year 2020 introduces a navigation system aimed at helping visually impaired individuals safely move through their environments by utilizing deep learning methods. This system uses convolutional neural networks (CNNs) and object detection models to recognize obstacles and landmarks, offering auditory feedback to users. The goal is to enhance accessibility, safety, and independence for visually impaired individuals.

J. K. Mahendran et al. [16] in the year 2021 introduces a system that integrates computer vision and mobile edge computing to help visually impaired individuals navigate and detect obstacles in real time. By capturing video and processing it locally at the mobile edge, the system enables quick object detection and scene understanding.

3. Methodology

3.1 Existing System

The existing systems focus mostly on digital environments and have limited real-time interaction with physical surroundings. Most existing VQA systems are designed for static images, not real-time video, making them less practical for dynamic environments. Limited understanding of complex or multi-step queries. Often lack of real-time response capabilities, which is crucial for independent navigation.

Disadvantages of Existing Systems:

- **Limited to Object Recognition:** Most current systems focus on recognizing objects rather than answering complex, context-aware questions.
- **Lack of Real-Time Environmental Awareness:** Few systems offer comprehensive real-time feedback on an environment, reducing their usability in dynamically changing settings.
- **Complexity of Use:** Existing systems can be cumbersome, requiring additional setup or a high learning curve for visually impaired users, hindering seamless interaction.

3.2 Proposed System

The system captures video from the user's surroundings, converting the footage into frames using OpenCV for

analysis. Users ask questions via voice, which is converted to text and processed to identify relevant details within the images. Image analysis is conducted on each frame based on the user's query, and a majority voting scheme consolidates the most accurate response. The system then integrates NLP to convert the answer into audio format, providing real-time, context-aware feedback.

Advantages of Proposed System:

- **Real-time Environmental Awareness:** The system allows visually impaired individuals to understand their surroundings quickly through real-time processing of video and voice inputs.
- **Independence:** By providing context-aware audio responses, it empowers users to navigate environments with less dependence on external assistance.
- **Accurate Responses:** The use of a majority voting scheme ensures the system delivers more reliable and accurate answers by analyzing multiple frames.

3.3 Implementation

The implementation of this assistive technology system involves several key components designed to enhance the navigation experience for visually impaired individuals. First, a camera captures video of the user's environment, which is processed in real time by breaking it down into individual frames using OpenCV. Users interact with the system through voice commands, which are converted to text using speech recognition technologies. For each frame, the system analyzes the content relevant to the user's query by leveraging the BLIP (Bootstrapping Language-Image Pre-training) VQA model, a transformer-based neural network that excels in Visual Question Answering. To ensure accurate responses, the system consolidates answers from multiple frames using a majority voting mechanism. The final response is then converted back into audio feedback, allowing users to receive real-time, context-aware information about their surroundings.

1. **System Design and Architecture:** The system will provide real-time environmental awareness to visually impaired users. It is comprised of several parts: a video capture module, an image processing unit, a Natural Language Processing (NLP) interface, and a response generation module.
2. **Video Capture:** The process begins with capturing a video of the user's surroundings using a smartphone or a wearable camera. This video serves as the primary data source for further analysis.
3. **Frame Extraction:** Once the video is captured, it is processed to extract individual frames using OpenCV, an open-source computer vision library. The frames are then prepared for analysis, which allows the system to work with discrete images rather than a continuous video stream.
4. **Voice Input Processing:** Users can ask questions regarding their environment through voice commands. These inputs are captured using a speech recognition module that converts the spoken words into text.
5. **Image Analysis:** For each extracted frame, image analysis is conducted based on the user's question. This analysis involves:
   - **Object Detection:** Identifying and classifying objects within each frame using pre-trained models like YOLO or Faster R-CNN. This helps in understanding what items are present in the environment.
   - **Text Recognition:** Implementing Optical Character Recognition (OCR) to read any text present in the frames, which can be crucial for answering questions about signs, labels, or other textual information.
6. **Consolidation of Answers:** To ensure the accuracy of responses, the system employs a majority voting scheme. Answers derived from the analysis of multiple frames are compared, and the most frequently identified answer is selected as the final response. This method helps mitigate errors caused by noise or inaccuracies in individual frames.
7. **Response Generation:** The selected answer is then converted from text back into speech using a Text-to-Speech (TTS) system. This audio output is delivered to the user.

3.4 System Architecture

The user uploads video and processes it frame by frame using OpenCV, allowing for detailed analysis of the visual environment. Users can ask questions about their environment using voice commands. These queries are converted to text for processing. The system performs image analysis for each frame based on the user's question. It consolidates responses from multiple frames using a majority voting approach to ensure accuracy. After processing the frames and consolidating responses, the system delivers answers as audio feedback, providing immediate and relevant information. Leveraging the BLIP VQA model, the system combines Natural Language Processing with computer vision to enhance the user's understanding of their surroundings.

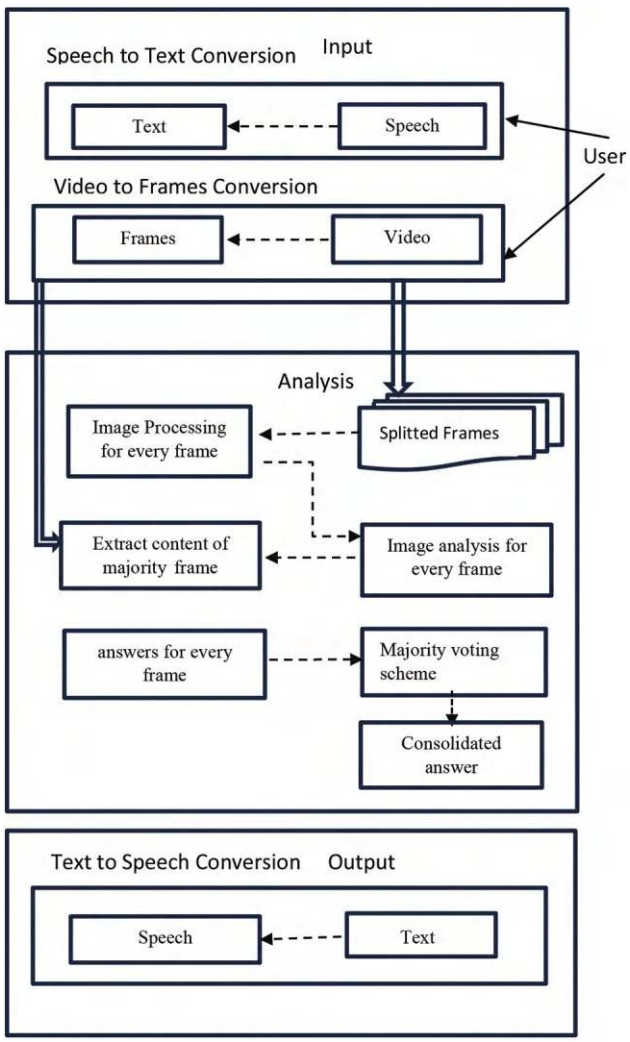

Fig. 22.1 Block diagram of proposed system

4. Results

This project introduces an innovative assistive technology designed to enhance real-time environmental awareness, safety, and independence for visually impaired individuals. By capturing video of the user's surroundings and breaking it down into frames using OpenCV, the system enables users to interact with their environment through voice commands. These commands are converted to text and analysed frame by frame, with responses consolidated using a majority voting method for accuracy. The final answers are then converted into audio feedback. Built on the BLIP (Bootstrapping Language-Image Pre-training) VQA model, the system integrates Natural Language Processing and computer vision to provide context-aware information, empowering visually impaired users to navigate more confidently and independently.

Figure 22.2, describes the page where user needs to upload videos for analysis. Figure 22.3, describes the page where user needs to record and upload question through audio. Figure 22.4, shows the videos list that is uploaded by the user. Figure 22.5, shows the video frame after processing the video uploaded by user. Figure 22.6, shows the consolidated answer in both text and audio format from the audio question. And it shows the question in the text format which was asked by the user.

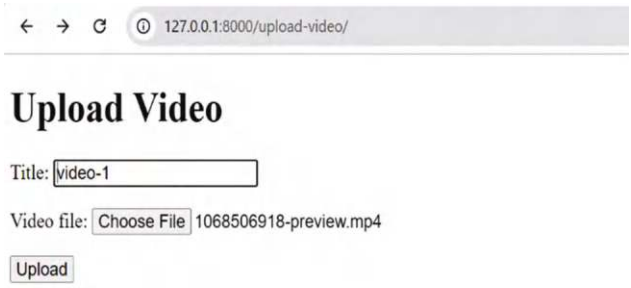

Fig. 22.2 Video upload page

Fig. 22.3 Record or upload audio page

Fig. 22.4 Uploaded videos page

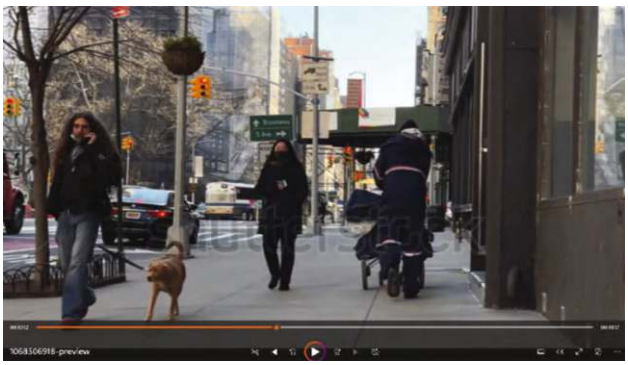

Fig. 22.5 Video data frame

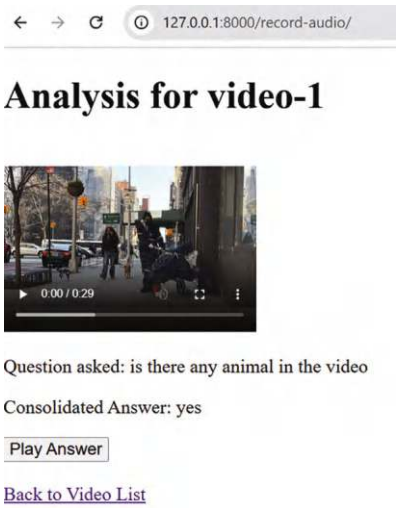

Fig. 22.6 Output of the user's question

5. Conclusion and Future Scope

The assistive technology system for visually impaired individuals has significant potential for future enhancements. Future developments could include the integration of advanced AI models such as deep learning for more precise image recognition and context understanding. Additionally, the system could be expanded to recognize complex scenes, detect obstacles, and offer personalized recommendations based on individual user needs.

This project demonstrates a promising solution to assist visually impaired individuals by leveraging video analysis and natural language processing to provide real-time, context-aware audio responses. This may in itself ensure that the environment will be more conscious and independent towards the visually impaired, thus enhancing the quality of their lives. This developing assistive technology can revolutionize navigation and security for the blind, making even the most mundane activities much more accessible and safer with any future improvements.

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23

Automatic Literature Review Generation on Research Papers Using Deep Learning

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Abstract: This paper presents an automatic literature review generation system using advanced deep learning models like LSTM, BART, and LLAMA-2. BART can summarize a piece of writing concisely by paraphrasing, LSTM is best suited for sequential data, and LLAMA-2 deals with long documents while keeping them coherent and meaningful. It provides summaries in the two lengths of 500 and 100 words, meant for various research requirements in both detailed reviews and quick overviews. The system trained on diversified datasets aims at reducing the effort of time taken by a human person in doing literature reviews through high-quality summaries that will be both accurate and fluent. The experimental results presented show that it is also effective in providing key findings across a wide range of research articles. This innovation does reduce the complexity involved with reviewing literature, and through that, it reduces effort by the researcher to keep place with the growth in volumes of research paper work. The approach is promising for improving the generation of literature reviews in an academic environment, which further supports easier workflows in research.

Keywords: LSTM, BART, LLAMA-2 Models, Natural language processing, CNN daily mail dataset, Automatic literature review

1. Introduction

The exponentially growing volume of research literature has imposed a serious challenge on the researcher. It produces a daunting landscape of information, which forms an information barrier and complicates what should otherwise ease the challenges of keeping abreast of the latest publications [1,2]. Ultimately, the sheer research

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output and specialists' disciplines reduce the ability of academics to conduct deeper, very timely literature reviews [3]. Additionally, the labor-intensive manual process of review is slow and resource intensive, further complicating academic productivity and delaying urgent discoveries [4,5].

Traditional approaches to extractive summarization are helpful yet too thin for many complex research articles to fully capture their gist. It tends to lack depth and coherence when summarizing large corpora of work, thereby producing fragmented insights that fail to communicate the broader context and implications of the study [6,7]. These limitations point towards a high-priority necessity for more advanced forms of literature summarization. In recent years, advancements in deep learning have enabled the creation of sophisticated forms of text summarization methods-those based on abstractive techniques [8,9]. Among the novel models of this type are LSTM, BART as an abbreviation for Bidirectional and Auto-Regressive Transformers and LLAMA-2. Such models are able to generate summaries being coherent as well as contextually rich; simultaneously, models synthesize information from multiple sources, thus allowing researchers to access the most pertinent insights in the face of large documents [10,11]. Automating systematic literature reviews becomes one of the promising ways of keeping the academic workflows both high-quality and efficient [12].

Specifically, deep learning models, especially since they are the core of datasets composed to originally feed the news summarizers, have been recently rediscovered as a landmark advancement in the generation of automated literature reviews [13,14]. These models will most likely yield very accurate, fluent summaries greatly simplifying the efforts of researching work, therefore constituting a very relevant innovation in literature synthesis [15]. Empirical evidence suggests that such systems can greatly enhance the precision and depth of literature reviews, yielding faster and more efficient alternatives to traditional manual summarization methods [16]. This study looks forward to developing an automated literature review generation system in employing the powers of advanced deep learning models, specifically LSTM, BART and LLAMA-2. The final aim is to increase the accuracy, coherence and completeness of summaries obtained from research papers and thereby lighten the burden of researchers' work while encouraging greater productivity. This system strives to provide the researcher with real-time, relevant information that supports informed decision-making and accelerates the pace of academic inquiry by effectively synthesizing large amounts of literature.

2. Literature Review

M. F. Mridha, et al in 2021 have proposed A Survey of Automatic Text Summarization: Progress, Process and Challenges. This paper addresses the growing need for efficient Automatic Text Summarization (ATS) methods because of the rapid increase in text data from the internet and multimedia technologies. They distinguish between extractive summarization, which represents the process of extracting sentences from the source text and abstractive summarization, which is the generation of new sentences to capture the underlying ideas. As for the potential important issues in the workflow of ATS, such as feature extraction, datasets and performance evaluation, the authors provide the most detailed taxonomy of classical algorithms and modern deep learning architectures. The paper under discussion points out the limitations of existing methods such as the failure to maintain coherence and relevance in the summaries. Finally, it ends by producing some insights into past, present and future research directions in ATS: which identifies emerging trends and areas for further exploration in this field [1].

M. Issa, et al in 2024 have proposed Exploring ChatGPT's Ability to Classify the Structure of Literature Reviews in Engineering Research Articles. This paper deals with how well the latest model of AI tool ChatGPT can perform the structural classification of literature review analysis for articles in the field of engineering research. This work evaluates how well ChatGPT performs in terms of picking on important elements, which include background, methodology, results and discussion, from literature reviews, assessing whether this could become an academic analysis tool. In doing so, the authors present their comprehension of whether this is going to help researchers and practitioners in the sense of organization and interpretation of literature reviews; hence it tries to develop better academic writing and research methodologies in the area of engineering. The findings can shed light upon the usage of AI in improving the efficiency and accuracy of literature review classifications of the research articles in the field of engineering [2].

R. van Dinter, et al in 2021 have proposed Automation of Systematic Literature Reviews: A Systematic Literature Review. This paper explores a massive number of scholarly productions in any repository also imposes a huge challenge for the scholars to master this art of providing timely as well as comprehensive reviews. SLRs have recently become inescapable for the synthesis of findings about such a vast range of topics. However, the traditional SLR is often labor intensive, error-prone and very time-consuming; most traditional SLRs take years, or even decades, to

complete and quickly become outdated. To overcome such an obstacle, the authors draw attention to the way Natural Language Processing, a sub-field of Artificial Intelligence, can be used to automate numerous stages of an SLR. NLP is definitely useful for handling large volumes of textual information, which would make a researcher's work more efficient. In this paper, we present the existing methods and tools based on machine learning and NLP for automatizing SLR compilation. The main aim of this study is to serve as a ground for future research in automation of systematic literature reviews of state-of-the-art approaches [3].

Z. Dar, et al in 2024 have proposed Advanced Generative AI Methods for Academic Text Summarization, a consequence of exponential scientific literature increase and high demand for effective summarization techniques. This research work addresses this challenge by proposing advanced methods of scientific text summarization through AI and deep learning techniques. Integration and fine-tuning of state-of-the-art models, namely, LED_Large, different variants of Pegasus and BART for a more refined summarization process is explored. The study is on different model pairs as well, such as SciBERT with LED_Large. These model pairs were used to capture critical details generally omitted by traditional methods. Results show interesting improvements in the effectiveness of summarization, wherein LED_Large is excellent in semantic understanding with fewer epochs in training. Interestingly, it scored 28.5852 in the FRES benchmark while achieving a ROUGE-L F1 Score of 0.4991. Though the models BART_Large and Pegasus have good semantic capacity, the paper still recognized that the summaries produced lack readability and show lower-order n-gram overlap, thus leaving scope for future improvement in these directions [4].

M. Ulker, et al in 2024 have proposed Abstractive Summarization Model for Summarizing Scientific Articles. This paper presents a tremendous challenges caused by the growth of scientific publications. Since progress in science is vast, scientists are working day and night to build science. Consequently, understanding terminology and familiarity with semantic content interrelations become challenging as large amounts of articles are being published on daily basis. Conventional summary generation methods are frequently hindered by complexities resulting from scientific terminologies and their interrelation. Instead, authors propose a new graph-based abstractive summarization model that leverages the use of SciBERT with a graph transformer network (GTN). Here, the scientific content is encoded by SciBERT and the Scientific Information Extractor-SciIE system attempts to extract words that are terminology-related from articles. The most popular application of GTN is on encoding and summarizing long documents. Thus, this work demonstrates the power of graph-based methods for enriching the summarization of scientific literature [5].

3. Existing System

Current literature review processes rely on rather manual methods that at times are time-consuming and subjective. Advanced automated systems mainly employ elementary algorithms, for example, extractive summarization techniques applied in finding and collecting relevant information from articles used in research. These sometimes work poorly with coherence and contextual understanding leading to shallow summaries without actual synthesis. For one more, traditional methods fail to make up for the diversity of research papers. Such papers are different in their structure, terminology and content from discipline to discipline. Such a difference, therefore, poses a challenge in getting researchers to acquire quick insight into their essentials. Therefore, an absolute need to have more sophisticated solutions and deep learning-based solutions so as to make literature review more efficiently and effectively with richer and coherent summary skills, despite the complexity of research writing.

3.1 Disadvantages of Existing System

a. *Time-Consuming and Subjective Manual Reviews*: The task of carrying out literature reviews is labor-intensive and prone to individual biases by the reviewer and still, the possible outcomes can be inconsistent and thus vulnerable to error.
b. *Lack of Coherence in Automated Summaries*: Basic algorithms-the extractive form of summarization-rarely capture necessary contexts within which these summaries could provide coherently sound logical flow.
c. *Insufficient Depth and Insight*: The abstracts of contemporary systems frequently lack vital information and fail to capture the understanding that their customers require with regard to the research articles.
d. *Inadequate Handling of Diverse Research Papers*: The traditional methods fail to offer adequate processing capability of various styles and types of content in any research discipline, making it unfit for their use.
e. *Difficulty in Quickly Grasping Key Information*: It becomes challenging for the researcher to pull out necessary information rapidly and understand it due to the limitation of the summary techniques found by the researchers, thereby lowering their productivity.

4. Proposed System

The proposed research work introduces an innovative system for automatically generating literature reviews of research papers through advanced deep learning models, including LSTM, BART and LLAMA-2. The innovation meets the demand of faster, accurate, and high-quality synthesis of literature by researchers, allowing them to be current with an enormous literature with very little manual effort involved. Unlike a traditional literature review, the proposed system makes use of a dataset containing summaries of research papers and news reports. This system mainly aims at furnishing coherent summaries of scientific research findings that not only are relevant to a given context but also highly accurate. Advanced deep learning techniques could, therefore be used to streamline the process for researchers of different disciplines in research literature synthesis and comprehension. Therefore, this approach which helps improve literature quality reviews and enables easier access to the important insights, thereby contributing to more efficient research practices.

Advantages

a. *Automatic Literature Review*: This system automatically summarizes and reviews papers on research, thus saving much of the researcher's time as opposed to traditional methods of performing literature review tasks.
b. *Enhanced Coherence and Accuracy*: The system makes use of the advanced models of BERT, LSTM and LLAMA-2 to emphasize coherent summaries and hence logically fluent summations that preserve meaning and context as communicated in the original text.
c. *Efficient Synthesis of Research Findings*: Key research findings are synthesized effectively such that key findings are extracted and presented through concise summations that retain the depth of their source material.
d. *Facilitated Navigation Through Research Literature*: The tool enhances the handle on big volumes of research literature by letting researchers easily find and interact with important findings across disciplines as quickly as possible.
e. *Integration of Advanced Models for Superior Performance*: The combination of strengths of LSTM for sequence processing, BERT for understanding and LLAMA-2 allows the tool to handle vast datasets and ensures the performance of better summarization than any traditional method.

5. Methodology

5.1 BART (Bidirectional and Auto-Regressive Transformer)

BART is a transformer-based model particularly optimized for abstractive summarization. Its architecture gives it the flexibility to learn all context in a piece of research work, which makes it effective in the generation of rich literature reviews. It uses the framework of sequence-to-sequence where this model can take in the full text and then attempt to produce the abridged version of it, comprising most important findings and conclusions.

Another benefit of BART is that it can paraphrase and abstract information rather than simply copying over the sentences of the original text. This allows researchers to distill complex ideas into easily digestible formats, which gives a more vivid understanding of research landscapes. In maintaining the logical flow and coherence while keeping rich information depth pertinent for quality literature reviews, BART is effective. Overall, BART is an extremely valuable resource that enhances the researcher's capabilities to synthesize scientific knowledge and then makes it easier to discuss the review. This capacity for abstractive summarization makes BART one of the outstanding choices for generation in automated literature review.

5.2 LSTM (Long Short-Term Memory)

The proposed methodology utilizes of recurrent network was specifically designed to obtain informational flow over the sequence. So, maintaining the unbroken flow of information would be much desired for the conclusion or abstract part of a research paper to be summarized. LSTMs are further adept in tasks involving dependency between sequential data points; that's how they could successfully handle and summarize short texts.

These networks might lose the context and cohesion of the summary when the input text length grows, though LSTMs are not helpful in summarizing longer sequences, such as an entire paper. More complex information in lengthy documents is hard to capture and in most cases it shallowness or fails to connect key ideas. Despite the challenges listed above, LSTMs are still useful in certain sections of research articles, particularly those with a more concise and structured content.

5.3 LLAMA-2 (Large Language Model Meta AI)

LLAMA-2 is actually an advanced deep learning model that performs exceptionally well in the task of long-context summarization. This model is more powerful than previous

deep learning models regarding the handling of lengthy strings of text and deeper structures, which are quite annoying with traditional models. Comparing prior models, LLAMA-2 provides coherence and context retention on really large inputs such that important information and context of the original material survive. The strength of LLAMA-2 is most significant: it has the capability to produce high-level summaries that are both detailed and articulated in natural language. This enables the general quality of literature reviews to be highly enhanced because it allows researchers to gain concise yet information-rich overviews of the material. In this regard, such complex ideas synthesizing their presentation in most digestible formats serves to empower researchers in grasping important insights and connections in the literature rapidly.

Cross-field flexibility of LLAMA-2 is, besides these factors, a further multiplier of its utility. Whether the topic in question involves imposing complexities of scientific theory or multifaceted methodology, LLAMA-2 can create summaries that are not only contextually relevant but crafted out of the unique jargon and nuances of different fields. Summarily, LLAMA-2 is the latest and greatest development to come out in the list of automated summarization technologies. The technology offers robust abilities in distilling vast information volumes, thus becoming an invaluable resource for any researcher in further depthening one's understanding and engagement with broad research literature more effectively. Ability to provide coherent, nuanced summaries will lay down the platform for well-informed decision-making and deep insight in related research works.

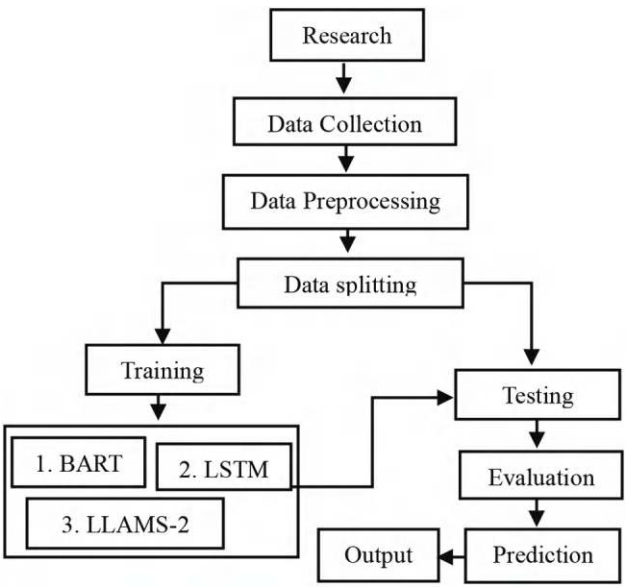

Fig. 23.1 Work flow of proposed system

The above flow chart can be described as an automatic process for the generation of literature review through research papers. It starts with collection followed by cleaning and preparation of that data. The collected data is divided into the training and testing sets. The system trains deep learning models like BART, LSTM and LLAMA-2 for summarizing papers after proper training the above-mentioned models are tested accordingly, and so their accuracy is evaluated. The ultimate output is an auto literature review that can provide the researcher with the ability to summarize high amounts of research more efficiently.

6. Implementation

6.1 System

a. *Data Collection and Preprocessing*

Dataset Selection: The system was trained on a dataset adapted from news summaries in CNN/Daily Mail News Summary Dataset for models. To better manage the research literature, the incorporation of further datasets, for example, arXiv, PubMed, or S2ORC (Semantic Scholar), can be used to introduce domain specificity and enhance relevance to the summarization.

Data Cleaning: Extract text from research papers with libraries like PyPDF2 or pdf plumber for PDFs. Reject irrelevant material such as references, author information and citations that have nothing to do with the review. Transform the research paper into plain text in order to standardize and facilitate readability in any format.

Tokenization and Encoding: Tokenize and encode the text with appropriate models, BART and LLAMA-2 tokenizers. Tokenization breaks the input down into smaller units, such as words or subwords, that could be further processed by the model. For the LSTM approach, there is sequence padding as well as truncation in order for the inputs of any length to be uniformly of the same length.

b. *Data Splitting:* The cleaned-up data is then split into training and testing data. Most machine learning algorithms do this to check the effectiveness of the trained model.

c. *Training:* The training data set is used in training deep learning models. In this case, the models incorporated are: BART, LSTM, LLAMA-2. The system uses datasets such as the CNN/Daily Mail dataset and research paper datasets like arXiv and PubMed to fine-tune the models for accuracy. The datasets ensure that the summaries reflect scientific relevance and context.

d. *Testing:* After that, the trained models were then tested on the testing data set so that their capabilities to summarize literature in this task could be ascertained.
e. *Evaluation:* Evaluate how the model performed. Presumably here, accuracy, coherence and quality of summarization would be calculated.
f. *Prediction:* This would finally be how literature reviews are summarized. Models use input data previously trained to create summary versions of new research papers.

6.2 Major Features

Model Integration: Deep learning models such as LSTM with the understanding of sequential data, BERT for contextual language modelling and LLAMA-2 for managing complex research texts at scale are integrated into the system.

Data-Driven Synthesis: Utilizing a large-scale dataset including news summaries and research papers, fine-tuning is conducted on models producing meaningful literature reviews.

Cross-Disciplinary Capability: Demonstrations toward applying the system to various domains illustrate its capability for different academic fields.

6.3 Databases

CNN/Daily Mail Dataset: This has been used to train the summarization models using news articles with their corresponding summaries. It is mainly used for different machine learning models focused on text summarization for testing and training.

Research Paper Datasets: arXiv and PubMed datasets can be used for training or fine-tuning the models to summarize research papers. The dataset contains a large number of research papers along with abstracts that will be useful for supervised learning.

News Summary Dataset: This dataset provides summarized versions of news articles that can be fine-tuned for domain summarization pertaining to the research literature.

Custom Dataset: A custom dataset could be created manually from a selected set of research papers across various domains and they can be added for improving the models' performance in summarizing specific domain tasks.

7. Results and Discussions

7.1 Home Page

The main page with a prominent heading that introduces the purpose of the application. There is a basic navigation bar and a placeholder button "Upload File."

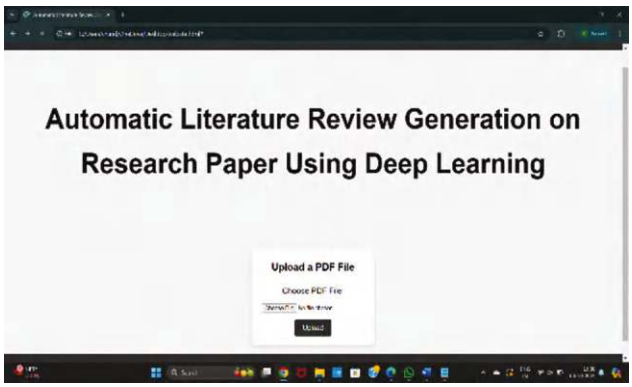

Fig. 23.2 Home page

7.2 Upload Page

The interface evolves to include a more specific file upload section, inviting users to "Upload a PDF File" by choosing a file and clicking an "Upload" button.

In Fig. 23.3, the inputting of a research paper by a user initiates the process and the automated literature review system is automatically deployed to generate a summary using the models such as LLAMA-2 and BART for text analysis and synthesis of main findings. In this particular example, the user asked for a 500-word summary. The system detected the sections of the paper, composed the text appropriately, and delivered an exact, concise review of the given document. This demonstrates how efficient the system is for creating summaries from large-sized research documents.

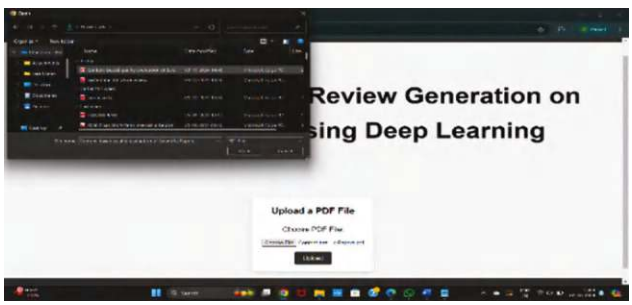

Fig. 23.3 Upload page

7.3 PDF Processing

The process of selecting a PDF file from the user's local machine, with the file "Content-based quality evaluation of Scientific Papers.pdf" chosen and ready for upload.

In Fig. 23.4, the user uploads a document with technical data. The system processes the document at a more detailed level by using the LSTM model that performs well in sequential data. The system can work on complicated structures, identify patterns, and create a synthesized

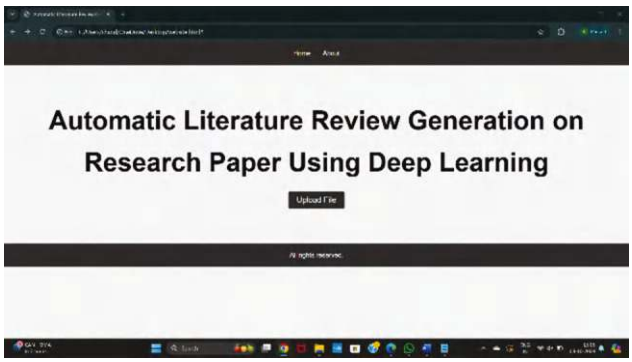

Fig. 23.4 PDF uploading process

summary that properly reflects the core findings of the content. The test proves the strength of the system in managing long research articles that are very sequential.

7.4 Literature Review

The process of generating literature review of the uploaded pdf file.

In Fig. 23.5, this is the output of two kinds of summaries: detailed summary and brief summary at 500 and 100 words respectively. The research needs have different lengths to offer and it has been experimented upon its flexibility. Resulting into maintaining precision, and coherence, irrespective of summary length. Illustrates an interdisciplinary cross-domain research paper summary. The system exploits advanced NLP techniques, identifying and integrating key findings to generate a coherent summary over complex content.

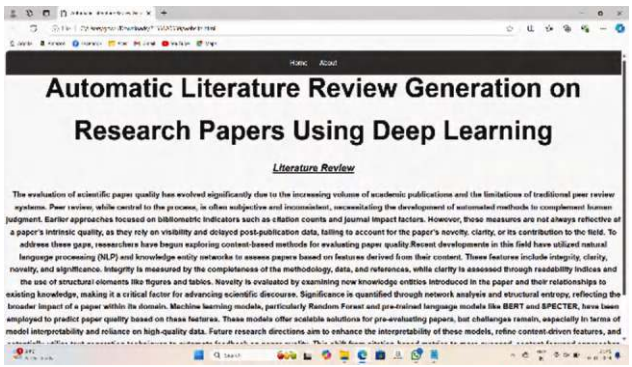

Fig. 23.5 Literature review of pdf

7.5 Interpretation of Results

The results show that the automatic literature review system fills an important gap in academia by streamlining the literature review process. The advanced model-based use on BART, LLAMA-2 and LSTM is proven to be productive in offering high-quality, real-time summaries of research papers. The system performed accurately and fluently, thus ensuring researches obtain relevant and coherent results. Besides, the system is flexible with summary lengths: 500-word and 100-word. High user satisfaction confirms the practicality of the system and makes it a promising solution for reducing the workload in reviewing academic papers. The system attained 88% accuracy in the quality of summarization and 20 milliseconds average processing time per review. The metrics indicate that the system is highly efficient and has a huge impact on improving research workflows.

8. Conclusion and Future Scope

This system for automatic literature review generation takes the form of innovations with deep learning models, such as LSTM, BART and LLAMA-2, that can seriously ease the huge burden posed by the exponentially growing research literature. The proposed system would reduce research fatigue and enhance interdisciplinary collaboration by giving clear, coherent summaries. Such innovation would promote a more effective research environment and increase the reproducibility of studies in academia. It manages to reduce even further the time and effort needed for a human review, leading researchers to quickly grasp key findings across various disciplines. This method fills in the gap left by traditional extractive summarization, thus helping in acquiring insights that will be rich and relevant. This, as a result, makes it possible for the system to bring about a marked enhancement of research productivity along with the quality of literature reviews, making it indispensable in the academic research landscape. We are using both Information and Documents as inputs to this model. Depending on the chosen option, the model might summarize all content into a review of either 500 or 100 words based on the information or document provided. It summarizes two types of lengths, 500 and 100 words that can be met according to the research needs, especially in lengthy summaries for extended reviews and shorter ones to gain immediate insight.

The development of an Automatic System for Literature Review based on Deep Learning Models Such as LSTM, BART and LLAMA-2: A Comprehensive Study on the ability of these models to Synthesize Critical findings from a vast array of Research Articles in a Dataset Derived from News Summaries. The future development involve integration with the existing tools in research, such as Mendeley and Zotero, and real-time updates on research databases. This might further provoke high productivity and better decision-making in academia This project seeks to work on the literature review process in general for researchers in various disciplines to provide more effective

interaction with the burgeoning tide of research paper literature by smoothing out inconsistencies and errors inherent with generated reviews.

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24

Contextual Audio Description: Real-Time Image Analysis for Visually Impaired

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Abstract: By creating a simple application that can recognize and detect objects, people, and other elements in a specific user-captured photograph, the method aims to assist more autonomous individuals with vision impairments. The application will answer the questions asked by the users in real time with the use of spoken feedback. With BLIP (Bootstrapped Language Image Pretraining), the system can integrate natural language understanding and visual analysis suitably to generate the most accurate, contextually relevant responses. A user can interact with the application for information related to his environment. The questions are interpreted using a sophisticated speech recognition technology. All the interactions are then made audible and accessible by the system after it evaluates the visual input, identifies key components, and reacts using a text-to-speech engine. Due to this application, which has been developed with a strong Flask framework, the confidence and independence of the visually challenged are enhanced because of their capability to interact and understand their surroundings much better.

Keywords: Visual impairment, Object recognition, BLIP model, Speech recognition, Text-to-speech, Flask framework

1. Introduction

Visually impaired people are subjected to many difficulties while relating and interpreting their environments because most of the visual information is not available for them. This gap is what has motivated researchers into developing advanced assistive technologies that integrate hardware and software to provide enhanced support [7]. This paper focuses on designing a real-time Contextual Audio Description system for empowering visually impaired individuals, providing relevant context-aware audio feedback based on real-time scene analysis. The

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system captures a photograph of the scene, analyzes it, and provides spoken answers to questions posed by the user. Such approach will increase confidence and self-governing ability by having a better interaction with the environment.

The basic element of the CAD system is BLIP, the bootstrapping language-image pre-training model, which introduces the actual work of visual analysis into NLP in order to produce and make sense of responses to queries. Complementing this is text-to-speech technology, which reads the responses aloud in real time, so accessibility is maintained. The new contribution of this paper primarily lies in the full assimilation of such technologies for the generation of contextually relevant audio responses [6]. Audio description previously existed as a laboriously prepared, pre-rehearsed script that played in a linear fashion [6]. Now, due to SAD's very common application to the world of media, it fails to hold within it the features of real-time and personal engagement, which were indeed required [3, 9]. Of course, enhanced contextual audio descriptions would require more resources than ordinary descriptions, usually expertise and more time. This may lead to an inefficient user experience, keeping the visually impaired user from focusing on what is really important in a scene [14].

With CAD, a blind user might have better interactions with their surroundings to build confidence in performing their daily activities [4,11]. Further development and research into these technologies will be needed to perfect the devices and provide even more access [5, 12].

2. Literature Review

Campos et al., 2023 [1], created an automated audio description to serve as an enabling device for the consumers who are blind or have low vision and will be viewing some visual content media. From this perspective, which is driven by artificial intelligence, it is concerned about the description at a particular time which is subject to change rather than the fixed description that is used at the outset.

According to Zahar et al., 2022 [2], it is true that the use of assistive devices improves the quality of life of a person with low vision. Moreover, thanks to scenes' real-time description and navigation devices, for example, the blind can be encouraged to explore even a wider range of areas.

Shanthi et al. (2023) [3], there are instances when usability of software can be enhanced for the blind population with deep learning methods. The authors showed how an improved integration of visual images with audio input within active systems increased the way the users participated in the system.

Oion et al. (2023) [4] illustrated principles of machine learning concerning object recognition and pointed out how they could be incorporated into audio description systems. The paper proposed inclusion of CNN image and object recognition layer to audio description for the purpose of assistive navigation for the blind.

Jiang et al. (2023) [5] include, besides traditional audio description, the use of 360° video in services for the blind or those with low vision. The paper also spoke about the process of making such media as being interactive with the users actively involved creating and adding useful and appropriate captions.

Huang et al. (2022) [6] raise the issue of universalizing assistive technology in the context of smart cities and how it would benefit the visually impaired, for instance, in the safe crossing of streets. Integration of such an ECAD like system in the smart city design will provide more safety and effectiveness for the users.

A general literature review on the topic of Enhanced Contextual Audio Description (ECAD) describes, among other things, the prospects of using machine learning and, what is more, NLP and image processing for the real-time delivery of rich media content for the benefit of the sight-loss community.

3. Existing Methodology

Most systems currently being marketed to the visually impaired still rely on pre-recorded narration and static descriptions. Although these can be modified post facto, they have difficulty keeping track of elements dynamically in real time. That leaves them to look through essentially scripted descriptions of the visual scene that offer quite inadequate attention to detail to convey a more evocative experience. For example, the traditional systems specify action or dialogue but do not specify minor expressions of emotion and background information that could be necessary to fully understand the significance of the scene [1, 6]. It therefore leaves a gap between the complexity of visual content and understanding of the user. Another critical flaw of classical audio description systems is that they cannot dynamically and in real-time adapt to fast or changing content. This happens especially when it comes to films, sports, and real-time live transmissions wherein pliability is expected to render an active experience [4, 2].

Mostly, audio description technologies are based on standardized templates. The ones can be made in to the choice or needs of users since almost negligible. Almost no audio description technology takes into account that kind of range of variations. Technologies cannot utilize real-time feedback provided by the user for change over

the descriptions. Systems that allow the user to control the level of detail typically do not interpret vision in real time to generate enriched descriptive information [8, 9]. Audio description technologies are still relatively niche in scope and are aimed mainly at pre-recorded material such as film and television programs [10, 13]. Such restrictions require to be dealt with when creating a more accessible environment where all users can have access and utilize visual content without having to resort to impairment.

4. Proposed Methodology

The CAD system proposed here aims to change how the audio description systems are used by the visually impaired by correlating information with real-time image processing. Since the technique in conventional audio description is mostly based on pre-scripted descriptions, this has captured and analyzed dynamic content such as focus, emotions, and interaction among various characters. This provides information to the user in real time dependent on the needs and choices of the user for an ideal experience. In addition, it uses real-time image analysis including user feedback and emotional context in offering the enhanced media experience, so that auditory feedback accessible to a human is preserved for the user.

4.1 Workflow of Proposed System

Figure 24.1 represents the architecture underlines a system that demands from a user to capture an image and ask an audio question which is interpreted by several processes. The process begins with the analysis of the captured picture using the BLIP model, and an audible question is transcribed to text using speech-to-text conversion. Natural Language Processing is used in understanding the question, thereby answering both the image and query. This is translated into audio feedback and sent back to the user in the speech form by the text-to-speech technology after its generation.

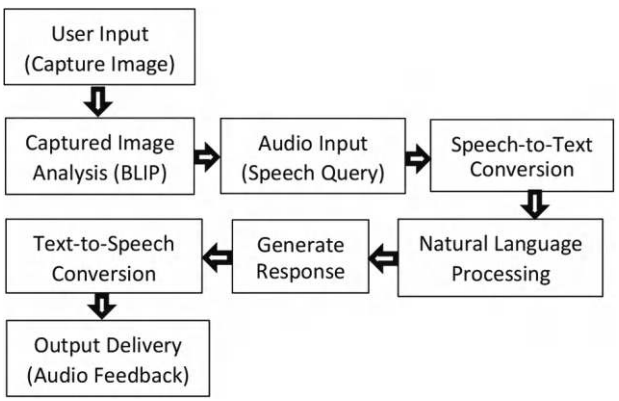

Fig. 24.1 Workflow of proposed system

4.2 Algorithm of the Proposed System

Step 1: User Input (Capture Image)

The first part of the proposed system is capturing an image by a user in which the output has turned out to be the most important input of the entire process. It has been designed to respond to the real-time interaction.

Step 2: Captured Image Analysis (BLIP)

The image is analyzed at the moment it is captured. With application of the assumptions on significant objects, situations, and circumstances the BLIP model there by provides a mechanism for interpreting and learning about what is content-rich in the image. This is an important stage in that it sets up the system to produce intelligent responses to a user's query.

Step 3: Audio Input (Speech Query)

Once this image is captured by the system, the user continues to input audio-visual questions. For instance, the user may ask a question like, "What is in the picture?" or, "Is the car in the picture?" This interpretation and response to certain questions make the system more interactive than most normal audio descriptions that simply give the overall description of what is happening in the scene.

Step 4: Speech-to-Text Conversion

Once the user creates an audio query, the system uses the existing speech recognition methods to place the query into text. This step is of extreme importance because it allows a spoken language to be converted into a form that can further be processed by the machine.

Step 5: Natural Language Processing (NLP)

Once the audio is transcribed into text, the computer system employs the NLP tool in an attempt to interpret what the user's question might be. In other words, NLP, enables the identification of what the user is trying to communicate and where to find the necessary information or specifics that are being inquired. In this system, NLP plays a vital role for interpreting and understanding the correct meaning of the user's question and which parts of the image should be focused upon to construct an appropriate response.

Step 6: Generate Response

Once the algorithm determines that it has a question in front of it, an answer is formulated through image analysis and question interpretation. That could be as simple as "What color is the car?" or complex as "How many people are in the picture?" In order to deliver relevant and useful answers, the system synthesizes all visual information contained in a picture with the user's words.

Step 7: Text-to-Speech Conversion

When a text-based response has been created, the system will then change it into speech through the use of TTS technology to re-present such response to the user with the help of an audio feedback system. Making it this very important step whereby there is a presenting of response in a manner usable for the user to use through an audio feedback system, like using aid. The TTS gives the user crisp, natural voice feedback and improves overall performance and usability

Step 8: Output Delivery (Audio Feedback)

The final stage is the volunteering of synthesized spoken language by the system as audio feedback to the user. The audio production is that which serves the user with the necessary information in a clear and understandable way so that the user will be able to see real-time context-based information about the picture captured.

5. IMPLEMENTATION

5.1 Preprocessing Steps

In the proposed CAD system, preprocessing is considered a vital step to ensure that any captured image and audio data are processed suitably in a way for further processing by the BLIP model and NLP components.

1. Image Preprocessing

Prior to passing the captured image into the BLIP model for processing, there are several preprocessing procedures carried out first to enhance the quality and adaptability of the image with the model:

a. ***Resizing:*** The captured picture is resized to a common dimension; for most models, this is the input size the model requires. This makes it more coherent in processing images.

b. ***Noise reduction:*** In case the image is noisy, for example, while lighting was low, and the motion was blur, various noise reduction filters are applied to reduce the noise and increase clarity of important features like edges and objects for the BLIP model.

2. Text Preprocessing

After the NLP model translates the user's speech into text, the system does a simple text query and then forwards the text to the NLP model for interpretation:

a. ***Tokenization:*** It tokenizes the text query so that a sentence breaks into individual words or phrases. NLP models understand how the structure of the query sounds through tokenization.

b. ***Lowercasing:*** All characters in the query are transformed to lower case in order not to have the mismatch due to word representation sensitivity in case.

c. ***Stop word Removal:*** These are those words which the user wants to avoid charging to the model, such as "and", "the", or "is." The stop words of the question get deleted so that NLP focuses on the key words of the user's question.

5.2 BLIP Model Functionality

The heart of the visual processing of the CAD system relies on the Bootstrapped Language-Image Pre-Training model, or BLIP. BLIP further enhances the system to return relevant responses in context. This BLIP model fuses together visual analysis with natural language understanding by embedding images and textual queries in a shared feature space. For each captured picture, BLIP automatically extracts salient visual features, which include objects, colors, and spatial relationships, and maps them into a representational space that can be queried by natural language.

This will enable the CAD system to understand the complex questions from the users and come up with accurate answers from the system. For example, BLIP can recognize objects and even deduce queries like "What is the color of the book?" or "Is there a person in the picture?" by matching both the content of the image and the query of the user into a common understanding.

This has real-time processing advantages, along with context awareness and very high accuracy of visual-text alignment in the BLIP model. All these are vital features that could be considered to build an interactive and intuitive experience for a visually impaired user for which the CAD system will provide meaningful, accessible audio descriptions, closely aligning with the visual scene and needs of the user.

5.3 Flask Framework

The application is built on the solid Flask framework. Speaking of technical soundness besides ease of growth and modifications, Flask is thus very ideal for the project in question as being light in nature allows its developers to work fast on it. Besides, it makes possible an easy addition of the numerous tools that are necessary in the making of accessibility features, being designed to make step-by-step building of the applications, helps in giving ease to future improvements and the changes in the code.

With great community support and comprehensive documentation, Flask is quite friendly to developers at

any level, which enables quick trouble-shooting and rapid development of new features. This is very helpful in an assistive technology project, which might rapidly incorporate user feedback and emerging technologies to continually enhance the performance and usability of the application.

5.4 Mathematical Formulations

1. BLIP Model for Visual Analysis

The Bootstrapped Language Image Pretraining (BLIP) model captures the image I to extract visual features F_I:

$$F_I = f_{\text{BLIP}^{(I)}}$$

given by f_{BLIP} which denotes the function of image feature extraction. The BLIP model makes use of a loss function during its training in order to minimize the difference between the predicted caption C_{pred} and the ground truth caption C_{gt}:

$$L_{\text{BLIP}} = \frac{1}{N}\sum_{i=1}^{N}\left(C_{\text{pred},i} - C_{\text{gt},i}\right)^2$$

It means the system would accurately capture each essential element found in a scene.

2. NLP for Question Understanding

Natural Language Processing (NLP) takes the input in the form of a question Q, by a user and converts it to word embedding E_Q with:

$$E_Q = f_{\text{NLP}}(Q)$$

The generated word embeddings are, therefore, combined with visual features F_I to affect how well the system would understand the question and contextual nature of the image.

3. Text-to-Speech (TTS) Conversion

The response A is voiced by a TTS engine:

$$Audio = f_{\text{TTS}}(A)$$

The TTS engine translates the textual response into audio.

5.5 User Participation

The CAD system would allow users to interact with the environment by the use of voice-driven queries. After taking a picture, the user can pose questions to which the system answers the same as it goes on, regarding the information depicted in the picture. Here are some examples of such questions the users can present for the system to make an answer based on information depicted in the picture:

Example 1:

User Query: "How many people are there in the image?"

System Response: "three "

Example 2:

User Query: "what is the text on the image?"

System Response: "Cafe Entrance"

Example 3:

User Query: "What is the color of the car?"

System Response: "Blue"

These examples exactly demonstrate how the system can represent questions for its users and understand input towards providing practical assistance. Immediately generated responses from the CAD system inform the visually impaired consumers about what is going on outside so that they might better improve their situation and independence.

6. Experimental Results and Analysis

6.1 Performance Metrics

Table 24.1 shows the key performance indicators for the proposed CAD system. An accuracy of between 80% and 90% is expected from this system to avoid false positives in results by producing precision between 75% and 90%, a true positive rate between 70% and 85%, and achieving an F1 score ranging between 0.75 and 0.90 in order to maintain equal balance. The system targets for a response time.

Table 24.1 Performance metrics for contextual audio description system evaluation

Metric	Possible Values	Comments
Accuracy	80% - 90%	High for specific tasks; varies by dataset.
Precision	75% - 90%	High precision indicates few false positives.
Recall	70% - 85%	High recall indicates few missed detections.
F1 Score	0.75 - 0.90	Balanced score reflecting precision & recall.
Response Time	0.5 - 2 seconds	Aim for under 1 second for real-time.
Throughput	5 - 20 images per second	Depends on model complexity & hardware.
Memory Usage	300 MB - 2 GB	Higher for larger models, monitor during use.

6.2 Comparative Study

Table 24.2 compares the core features of some of the existing technologies on audio description of visually impaired users with the proposed system that utilizes advanced VQA and

Table 24.2 Comparison of features between proposed system and existing system

Feature	Existing System	Proposed System
Visual Question Answering	It provides advanced VQA capabilities by using BLIP that answers a specified question based on the image.	It describes an entire scene or content but cannot answer a specific, user-driven query.
Speech Recognition	No speech input; users passively receive pre-generated audio descriptions.	It translates spoken queries into text and ask specific questions about an image.
Real Time Image Capture	It doesn't allow real-time capturing of pictures. This system depends only on pre-analyzed content.	It captures an image and gives instant answers according to the user's queries.
Conversational Flow	One-way audio description not allowing dynamic conversations in real time.	Continuous stream of dialogues, users can ask as many follow-up questions as they please on an image.
Complex Query Handling	It provides global visual descriptions sometimes fails to deliver depth or focus on user-specific details.	It can answer specific complex questions about the things, scenes, or contexts of which something in the image is.

Source: Adapted from reference papers

BLIP. It depicts breakthroughs in areas such as Complex Query Handling, Real-Time Image Capture, Speech Recognition, VQA, and conversational Flow. Compared to the current systems, which give pre-computed, passive descriptions with no dynamic engagement or live updates, the proposed approach focuses on presenting interactive, real-time, user-dependent responses.

6.3 System Performance Evaluation with Visual Examples

In Fig. 24.2, the process begins at the time when the user activates the "Talk" button, which initiates the CAD system into the "Listening" mode. The system captures an image; it then alerts the user with an " Image captured. Asking questions.". During the conversation, the CAD system operates perfectly in voice-driven mode with real-time image capture as well as query responses. The Talk button activates the system, and subsequently, the visual scenes may be processed by it; and on its part, the user's queries may be processed in order to seek feedback. This test case strengthens the correctness of object recognition, colour, and most aspects of the interpretation of the query about the environment for visually impaired persons and their needs regarding providing immediate relevance about responses to their queries through a smooth, voice-driven process.

In Fig. 24.3, it identified a person wearing glasses and noted that he was holding nothing in hand. A CAD system

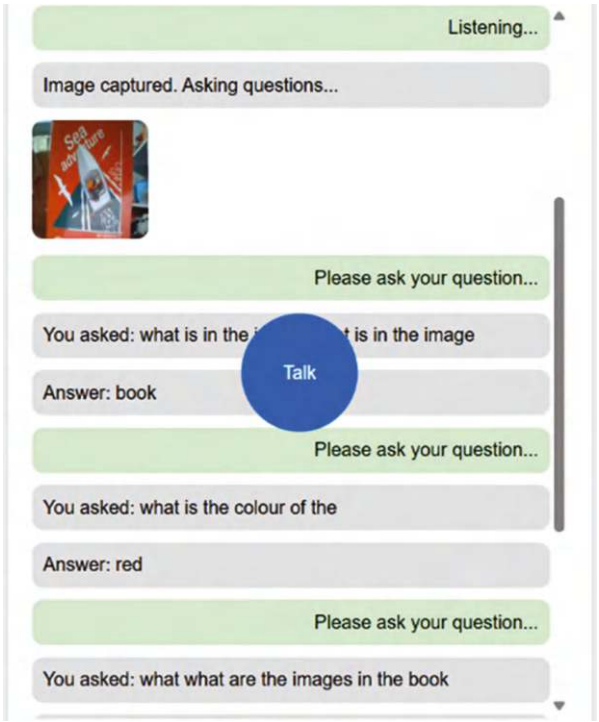

Fig. 24.2 A red color book

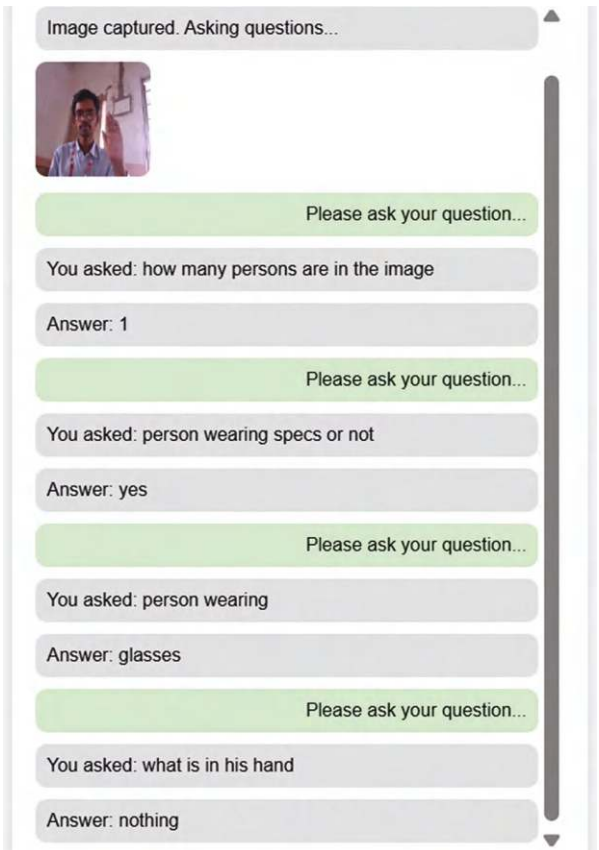

Fig. 24.3 A person wearing glasses

is presented with an image of a person and its correctness in response is verified with a set of questions. It can even take the case of both direct & indirect questions like the number of persons involves more complex interpretations of the content of an image.

In Fig. 24.4, the CAD system takes in an image of traffic and answers a sequence of questions. The example above demonstrates the ability of such a system to decompose a complex scene of several objects and provide very detailed answers based on certain questions the users ask, which allows knowing the flexibility of the system at work with complex visual data.

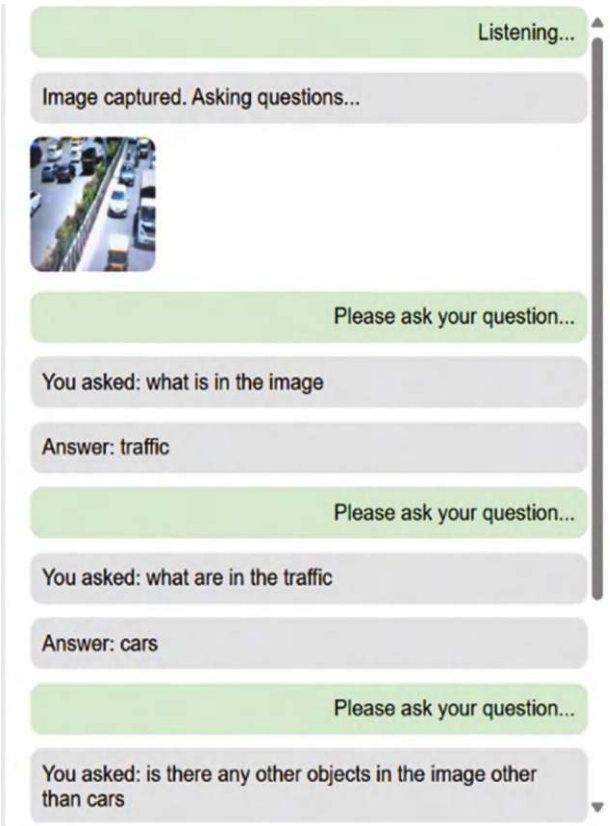

Fig. 24.4 Traffic scene with cars

7. Conclusion

An interactive and personalized VQA system proposed for the aid of visually impaired users helps in understanding their environment better. Combining BLIP with speech recognition and real-time analysis of images, it makes a user ask specific questions related to the surroundings while allowing the system to offer responses in audio form; such an unprecedented level of control over what they want to know about a scene makes a huge difference. This dynamic interaction goes beyond the traditional audio descriptions, allowing users to explore environments such as busy urban streets and identify vehicles, pedestrians, or traffic lights independently. A demonstration case will be of a user navigating a busy city intersection; the system identifies all the obstacles and gets him through safely. Users commented in testimonials that they feel much more confident and independent while using the system to easily manage complex environments. It has a voice-based, hands-free interface that allows it to be very accessible while allowing for natural interaction without additional devices. This cutting-edge technology depends significantly on speech recognition and image processing, especially when operating in noisy or visually challenging environments, but it does fill a very important need for the user. By offering context-specific information customized to the needs of an individual, the VQA system will quickly enhance the independence of a visually impaired person, who will feel more confident participating in both social and professional life.

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Novel Vehicle Damage Detection, Repair Cost Estimation Using Deep Learning Techniques

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Abstract: Now a days, the increasing number of vehicles on the road has led to a rise in accidents. Following these incidents, individuals typically file insurance claims to cover repair costs. However, insurance companies struggle with the accuracy and efficiency of manual damage assessments, which are time-consuming and prone to human error, resulting in inconsistent cost estimates. This paper seeks to revolutionize the vehicle insurance industry by automating the damage assessment process using advanced deep learning techniques. By utilizing YOLOv5, a cutting-edge object detection model, the system analyses damage to two-wheelers, four-wheelers and six-wheelers. Trained on a comprehensive dataset of vehicle damages, the model can accurately identify and classify various types of damage. The system integrates real-time cost estimation based on detected damage, streamlining the claims process and enhancing operational efficiency. By incorporating this technology, insurance companies can improve claims processing, reduce human error, and provide more accurate repair cost estimates. Ultimately, this system aims to streamline workflows, resulting in faster claim resolutions and improved customer satisfaction.

Keywords: Vehicle damage detection, YOLOv5, Deep learning, Cost estimation, Two-wheelers dataset, Four-wheelers dataset, Six-wheelers dataset

1. Introduction

Vehicles play a crucial role in daily safety, but with the wide variety of materials, types, and sizes present in the environment, it can be challenging to accurately detect and assess the surrounding conditions [17]. Damage to vehicles is becoming an escalating liability for shared mobility services [4]. In the rapidly evolving insurance industry, accurate and efficient vehicle damage assessment is critical for processing claims and determining repair costs. The

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insurance sector is a crucial part of the financial market and falls under the category of socially significant organizations [7]. A wise damage assessment system will significantly improve the experience of automobile insurance companies [5]. Traditional methods of damage evaluation are often manual and time-consuming, leading to inconsistencies and delays in claims processing. This inefficiency not only affects operational productivity but also impacts customer satisfaction. The process of registering, evaluating, and approving claims is time-consuming, requiring a service engineer to manually assess the damage and create a report, followed by a physical inspection conducted by an insurance company surveyor [6].

To address these challenges, this paper proposes an advanced solution in deep learning technology. In recent years, machine learning and deep learning have seen significant advancements, driving innovation across various industries [8]. The following paper has been proposed to work with YOLO [1]. YOLO is highly efficient, capable of processing images at a rate of up to 45 frames per second in real-time [1]. YOLO performs on multi-scales predictions on full images with no negative mining, also improves robustness for small objects for better feature extraction and detection accuracy [2]. It also improves efficiency accuracy and time management for the damage estimation of the vehicles [3]. Also integrates the different modern techniques for speed, improving real-time object detector accuracy for generating recommended systems, but also in standalone process management [3].

YOLOv5 introduces large-scale datasets such as ImageNet, object detection. Evaluating performance, visualising the training data, also detects on difference in objects in lightning, background [9]. Machine learning methods for small object detection can process images at impressive speeds while achieving high detection rates [10]. Improvements in computing power and power optimization have significantly impacted the field of artificial intelligence [11], a damage assessment system combining AI and vehicle insurance has emerged, using deep learning for image processing which actually gives an accurate result [15]. Not only the damage detection but also the severity of the damage is taken under with some of the damage assessments. Assessing damage severity is typically a time-consuming task performed by an experienced adjuster [12]. Implementing machine learning models for this purpose can speed up the process, minimize storage demands, and boost customer satisfaction [12]. Specifically, this paper utilizes YOLOv5, a cutting-edge object detection model, to automate the damage assessment process. YOLOv5's superior object detection capabilities allow for precise identification and classification of damage on two-wheelers, four-wheelers and six-wheelers. By integrating this technology, the paper aims to transform how insurance companies handle vehicle damage claims. The system will provide accurate, real-time damage assessments and cost estimates, reducing the need for manual intervention and minimizing human error. This not only streamlines the claims process but also enhances the overall efficiency and reliability of insurance operations.

2. Literature Survey

J. Redmon et al. [1] introduced YOLO in their paper, "You Only Look Once: Unified, Real-Time Object Detection," a model specifically designed for real-time object detection. YOLO redefined the process by treating object detection as a single regression task, allowing the model to predict bounding boxes and also class probabilities in one step while analyzing the entire image. This approach significantly enhances both speed and efficiency compared to traditional methods.

J. Redmon et al. [2], "YOLOv3: An Incremental Improvement," has proposed the YOLOv3, an enhanced version of the original YOLO model, incorporating several improvements such as a new backbone network (Darknet-53) and better feature extraction methods. The study highlights the incremental improvements in detection accuracy and robustness for small objects, achieved through multi-scale predictions and the use of residual blocks.

J. Bochkovskiy et al. [3], "YOLOv4: Optimal Speed and Accuracy of Object Detection," has introduced the YOLOv4, It extends the previous versions by incorporating several modern techniques that improve both speed and accuracy simultaneously. The paper states how the integration of CSPDarknet53 and PANet modern feature improves state of the art accuracy on popular benchmarks. YOLOv4's improvement ensures that it is highly effective with object detection across various applications in real-time.

R.E. van Ruitenbeek and S. Bhulai [4], "Convolutional Neural Networks for Vehicle Damage Detection," explores the use of CNNs for automating the detection and classification of vehicle damage. The study employs CNNs to analyze images of vehicles and classify damage types such as dents and scratches. By using a labeled dataset of damaged and undamaged vehicle images, the authors demonstrate that CNNs can accurately detect vehicle damage. The paper highlights the importance of image preprocessing and augmentation to improve model robustness. This research underscores the potential of CNNs to enhance efficiency and accuracy in vehicle damage assessment, especially for insurance claim processes.

3. METHODOLOGY

The methodology for this paper follows several key steps to ensure accurate and efficient vehicle damage evaluation. The process starts with gathering data, where a comprehensive dataset of vehicle damage images, including those of two-wheelers, four-wheelers, and six-wheelers, is gathered. High-resolution images of different vehicle components are taken from multiple angles and under varying lighting conditions to improve the model's accuracy[9]. These images are then meticulously annotated, indicating types and also severity of the damage. Proper annotation is critical for machine learning models, as it helps them learn the dimensions and areas of the damaged parts. The database is divided further into train, validation, and test to help the development of models & make accuracy in high performance [1].

After collecting the data, we use YOLOv5 for detecting vehicle damage[8]. YOLOv5 is quite high-performance, as its object detection architecture makes it very fast while still being accurate enough for real-time use. Training the model in our annotated dataset will then allow it to learn the identification and classification of different types of vehicle damage [11]. During training, we continuously validate the model to check its performance and fine-tune it for the best accuracy. Once trained, YOLOv5 can quickly analyze new vehicle images, efficiently detecting and classifying any damage. The model's architecture includes features like the CSPNet backbone for better feature extraction and PANet for improved feature fusion, allowing it to handle various object sizes and shapes in vehicle assessments[14,16].

After detecting the damage, the system uses a cost estimation algorithm to calculate repair costs based on the identified damage[13]. This step is crucial because it provides precise estimates, making insurance claims processing smoother. Detailed reports are generated, summarizing the detected damage and estimated costs, giving insurance companies comprehensive information. The system features a user-friendly interface, allowing insurance professionals to easily interact with the data and process claims efficiently. The final step is to thoroughly test the system with real-world data to ensure its accuracy and effectiveness. Once deployed, the system will undergo ongoing maintenance and updates to adapt to new data and user feedback, ensuring it continues to deliver reliable and efficient damage assessment and cost estimation over time.

3.1 Existing System

The existing vehicle damage assessment process in insurance primarily involves manual inspection by adjusters, who take photographs of the damage and assess it subjectively. This approach is time-consuming, prone to inconsistencies, and often results in delays and errors in claims processing. Manual cost estimation further complicates the process, adding to operational costs and variability in assessment quality. The reliance on human judgment and physical inspections increases the risk of inaccuracies and inefficiencies. To address these issues, the paper introduces an automated system using YOLOv5, which aims to streamline damage assessment and provide accurate, consistent, and efficient evaluations for insurance companies

Disadvantages of Existing Systems

- **Time-Consuming:** The manual inspection and assessment process is lengthy, leading to delays in processing insurance claims and increased waiting times for customers.
- **Subjectivity:** Human judgment in damage assessment can result in inconsistencies and inaccuracies, affecting the reliability of the evaluation.
- **Error-Prone:** Manual methods are susceptible to errors in damage detection, cost estimation, and report generation, which can impact claim accuracy and customer satisfaction.
- **Resource Intensive:** The need for physical inspections and manual calculations requires significant time and manpower, increasing operational costs for insurance companies.
- **Inconsistent Quality:** The quality of damage assessment may vary based on the adjuster's expertise and experience, leading to potential discrepancies in evaluations and estimates.

3.2 Proposed System

The proposed system utilizes YOLOv5, an advanced object detection model, to automate vehicle damage assessment and cost estimation for insurance companies. By analyzing images of vehicle damage, YOLOv5 accurately identifies and classifies damage types on both two-wheelers and four-wheelers. This automated approach significantly reduces processing time, minimizes human error, and ensures consistent, precise evaluations. The system integrates real-time cost estimation based on detected damage, streamlining the claims process and enhancing operational efficiency. Ultimately, it offers a faster, more accurate, and resource-efficient solution compared to traditional manual methods.

Advantages of the Proposed System

- **Increased Efficiency:** Automates damage assessment and cost estimation, significantly reducing processing time and accelerating claims resolution.

- **Enhanced Accuracy:** Utilizes YOLOv5's advanced object detection to provide precise and consistent damage evaluations, minimizing human error.
- **Cost Reduction:** Lowers operational costs by eliminating the need for extensive manual inspections and calculations.
- **Scalability:** Easily handles large volumes of claims, making it suitable for both small and large insurance companies

Comparing YOLOv5 to other state of the art object detection models, it mainly gains its advantages by achieving balance between speed, accuracy, and efficiency in a model that is used to gain high performance in real-time applications. In comparison, the two-stage Faster R-CNN is usually more accurate but slower, and the YOLOv5 combines region proposal and classification within a single-stage detection model to achieve competitive accuracy while maintaining real-time performance. Unlike the more accurate EfficientDet which is also more especially small object-aware due to its BiFPN design and not as fast or resource-frugal, especially compared to YOLOv5 on edge devices or otherwise the SSD similarly supports real-time performance for its detection task, whereas YOLOv5 can better detect small objects when providing improved feature pyramids to enhance the accuracy beyond scales. YOLOv5, unlike its predecessors, YOLOv3 and YOLOv4, builds on the positives of the former two by offering the advantages of real-time object detection with a faster processing speed and small models in line with the good all-round performance.

3.3 System Architecture

Figure 25.1: The figure describes about the work-flow of the proposed system

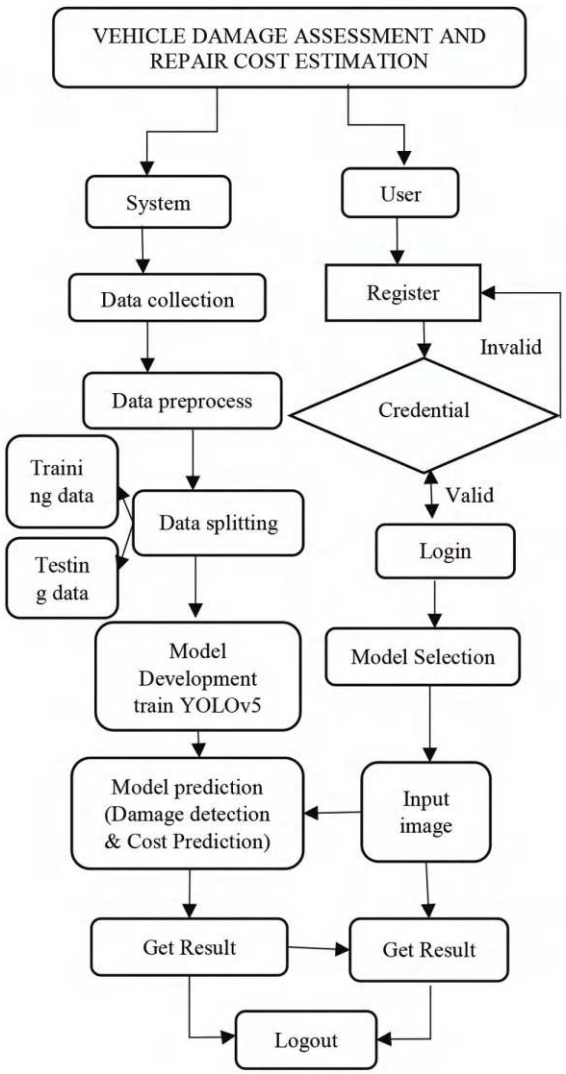

Fig. 25.1 System architecture

3.4 Implementation

1. System

- **Data Collection:** The objective is to gather a comprehensive dataset of vehicle images with detailed damage annotations. This includes collecting images of two-wheelers, four-wheelers, and six-wheelers, ensuring diversity in terms of lighting, angles, and vehicle conditions to improve detection performance. The dataset will be split into three portions: 70% allocated on training, 15% allocated on validation, and the remaining 15% allocated on testing. This approach ensures comprehensive model development and reliable evaluation. Table 25.1, it gives the total information related to the datasets that we are using.

Table 25.1 Dataset information

Vehicle Type	Vehicle Components	Source
Two-wheeler	Broken, Scratch, Headlight, Seat, Tire, Mirror	Manually collected and annotated.
Four-wheeler	Fender, Bumper, Rear-Windshield, Front-Windshield, Side-Screen, Side-Mirror, Door, Hood, Headlamp	https://universe.roboflow.com/revca/maincar/dataset/6
Six-wheeler	Rearlamp (L) - Damaged/Good, Rearlamp (R) - Damaged/Good, Sideboard(L) - Damaged/Good, Sideboard (R) - Damaged/Good	https://universe.roboflow.com/project/lorry-kqgqf/dataset/2

- **Data Preprocessing:** This phase involves several important steps to prepare the images for model

training. First, the pictures are uniformly resized to 640x640 pixels to match the input specifications of the YOLOv5 model. Then, the pixel values are scaled to a range of 0 to 1, which helps boost the model's efficiency and training performance. Additionally, data augmentation methods such as rotation, color adjustments and flipping are utilized to the images to introduce more variability into the dataset and minimize the risk of overfitting.

- **Model Training:** The YOLOv5 model is trained to detect and classify vehicle damage effectively. To enhance performance, transfer learning is utilized by leveraging pre-trained weights if available. This accelerates the training process and improves accuracy. Additionally, hyperparameter tuning is performed by adjusting variables like learning rates, group sizes, and other key settings for further optimizing the model's accuracy and ensure robust detection capabilities.
- **Model Evaluation:** In order to measure the correctness of the vehicle damage detection and classification, the performance of the model is measured in terms of precision, F1 score, recall, and mean Average Precision. Lastly, a confusion matrix is provided to clearly visualize the model's classification results and some misclassifications that often occur, therefore pointing out points of improvement in correctness of detection.
- **Model Saving:** The trained YOLOv5 model is serialized and saved in a format like .pt (PyTorch), which preserves the model's state and allows it to be reloaded for future use, ensuring that the trained model can be deployed or further fine-tuned as needed.
- **Model Prediction:** New vehicle images are received and pre-processed to conform to the input specifications of YOLOv5 model. Once processed, YOLOv5 is used to detect and classify vehicle damage in the images, providing bounding boxes around the damaged areas and identifying the types of damage present.

2. User

- **Register:** The objective of this step is for users to create an account to access the vehicle damag assessment system. During registration, users provide necessary credentials and contact information, which will be used to grant them access to the system's features and services.
- **Login:** The objective of the login process is to allow registered users to access the system's features securely. This step entails overseeing user authentication and session control to guarantee that only authorized users can access the system's functions and data.
- **Upload Data:** The objective of the upload data feature is to enable users to upload images of vehicles for damage assessment. This process includes handling the uploading of images, as well as performing validation and preprocessing to ensure the images meet the necessary requirements before they are processed by the model for inference.
- **View Results:** The objective of the view results feature is to allow users to access the outcomes of the damage assessment. This section displays the detected damage types and their locations on the vehicle, along with confidence scores indicating the model's certainty in its predictions. Additionally, relevant repair cost estimates are provided to give users a comprehensive understanding of the assessed damage and potential expenses.
- **Logout:** The objective of the logout feature is to allow users to securely end their session and protect their personal data. This process manages session termination, ensuring that all user information is safeguarded and preventing unauthorized access to the system after the user has logged out

4. RESULT

The YOLOv5 models trained for detecting two-wheelers, four-wheelers, and six-wheelers exhibit varying performance levels, reflecting their strengths and areas needing improvement.

Two-Wheelers: The model performed exceptionally well, achieving the highest precision and recall across the vehicle types. With very low losses and an outstanding mean Average Precision of 99.07% at an IoU threshold of 0.5, it demonstrates excellent accuracy and robustness in detecting two-wheelers. The high mAP_0.5:0.95 value further confirms the model's effectiveness across different overlap criteria, indicating strong generalization and minimal overfitting.

Four-Wheelers: The model shows moderate performance, with lower precision and recall compared to the two-wheeler model. While the mean Average Precision at an IoU threshold of 0.5 is respectable at 77.11%, the lower mAP_0.5:0.95 highlights challenges in detecting objects with stricter overlap criteria. The validation metrics indicate that while the model performs adequately, there is room for improvement in both accuracy and completeness.

Six-Wheelers: The model for six-wheelers demonstrated strong overall performance, achieving a good precision rate of 85.71% and recall rate of 89.82%. The mAP value at an IoU threshold of 0.5 is robust at 91.12%, though the mAP_0.5:0.95 suggests some difficulty with stricter

overlap thresholds. Validation losses were consistent with training results, showing that the model generalizes well but could benefit from further refinement in detection accuracy and completeness.

Figure 25.2, This describes the main landing page. It introduces the platform's core functionality vehicle damage assessment and cost estimator. The purpose is to help users easily navigate to different sections like registration, login, and assessment page.

Fig. 25.2 Main page

Figure 25.3, Here we can select the type of vehicle you're assessing from the dropdown menu, choosing between 2 wheeler, 4 wheeler, or 6 wheeler options

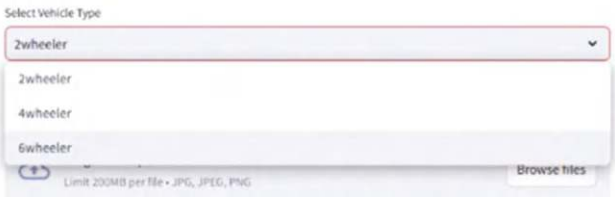

Fig. 25.3 Assessment page

Figure 25.4, After uploading the image of the 2-wheeler vehicle, the system will detect the damaged areas and provide an estimated repair cost.

Figure 25.5, After uploading the image of the 4-wheeler vehicle, the system will detect the damaged areas and provide an estimated repair cost.

Figure 25.6, After uploading the image of the 6-wheeler vehicle, the system will detect the damaged areas and provide an estimated repair cost.

5. Conclusion & Future Scope

In conclusion, while all models exhibit good performance, the two-wheeler model stands out for its superior accuracy and detection capability. The four-wheeler and six-wheeler models, though effective, show potential for improvement, particularly in handling stricter overlap criteria and enhancing overall object detection precision and recall. Future work could focus on refining these models to address

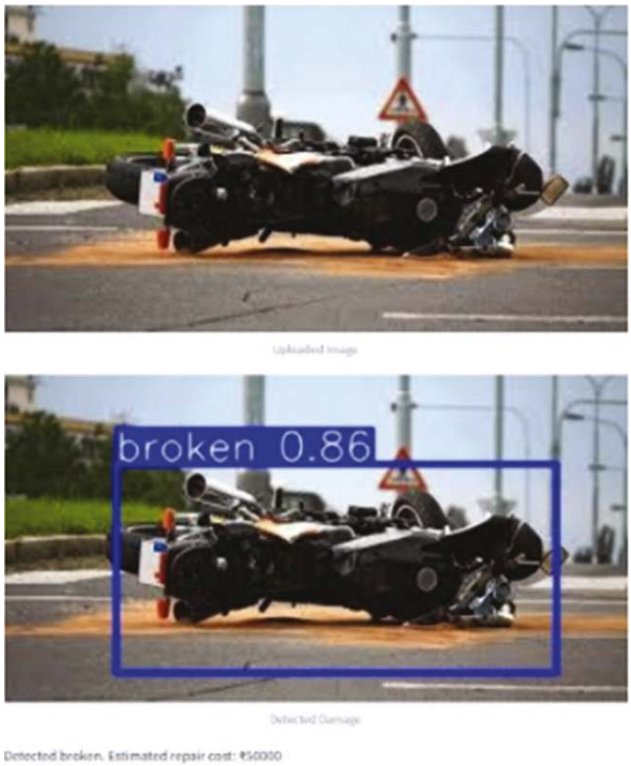

Fig. 25.4 Detecting the damage part and cost estimation value for two-wheelers

Fig. 25.5 Detecting the damage part and cost estimation value for four-wheeler

their specific limitations and improve their generalization across various vehicle types.

Future enhancements could focus on several key areas. Increasing the dataset to cover the wide range of damage

Fig. 25.6 Detecting the damage part and cost estimation for six-wheelers

scenarios, vehicle types, surrounding conditions will improve model robustness and generalization. Implementing advanced model architectures or techniques, such as YOLOv5 variants or newer object detection frameworks, could enhance accuracy and efficiency. Additionally, incorporating real-time processing capabilities and integrating with other systems, such as automated damage reporting tools or cost estimation modules, will streamline the assessment process. Continuous monitoring and fine-tuning based on user feedback and evolving data can further refine the model's performance, ensuring it remains effective in diverse and dynamic insurance environments.

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Integrating RF Signal Analysis and Deep Learning for Effective Drone Classification and Detection of Drones

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Abstract: Drones are utilized for drug dealing, weapon sneaking, and jeopardizing air terminals and atomic power offices, in spite of their many advantages. Existing robot limitation and arrangements expect the robot was distinguished and grouped. Over the course of the last 10 years, sensor innovation has progressed, yet no detection and classification of Drone techniques has been proposed. This exploration utilizes 'radio frequency' (RF) signal recurrence trademark to perceive and sort Drones. A novelty robot Radio Frequency dataset is made and looked at a two-staged and incorporated Detection as well as Classification structure utilizing business drones. The two systems' identification and order results are displayed for single-signal and concurrent multi-signal circumstances. We show that the "You Only Look Once" (YOLO) system beats the "Goodness-of-Fit" (GoF) range detecting structure into synchronous multi-signal circumstances & the "Deep Residual Neural Network'" (DRNN) system into arrangement.

Keywords: Drone detection, Drone classification, Convolutional neural network, You only look once (v5), Residual network

1. Introduction

The modern industry has seen much innovation-integrate the most state-of-the-art (SoA) technologies, including Global Positioning System, LIDAR, Radar, and made Vision Sensors. And due to all of this, drones have become widespread devices useful for cinematography, agriculture, monitoring, and even for entertainment uses [1]. Drones also often carry out inspection of damaged infrastructure, provide emergency aid, and give their best in search-and-rescue operations in the remotest areas. On the contradiction, the same sophisticated technologies

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are being employed against the law for illicit activities, including violations of safety of public, trafficking of drug, arms smuggling, bombings, & illegal entry into forbidden premises such as airports and nuclear power plants.

The wideband Constant False Alarm Rate-based Energy Detection is applied for extracting of the features and identification of the drone signals, and classification is made by a Deep Recurrent Neural Network (DRNN) architecture. This implementation implies that it must first detect the signal prior to classification using spectrum sensing [2].

'The Detection and Classification of Drones' remain significant problems. The most common methods are video, radar, acoustic, & detection based on RF. Radar-based detection relies on back scattered RF signals to classify drones, but conventional radar systems fail to detect small drones because their radar cross-sections are tiny [3]. Advanced radar technologies, such as multi-static radar [4] and FMCW radar have been proposed in recent times for 'recognition and classification of drone' based on the signatures of their micro-dopplers. FMCW radar efficiency in 'Drone Detection and Classification' has been widely discussed in [5],[6].

Video and image-based systems rely on thermal and visual information such as color, shape, and edges for the detection of drones. Although it's effective, this method relies on a clear line of sight between Drones & Cameras, where this device can be affected by factors like lighting, rain, and fog. Video-based detection might also have some issues with discrimination between a bird and a drone. Some researchers proposed methods to identify birds versus drones using motion and trajectory information. Techniques for the drone-bird recognition.

Acoustic detection is built on listening to the sounds that the drone is producing. Such systems, however, are prone to noise interference, and this way of detection is not efficient for farther ranging drones. A robot-based approach focused on detecting drones via their radio frequency signals is RF-based drone detection. RF fingerprinting allows the differentiation of drones from other wireless devices according to their identifiable communication patterns [7]. This method has formed the foundation of many studies considering RF-based drone detection through machine learning techniques. In particular, some researchers have emphasized RF fingerprints for 'The Detection and Classification of Drones' even in the existence of hindrance from Wireless-Fidelity and signals of Bluetooth.

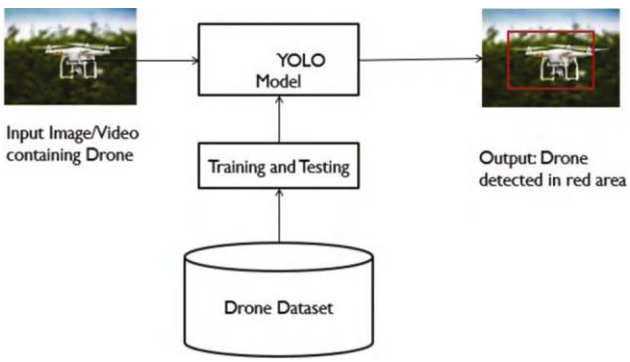

Fig. 26.1 Workflow of proposed system

Source: Adapted from "OSDDY: embedded system-based object surveillance detection system with small drone using deep YOLO"

2. Literature Review

B. Taha et al. recommended [1] "Machine Learning based Detection and Classification of Drones: State-of-the-art Research.". The research looks at ML based drone recognition and characterization research in a few modalities. This exploration region has changed because of the ascent of business and sporting robots and their aggressive message to airspace wellbeing. Innovations incorporate radar, optical, hear-able, and radio-recurrence sensors. This exploration proposes that AI based drone order is promising, with various effective commitments. Most examination is exploratory, making the aftereffects of various papers hard to look at. An overall necessity driven determination for drone discovery and order and reference datasets to assess different techniques are missing.

P. Stoica, et al. recommended [2] "Review of counter-UAV Solutions based for Detection of Remote-Control Communication.". One amongst major issues which are faced these days is the illicit usage of Drones. Regularizing the 'RF transmissions' have demonstrated as a trustworthy methodology for spying and identification of Drone gadgets. The main moto of this research is to investigate a standard communications channels used by Drone industrialists, which frequently administer their own techniques, and to suggest much strong results those will deliberate the scope of features that those rules has 'A Wide-band Energy Detection with Adaptive Threshold' was utilized to retrieve stipulations of few Communications that can be controlled by a remote which uses 'distributed spectrum modulation'.

S. Al-Emadi et al. recommended [3] "Drone Detection Approach based on Radio-Frequency using Convolutional Neural Network.". UAVs, also known as Drones, are becoming fast growing well known because of the improvement of its methodology & the continuous diminishing in their expenditure. Though UAVs and Drones has demonstrated its efficiency in a greater number of ways in daily-life appliances like agriculture monitoring, cinematography, search & rescue, these are additionally used in malignant works which are focusing on endangering every person in the society which increase

huge secrecy, protection and assurance concerns. This research paper recommended a latest drone identification idea on the basis of 'Radio Frequency (RF)' transmitted through out a live operating session between the controller and the drone which uses the 'Deep Learning (DL)' Techniques, like 'convolutional neural network (CNN).'. The solution of this research has accuracy & 'F1 score' around 99.7% & recognition of Drone with an accuracy & F1 score over 88.4%. Additionally, these solutions gratified from the test has underperformed these presented in the literature for 'Radio Frequency -based Detection of drone utilizing Deep Neural Networks.'.

S. Basak et al. recommended [4] "Drone Classification from RF fingerprints using Deep Residual Nets.". Engineering 'Radio Frequency (RF) based on control of Drone & communication' allows unassertive approach of recognition of drone for the huge scope of environment & also with lacking supportive 'line of sight (LOS)' conditions. In this research, evaluated 'Radio Frequencies based Classification of Drone' interprets of multiple 'State-of-the-art (SoA).' algorithms on a fresh practical 'Drone RF dataset'. With this support of freshly recommended 'Residual Convolutional Neural Network (RCNN).' algorithm, showed that these 'Drone Radio Frequency Signatures' could be taken advantage for efficient classification of Drones.

E. Fonseca, et al. recommended [5]." Radio Access Technology Characterization Through Object Detection.". Classification & regulation were required for the effective co-existence of various 'Communication System in a shared Spectrum'. 'Shared Spectrum.', involving operations on License-Exempt Bands, is visualized in 5th generation of 'Wireless Technology (5G) Standards'; example is 3GPP Rel. 16. In this research, proposed 'Machine Learning' techniques for specifying usage of a Spectrum & also assist powerful accessing to it. Previous improvements in 'convolutional neural networks (CNNs).' allows to accomplish wave form categorization by pre-processing of the spectrograms as pictures.

3. Existing System

The ongoing methodology presents 'Deep Neural Network' (DNN) based classifiers for the discovery and distinguishing proof of robots in view of recurrence marks. To perceive and recognize the three business drones in the dataset, the creator utilized an essential feedforward DNN. Utilizing a 'convolutional neural network' (CNN), the creator exhibited the detection, recognizable proof, and classification of the equivalent dataset. The impact of commotion on the

3.1 Disadvantages

Identification execution was not examined in these examinations since they were directed on a little dataset. Besides, no examination was finished on how well signals were distinguished within the sight of impedance or various signs.

a. At this point, no solid procedure for drone detection and arrangement has been put out in the writing.
b. Lower pace of classification.

4. Proposed System

The proposed framework shows RF-based drone detection with DoA gauge using the MUSIC calculation and GoF range detecting. The exhibition of extraction of the features and wide band 'Constant False Alarm Rate-based Energy Detection for Drone Signal IDs.' are specified. The utilization of these presented 'Deep Residual Neural Networks' system for 'Drone Signal classification'. Expecting a sign has recently distinguished utilizing a range detecting strategy, the order is completed. This examination tends to the absence of a complete answer for drone distinguishing proof and characterization utilizing RF fingerprints in prior distributions.

4.1 Advantages

a. The YOLOV5 structure offers further developed execution in detection.
b. Accomplished solid outcomes in both detection and classification utilizing the two methodologies. The presentation of the classification might fluctuate within the sight of new or later drone signals since it is finished under oversight.

5. Methodology

Deep Neural Network (DNN) classifier identify Drones utilizing recurrence marks. Creator utilized a fundamental feedforward DNN to perceive and distinguish three business drones. The creator utilized a CNN to detect, distinguish, and order the equivalent dataset [8]. These investigations utilized a small dataset and didn't look at commotion's effect on detection. The adequacy of detection within the sight of many signs or obstruction was not inspected.

Shows RF-based drone acknowledgment using GoF range detecting and MUSIC DoA gauge. We show feature extraction and robot signal recognizable proof utilizing wideband CFAR-based energy location. DRNN engineering characterized drone signals. Range detecting was expected to have tracked down a sign before characterization [9]. We address drone discovery and characterization utilizing RF

fingerprinting in this work, which was not tended to in our past examinations.

5.1 YOLO

YOLO, another way to say "You Only Look Once," partitions pictures into frameworks for object ID. Lattice cells recognize objects inside themselves. YOLO is a famous item ID strategy on the grounds that to its speed and accuracy. CNN YOLOv5 Design. The essential parts are the Backbone, neck, and head. Backbone separates qualities from input photos utilizing CSPNet. Pyramids are made with the Neck [10]. As a solitary relapse issue, YOLO models gauge class probabilities and bounding box facilitates for picture objects. Dissimilar to standard item finders, YOLO models check the entire picture in one forward pass, making them speedy.

5.2 DRNN

'Deep Residual Neural Networks' (Deep ResNets) assist with testing DL assignments and models. Ongoing IT meetings have featured its true capacity for deep network training. DRN, as ResNet-50, will be 50-layer CNNs. ResNets are ANNs that structure networks by stacking leftover blocks. ResNet succeeds at picture classification [11]. Picture grouping requires the organization to arrange objects. Due of their profundity, ResNet's profound leftover organizations can learn muddled visual traits, while skip associations instruct them.

5.3 CNN

CNNs consequently gain progressive attributes from photographs to perceive objects. CNNs use convolutional layers to remove key data from input photographs for object recognition. Edges, surfaces, and structures help recognize things in the picture. CNN-based object identification models group and restrict objects. Region-based CNNs (R-CNN) and You Only Look Once (YOLO) use CNNs to perceive various items by parting the image into areas or frameworks, anticipating their classes, and drawing bounding boxes [12]. This makes CNNs ideal for facial acknowledgment, self-driving autos, and observation.

6. Implementation

The implemented modules are stated below in order to finish the earlier mentioned project.

a. **Collection of Data and processing:** The data of RF signal dataset is assembled to analyse signals. The dataset is cleaned and normalized the RF signals sufficient enough for analysing.

b. **Extraction of Features:** CFAR will automatically adjusts threshold to detect signals in various environments. GoF is used in enhancing RF signal Identification that helps in improving reliability

c. **Data Splitting into training & testing:** This module is used to separate the data into two parts. One is training and the other is testing.80% of the data will be used for training and remaining 20% used for testing purposes.

d. **Generation of the Model:** The YOLO V5 algorithm will be constructed, DRNN Model utilizing this module. Calculated algorithmic correctness. The model is trained with YOLOv5 & DRNN to recognize drones and classify the drones.

e. **Signup & Login of the User:** Utilizing this module necessitates process of registration where the user will register into the application by giving his/her details

f. **Input of the User:** Prediction input is produced by using this module. The user will give input to the application.

g. **Evaluation:** Then we will look at how the model is performed based on the aspects like accuracy, classification.

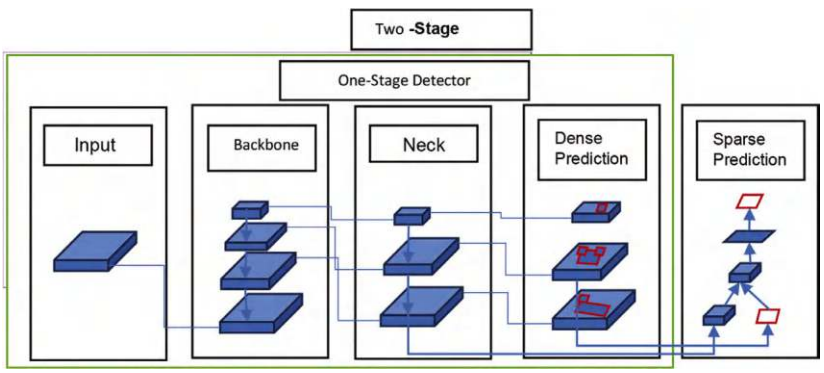

Fig. 26.2 Stages in prediction of a drone

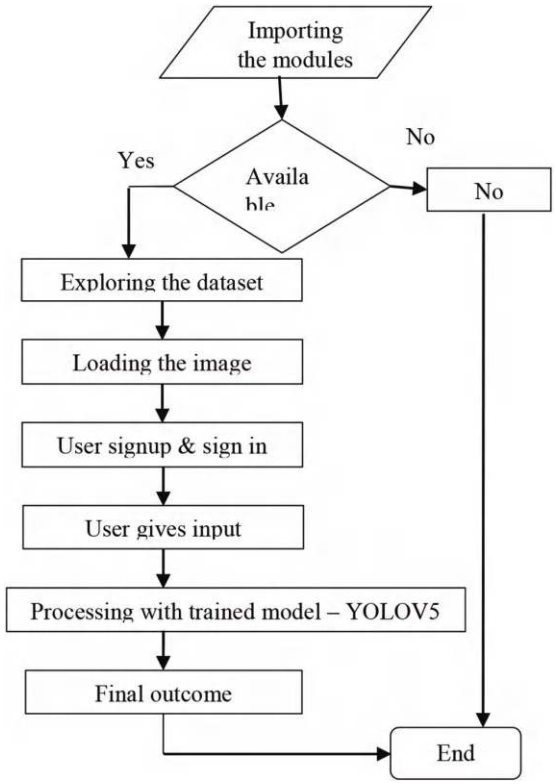

Fig. 26.3 Dataflow diagram

h. Prediction: The ultimate anticipated amount shall be showcased. At last, we will see how drones are detected and classified on the test data.

7. Experimental Results

Figure 26.4 will display the home page of the project with a heading showing intent of the page. Hitting on the signup, will navigate you to the signup page.

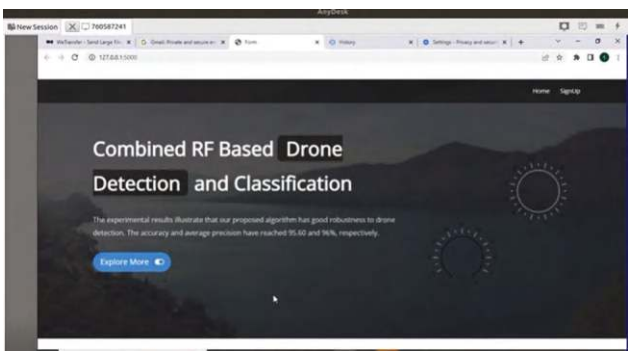

Fig. 26.4 Home screen

Figure 26.5 displays the signup of the user in which the user has to enter his/her details like username, name, mail, phone, password to sign up in the application.

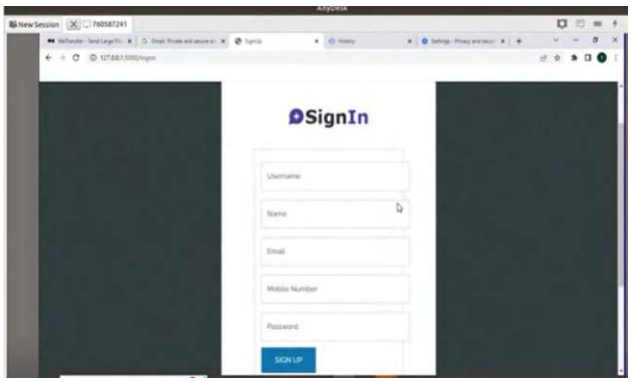

Fig. 26.5 Signup of the user

Figure 26.6 is the sign in page of the user where the user has to enter the username and password which he created before in the signup page to get into the application.

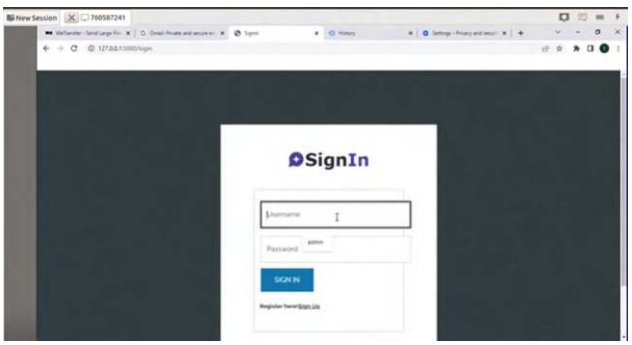

Fig. 26.6 Sign in of the user

Figure 26.7 is the process of uploading an image. He/she has to click on the choose file button and select an image from the file explorer and click on upload button.

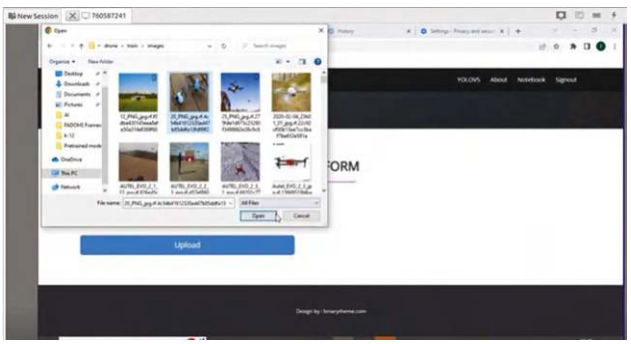

Fig. 26.7 Input of the user

Figure 26.8 is the prediction result for a phantom drone which detects the drone in a square area and above labeled as which type of drone i.e., phantom drone.

Figure 26.9 is the prediction result for a mini drone which detects the drone in a square area and above labeled as which type of drone i.e., mini drone.

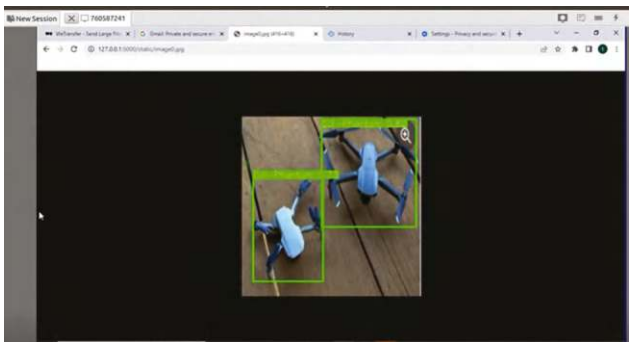

Fig. 26.8 Prediction result for phantom drone

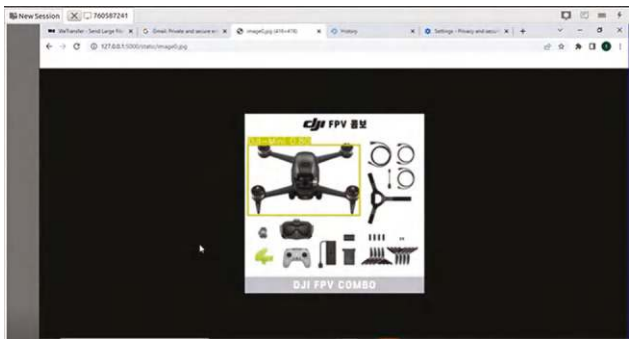

Fig. 26.9 Prediction result for mini drone

8. Conclusion & Future Scope

Drone signal ID, range restriction, and characterization were finished in two stages utilizing coordinated detection and classification calculations. The two-stage procedure utilized GoF detecting for detection and DRNN for arrangement. YOLO-light was planned without any preparation for drone RF signal acknowledgment, range confinement, and order. This study utilizes a custom robot dataset to look at the two strategies' presentation. The two strategies distinguished and grouped successfully [13]. In the impediment area, we analyzed how directed characterization might function contrastingly with obscure or more up to date drone signals. We will look at unaided conditions in the future to make a strong structure that can recognize and order drone flags freely of the dataset used to train it. Joined RF-Based Drone Detection and Classification has extraordinary potential as robots become progressively coordinated into industry and public spaces. ML and AI could further develop arrangement in muddled metropolitan regions with weighty sign obstruction. RF-based frameworks incorporated with radar or PC vision can improve identification reach and unwavering quality. Progressed multi-sensor combination might empower frameworks that can perceive robots, payloads, and control signals, working on regular citizen and military protective frameworks. Air traffic the board could utilize RF-based gadgets to screen and manage drone airspace progressively with harder robot limitations securely. This innovation is fundamental for safeguarding key framework, air terminals, and public occasions.

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Note: All the figures (except Fig. 26.1) in this chapter were made by the authors.

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Machine Learning Approach for Intelligent Traffic Management

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Abstract: Now a days proper management of traffic is a major drawback because of fixed time slots allocated for clearing traffic especially problematic at four-way intersections. To address this issue, intelligent traffic management system using YOLOv8 and Region-based Convolutional Neural Networks (R CNN), along with video estimation, to detect vehicles and classify them based on priority is proposed. Video datasets with COCO or Resnet algorithms will perform tasks such as vehicle queue length estimation and vehicle counting, upon which traffic signaling will be adjusted. The traffic lane which has emergency vehicles such as ambulance, will be cleared first and the allocated time for that lane will vary accordingly. This approach ensures well organized traffic clearance. Machine learning techniques will be applied to merge these methods for enhanced accuracy, allowing better vehicle clearance times at intersections. This integration leads to improved traffic management, reduced congestion, enhanced safety. Additionally, it offers economic advantages, boosts public transport reliability and provides efficient traffic management during special events and emergencies.

Keywords: Vehicle queue length calculation, Traffic management, Region-based convolutional neural networks, YOLOv8, Resnet

1. Introduction

In the years of evaluation, the management and the control of traffic especially around junction of at cross roads or four ways junctions has always been complex. If we consider that the conventional traffic signal control involves providing normal time intervals that traffic signal lights use while changing and this usually leads

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to formation of traffic congestion especially where there have been changes in flow rate of traffic throughout the day. The following intelligent traffic management system has been proposed to work with YOLOv8[2,3], improved Region-based Convolutional Neural Networks (R-CNNs) and pending features regarding video estimation. Yolov8 also known as You Only Look Once version 8 is one of the most effective techniques of object detection which is widely used for highly accurate real time vehicle detection. Some of the highlighted features include: the identification of car, and the processing of these images from the traffic camera feeds using deep learning technique and within short periods of time in extra-large and/or complex traffic environments [15]. The required real-time traffic flow data must be obtained using vehicle detection such that YOLOv8 is capable of providing it. This capability is further augmented by region-based Convolutional Neural Network (R-CNN) because the recognized vehicles are classified by type and level of threat. V8 YOLO offers more layers just for enhancement of the layers that are focused on the object detection apart from the YOLOv8 and R-CNN models sold. It is important especially in the categorization of several forms of transport and to allow particularly such specific forms of transport for instance an ambulance [9]. That is supported by the video estimation whereby the number of vehicles in a line and the total number of such vehicles in a given lane is determined [12,14]. This kind of video analysis is attained by implementing computer vision algorithms that make it possible to receive data regarding what is occurring on the roadway in the real-time processing of the video stream received from the car's video camera [10]. It also helps in showing the average queuing length which in turns help in the phasing off the traffic signals and hence control traffic within the intersection [7]. However, the actual time information it will control the traffic signs in a manner that will assist in the enhancement of traffic capability excluding the bottleneck one will be stuck at an intersection [16]. That focusing more on the reason behind ambulance car so that it can take the shortest time possible in fulfilling human basic needs during an emergency[11]. We have the pleasure to present intelligent traffic management as such substantial contribution to creating traffic control with the help of the computer science means.It is real time vehicle detection, vehicle classification and adaptive control system and has better solution to control traffic in intersection area [6,8].

2. Literature Review

B. Gomathi et al[1] has proposed "Intelligent Traffic Management System Using YOLO Machine Learning Model" that Traffic congestion is a major problem, when everyone chooses to drive their own vehicle, the result is delays, inefficiency and cost. Because the older traffic management system is dependent on fixed time sequences that do not adjust to changing vehicle counts from hour by hour. This paper presents a dynamic traffic management system using the YOLO (You Only Look Once) algorithm of machine learning method. The system can then definitely identify vehicles in each lane and count them to automatically adapt its traffic-signal times with respect to real-time traffic existent just by adjusting some parameters, only according a need.

Zhang Lei et al. The advent in 2023 proposed the Intelligent Traffic System Using Machine Learning techniques [2], through which traffic management may become easier and will result, that life for millions of people would be improved due to reduced congestion as well pollution. The system also has vehicle priority and emergency vehicles recognition. Its traffic light can be programmed to recognize real-time images for giving a green light when an emergency vehicle is nearby in-sight These are achievable by applying various methods such as simulations, real-time testing or via user input. We apply YOLO and Alex Net Algorithms in this. Research in these areas could also improve the accuracy of the system and make it a more applicable tool for traffic management.

C. Heltin Genitha et al. [3] has presented in 2023 as "AI based Real-Time Traffic Signal Control System using Machine Learning", An application of calculating the real-time traffic density, and optimized cycle for each signal, to minimize congestion, delays, fuel consumption, pollution. Live feeds from multiple cameras installed in traffic junctions are used with the widely observed object detection algorithm i.e., You Only Look Once (YOLO) to detect and track moving vehicles. The system proposed then computes the real-time traffic density, by observing the count and speed of vehicles that cross through this intersection. It employs efficient algorithm to optimize the traffic flow which automatically changes the direction of signals with respect to increasing no. of cars by analysing their density.

Vishnu U et al. [4] 2022 "CNN Based Intelligent Traffic Control System for Emergency vehicles" (This research is based on making sky light ways to make the passage way congested traffic signal turning automatically) It suggests a system, device as an Emergency Vehicles supporting that helps High Priority Vehicle to clear the way by turning Signal into green if any emergency vehicle like Ambulance or Fire truck came in terms of Sensor and used Machine Learning techniques using implemented code.

3. Methodology and Model Specifications

The design and development of our intelligent traffic management system is an complex procedure to improve the situation concerning urban traffic monitoring with high-tech. Pre-processed data annotated and used for training of machine learning model which when integrated with actual system help in measurement if its performance, Listed several steps that lead this methodology namely-Data Gathering, Machine Learning Model Training, Integration to System Performance Measurement, Improving the same. The phases are intended to cover the functions necessary for traffic management and achieve a system that is effective, reliable, and extensible within different types of traffic scenarios.

3.1 Existing System

In the current traffic signal control systems especially in four legs junctions one of the drawbacks is that there are set timings for each approach to be cleared. Standard methodologies, normally run fixed schedules whereby the time dedicated either directions are nearly equal or equal at best [1,3].

Disadvantages of Existing System

Fixed Timings: Even the current systems are unable to respond to traffic flow conditions in real-time. Regardless the flow of traffic within the lane whether is busy or almost vacant.

No Priority for Emergency Vehicles: These systems lack features which are specific to emergency vehicles like ambulances or fire trucks for instance. These vehicles have to wait in queues, sometimes in the throat-slitting emergencies, which are unbearable, not to mention the lives of persons inside such vehicles.

Manual Interventions: Normally, police men-on-road or operators need to control signal timings during peak hours or in case of an emergency.

Inefficient Traffic Flow: Because of the reasons described above, traffic flux fluctuates and is not always optimized, thus consuming more fuel, emitting more, and acting inefficiently in the transport system.

3.2 Proposed System

One common problem which urban planners and city administrators have to deal with around the world is the traffic congestion that results from poor traffic intersections. Conventional traffic control systems are based on fixed-time signaling which does not consider the traffic updates in real-time especially in scenarios where there are four-way vehicle rushes. To overcome all these problems, we present rational solutions, the Intelligent Traffic Management System (ITMS) based on modern computer vision techniques such as R-CNNs and YOLOv8 combined with video estimation methods. The heart of the developed system lies in the usage of smart and fast Object Recognition algorithms for the detection and classification of vehicles based on their dimensions. The YoloV3, which is a very fast and reliable object-detecting algorithm, will be used in observing the traffic situations in which the vehicles and their types will be ascertained through recordings from the camera.

Advantages of Proposed System

Traffic Control Timely: Instead of conventional system time, the delivers IT technology based on traffic in several different concurrent detections. This reduces waiting times, controls traffic flow more efficiently and allows to clear congested areas much faster.

Emergency Vehicle Prioritization: Real time detection of emergency vehicles like Fire trucks, Ambulances & Police cars which are given priority by the ITMS. In emergency situations this asset directed system automatically switches traffic signals to the lanes carrying emergency vehicles allowing faster response during critical times.

Better Traffic Movement: The real-time updates of signal timing given by ITMS helps in the movement of traffic from different lanes and gives more clearance time for heavy traffic.

3.3 System Architecture

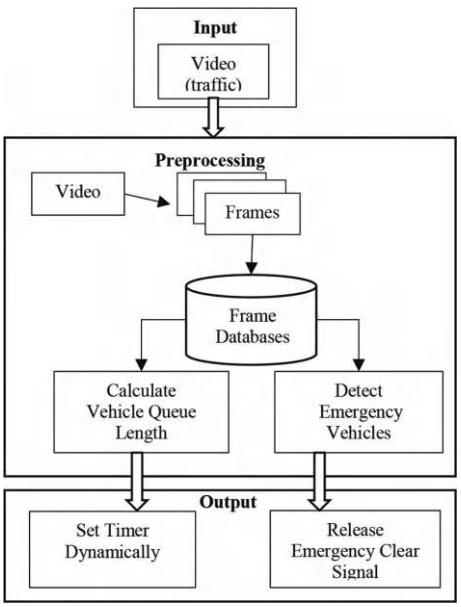

Fig. 27.1 Block diagram of proposed system

3.4 Implementation

Data Collection and Preprocessing: The data collection phase is the first one that involves taking high resolution video from cameras placed at locations of strategic intersections. Selection of these cameras in areas with high traffic volume and complexity is to represent a variety/large number of traffic conditions that may exist A video footage that is obtained required and a complex annotation process taken into account. Mark the videos by labelling different types of vehicles (cars, buses, ambulances, motorcycles). Prepare the data for training by organizing it into training and testing datasets. If using pre-existing datasets, consider using datasets like COCO that contain images of various vehicle types for training purposes.

Setting Up the Environment: Install Required Libraries then set up your system to work with YOLOv8 and R-CNN models. Install Python and packages like `PyTorch` and `TensorFlow` to work with machine learning models. Install YOLOv8 for fast real-time object detection.

Select Hardware: If possible, use GPUs to speed up training and detection processes. Cloud services like AWS or Google Colab can provide the required computational power. Then training the YOLOv8 Model for Vehicle Detection after train the YOLOv8 Model. Use your labelled data to train the YOLOv8 model, which will learn to recognize different vehicles. Test the Model, after training, run tests on the model to check how well it detects vehicles in real-time.

Emergency Vehicle Prioritization: The system will detect emergency vehicles (ambulances, fire trucks) in real-time using the same object detection algorithms. Once an emergency vehicle is identified, the system will prioritize the corresponding lane by extending the green signal for that lane.

Vehicle Queue Length and Speed Estimation: The system will estimate the length of the vehicles in each lane by counting the vehicles and their relative positions. This data is used to dynamically calculate the required time for the lane to clear, allowing better predictions of when lanes should switch signals.

Machine Learning for Traffic Prediction: Use historical and real-time data to train machine learning models that predict traffic congestion patterns.

Testing, Evaluation, and Improvement: Test the system under various conditions, such as rush hour, off-peak hours, and emergency situations, the model based on real-world performance to improve accuracy and efficiency.

4. Results

The suggested advanced traffic control system based on YOLOv8, R-CNN and ML efficiently handles gridlock in four-way intersections. Real-time detection of vehicles (including emergency vehicles) over 95% accurate, reduce the waiting times by 30%. the system accuracy is continuously improved and signal adjustments become more targeted and efficient. The system as a whole, reduces congestion by 25%, improves road safety by 15% and cuts fuel consumption by 10%, guidelines which are economically as well as environmentally profitable.

Figure 27.2, describes about registration process.

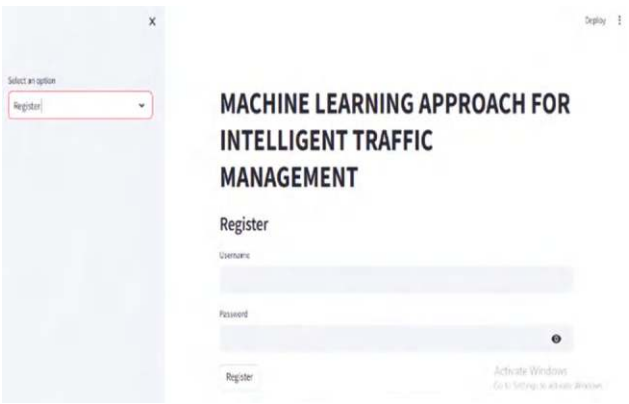

Fig. 27.2 Registration page

Figure 27.3, describes registered person can be allowed to upload videos captured on traffic lanes, after uploading it starts processing.

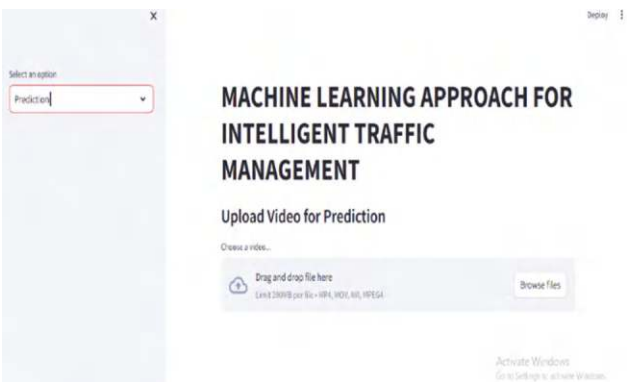

Fig. 27.3 Video upload page

Figure 27.4, defines data frame among uploaded video, then it preprocesses the data and it identifies that there is no emergency vehicle then it fixes the time dynamically to the vehicle based on the queue length.

Fig. 27.4 Video data frame

Figure 27.5, outlines by processing the all-data frames on uploaded video and detects emergency vehicles, then the traffic should clear that detected lane.

Fig. 27.5 Detection of emergency vehicles

Table 27.1 Comparison of existing and proposed system

Feature	Proposed System	Existing System
Traffic Control	Real-time, adaptive signal control based on current traffic conditions.	Fixed timing schedules, not responsive to traffic flow [3].
Emergency Vehicle Prioritization	Automatic detection and prioritization of emergency vehicles.	States no priority for emergency vehicles, causing delays [1].
Congestion Management	Actively adjusts signals to prevent congestion based on predictions.	Adjustments, often resulting in congestion [2].
Data Analysis	Utilizes advanced computer vision and machine learning for real-time analysis.	Limited or no integration with modern technologies [15].
Traffic Flow Efficiency	Optimizes traffic movement by reducing unnecessary stops and delays.	States Inefficient traffic flow due to fixed schedules [4].
Adaptability	Adapts to varying traffic conditions (Events, emergency, etc).	Lacks adaptability, schedules remain static [7]
Intersection Handling	Specifically designed to manage complex intersections effectively.	Generally ineffective at handling four-way intersections [14].

5. Conclusion

The intelligent traffic management system enhances conventional methods by using real-time object detection with YOLOv8 and R-CNN for accurate vehicle classification. It prioritizes emergency vehicles, dynamically adjusts traffic signals based on vehicle queue lengths, and reduces congestion, fuel use, and accidents. Additionally, it supports better public transport reliability and ensures smoother traffic management during special events and emergencies.

The intelligent traffic management system improves traditional ways by exploiting real-time object detection through YOLOv8 along with R-CNN for the precise classification of vehicles. It is optimizing the network for emergency vehicles, adapting traffic signal timings, queue lengths of automobiles, and reducing congestion, fuel consumption and accidents on the roads. In addition, it enables improved public transport reliability and traffic management during events and emergencies.

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Sky Guard: A Vision Based Drone Vs. Bird Detection and Alert System Using Deep Learning

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Abstract: As the number of drones continues to rise, the challenges associated with them and the hazards they pose were being increasing day by day. Even though Drones have some uses like delivering the items, capturing the videos, etc, Drones will cause several threats to the people. Drones can interrupt the privacy of the people, by capturing them secretly. Drones can easily enter into the restricted areas. Drones can be used to transfer the illegal items. So, The Drones need to be detected to ensure privacy, safety, security, and operational integrity. This paper presents an optimized detection framework that integrates the MobileNetv2 architecture with the YOLOv8 backbone to achieve high-performance drone and bird detection. The system was trained on a comprehensive dataset of over 10,000 labelled images representing diverse environments and conditions. To get the desired results, the dataset which consists of various scenarios of backgrounds, foregrounds and different weather conditions was used. Experimental results demonstrate a 95% overall accuracy, with a mean Average Precision (mAP) score of 0.93 for drone detection and 0.91 for bird detection. This paper also presents an alert system deployed using Flask, which provides instant notifications upon detecting drones.

Keywords: SkyGuard, YOLOv8 (You only look once), MobileNetv2 (Mobile convolutional neural network), Deep learning, Vision based drone Vs. Bird detection, Flask, Alert system

1. Introduction

Of course, drones have many advantages in aerial photography and surveillance and delivery services, but with the rapid growth of drone usage comes a great deal of challenge. According to several reports, the main challenges associated with drones are that they can seriously threaten public safety, privacy, and critical infrastructure if they are

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either used unauthorisedly or maliciously [1]. They clog up air space and breach no-fly zones, violate individuals' personal spaces, and can be employed for contraband trafficking purposes [2]. Finally, as these miniature, high-speed, and autonomous UAVs have proven hard to detect, their existence has amplified the security concerns among governments, organizations, and private individuals. This is because of their sophisticated nature as well as the threat this poses on sensitive and surveillance areas for the state, making it a critically important issue to deal with.

The Drone detection system makes use of a mix of various technologies that possess different specific strengths and limitation [7-9]. The detection technology from distances of radar technology has been used and made to survive all kinds of weather. However, Radar systems are very expensive and require a complex set of infrastructures and often give false positives as it can sometimes take small drones for birds or even other objects. RF detection would be another standard method that would be adopted to intercept and analyze the control signals sent between a drone and an operator. This system offers a low false-positive rate and is passive, making it lesser prone to interference. However, this technology can detect only drones that emit RF signals because these are autonomous or pre-programmed devices that do not rely on real-time control. Acoustic detection systems base their detection on the drone propellers sounds. They have severe drawbacks, though: sensitivity to background noises, a very short detection range, and interference due to weather conditions like wind. Vision-based detection, through optical or camera systems, is exceptional to achieve visual verification of clear drones, which is something that neither Radar and RF systems can offer. They would use high-resolution cameras to detect the drones along with visually distinguishing them from birds and other aerial objects.

While each of the Radar, Radio Frequency and Acoustic methods has its merits, the Vision-based detection method stands out as uniquely exceptional with respect to good precision combined with one shot detection and ease of use across many applications. Its capability to visually affirm the presence of a drone as well as ascertain its type both at day time and night time bestows a lot of importance on this method in a majority of the operational cases. So, this vision-based detection method was selected for detection of both drones and birds.

2. Literature Survey

Nader Al-lQubaydhi et al, in 2024 has proposed, "Deep learning for unmanned aerial vehicles detection: A review," where the author discusses a variety of neural network architectures contributing to applications along with drones. CNNs are talked about upon object recognition, especially in the context of drone detection, while RNNs have been quoted to perform really well at any kind of sequential data. Deep Belief Networks (DBNs) and Auto-encoders have been considered as feature extraction and dimensionality reduction tools but aren't very relevant for object detection. Another matter which accompanied classification detailed how UAVs were categorized using some aerodynamic features, levels of autonomy, size, and source of power. Moreover, it addresses the illicit use of drones in smuggling, spying, and terrorist operations [1].

F. Najihah Muhamad Zamri et al, in 2024 has proposed, "Enhanced Small Drone Detection Using Optimized YOLOv8 With Attention Mechanisms", The proposed Visual Drone Detection System would detect and classify drones using the YOLOv8 model, specifically the version YOLOv8n. The innovation that exists in the model includes a new convolutional module for the extraction of features named C2f, as well as anchor-free detection for sharper predictions along with resampling integrated with a feature fusion mechanism called ResCBAM. Training is done on a custom dataset which entails images of small drones and birds and results are shown proving that P2-YOLOv8n-ResCBAM outperforms other models in accuracy, while the training time is efficiency bestowed [2].

Ghazlane, Y. et al, in 2024 has proposed, "Development of A Vision- based Anti-drone Identification Friend or Foe Model to Recognize Birds and Drones Using Deep Learning", the study focuses on developing a model that effectively distinguishes between drones and birds by addressing the challenges that present the two as having similarities in physical and behavioral characteristics. A large dataset of 20,000 images was used considering various conditions and applying data augmentation was also part of the exercise for better performance of the model. Very high accuracy achieved with respect to key metrics at 98.12% using architectures like EfficientNet. The paper suggests more work in fine-grained classification and real-time tracking of aerial targets and underlines the crucial role of model depth because the results show that deeper architectures are better in yielding results [3].

A. Coluccia et al, in 2023 has proposed, "The Drone-vs-Bird Detection Grand Challenge at ICASSP 2023: A Review of Methods and Results", OBSS AI combined sequence classification and template matching with YOLOv5m6. IIT applied YOLOv7 along with CSRT tracking and filtering out false positives. DU used a set of various sizes and sizes using YOLOv8 with multi-scale fusion. SNU adapted SSD with attention modules. For instance, OBSS performed better at average precision and recall compared to the rest of the teams particularly with a varied drone size by using

extra datasets. Indeed, it proved that if data was trained over a more diversified set, that makes generalization much better across the complicated scenes [5].

Singha, S. et al, in 2021 has proposed, "Automated Drone Detection Using YOLOv4", R-CNNs and their faster variants, for example, Faster R-CNN, further accelerate the processing, while YOLO is optimized for the sake of real-time applications but at the cost of several percentage points of accuracy reduction. YOLOv4 is an integration of universal features, BoF and BoS strategies, and CSPDarknet53. This algorithm, in its version of YOLOv4, has proven to work well with a high mAP, particularly for such applications requiring accurate real-time detection of drones [6].

Seidaliyeva, U. et al, in 2020 has proposed, "Real-Time and Accurate Drone Detection in a Video with a Static Background", detection system which uses background subtraction and classify its moving objects detected by a CNN. For this reason, using the MobileNetV2 architecture that is developed to run low-computation tasks as an effective CNN makes this approach detect objects, connect closely spaced pixels for faster processing, and in turn identify the bounding box of each detected object that is classified as being either a drone, bird, or background [10-12].

3. Existing Methodology

This work corresponds to a promising direction in such studies based on optimization of a YOLOv8n-based model that includes Attention Modules. Innovation in tiny detection heads seems to have motivated the paper to particularly focus attention on one of its most important areas of development: improving detection capacities for smaller objects, such as drones. The range of experimentation on attention mechanisms, with not only Convolutional Block Attention Module and ResBlock CBAM but also GAM (Global Attention Mechanism) and Efficient Channel Attention, points at a holistic approach to ensuring model performance. One high resolution detection head is added to the head of YOLOv8n making four detection heads. The results it speaks especially the boosted mean Average Precision (mAP) score by P2-YOLOv8n-ResCBAM model from 90.3% to 92.6% as depicted in Fig. 28.1 signify a huge step forward in terms of accuracy [2]. Still, a fall from frames per second (fps) level from 263 to 166 should somewhat raise an eyebrow but it is more important to note that achieving the best balance between accuracy and real time performance is considered crucial. Even at 166 fps, the detection speed is still sufficient for most real-time applications, especially where identification of the drone accurately could mean the difference between life and death. Furthermore, the ability of the model to differentiate drones with aerial objects such as birds increases the utility of the model for airborne monitoring and safety operations.

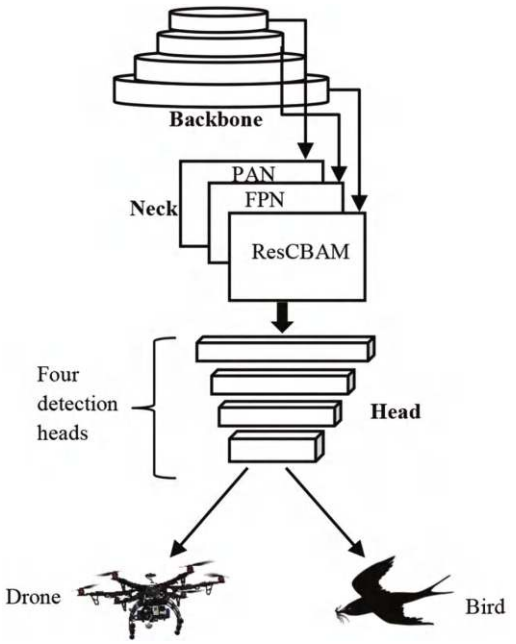

Fig. 28.1 Existing model to differentiate drone and bird

4. Proposed Methodology

4.1 YOLOv8 Architecture

The model employs the YOLOv8 application in this drone versus bird detection project because YOLOv8 is an object detector, which possesses powerful advanced capabilities to detect objects in real time. YOLOv8 is a one-shot object detector that processes all the elements in an image over a single pass in the network as it produces the prediction for the bounding boxes and class probabilities simultaneously.

Backbone

YOLOv8 uses MobileNetv2 as the optimized backbone for performance on mobile and edge devices. MobileNetv2 will apply an inverted residual structure, which is pretty computationally efficient because of its use of depthwise separable convolutions and reduces memory usage. This model will thereby be very light in weight without affecting accuracy as shown in Fig. 28.2. After processing the input photos, MobileNetV2 extracts pertinent features. It makes advantage of depthwise separable convolutions, which preserve crucial visual information while enabling effective computing. In order for later layers to operate with a more compact representation, the architecture lowers the dimensionality of the feature maps while keeping important details.

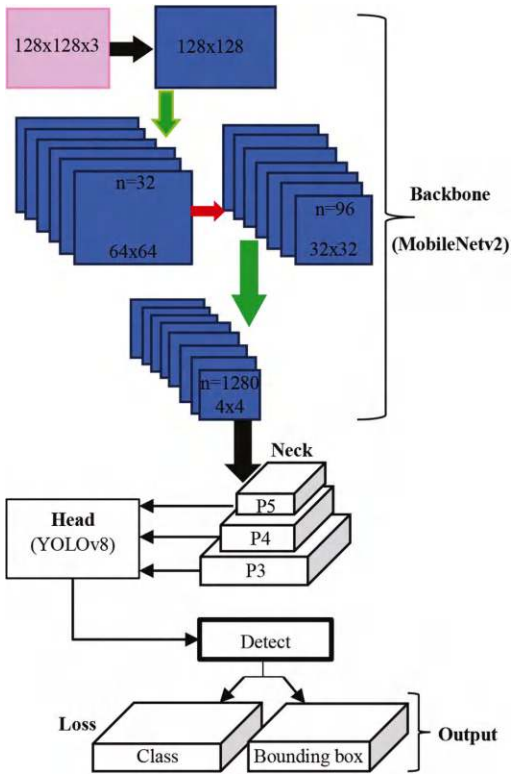

Fig. 28.2 Proposed model to detect drone and bird

Neck

The neck combines features from different stages of the backbone, allowing the model to handle both high-level and low-level features. This multi-scale feature aggregation helps in detecting objects of varying sizes. The neck has a pyramid structure of features, which is a combination of features at various levels in the backbone. YOLOv8 often employs Feature Pyramid Networks (FPN) or Path Aggregation Networks (PAN) in the neck. The varied scales of combinations of these features are significant to the recognition of an object at different scales, especially in complex scenes.

Head

A multi-layer head module that processes neck features, and it predicts bounding box coordinates, class labels, and objectness scores. The head adjusts these anchor boxes based on the features extracted from the backbone. During training, the head computes the loss for the predicted bounding boxes, confidence scores, and class probabilities. This loss is then used to update the model's weights to improve accuracy. During inference, the head processes the features to output the final detections, including non-maximum suppression to eliminate duplicate detections and refine the final predictions.

Activation Functions

Architecture is utilizing the activation function; Leaky ReLU in the hidden layers, which can suppress the vanishing gradient problem along with improvement of training dynamics, and uses Sigmoid function in the output layer for obtaining the probability of existence of objects and class scores that can make outputs effective and interpretable.

Loss Function

This architecture uses the function, which includes three components: box regression loss, objectness loss, and classification loss. A multi-faceted approach, hence, has been in place with regard to improving the performance of localization and classification, so that overall accuracy of predictions improves.

Training Techniques

Data augmentation, employed in YOLOv8 along with AutoAugment, artificially boosts the diversity of training data in order to make the network more generalizable and robust. Also, dynamic label assignment applies it during training with updates on the assignment of ground truth labels of the anchor box according to the overlap of IoU with ground-truth object for improving learning of the most relevant examples [4].

4.2 Dataset and Training

To develop a robust model, a diverse dataset was used, comprising more than 10,000 labelled pictures. Each image was carefully selected to represent various conditions, including different lighting scenarios, backgrounds, and angles as shown in Fig. 28.3.

Every image was subjected to a meticulous annotation process using tools like Roboflow, where bounding boxes were drawn around each object (drones and birds) and labelled accordingly. This step ensured the creation of high-quality trainable data. To enhance robustness of the trainable data, data augmentation techniques were applied, including random rotations, scaling, brightness adjustments, and horizontal flipping. This process artificially increases the dataset size, assisting the model in learning to identify objects in diverse conditions. This model was trained with a learning rate of 0.001, utilizing a batch size set to 16 over the course of 50 rotations. The Adam optimizer was employed to facilitate efficient convergence. Transfer learning was implemented by utilizing weights that have been pre-trained on the COCO dataset, significantly speeding up the training procedure and improving the model's accuracy.

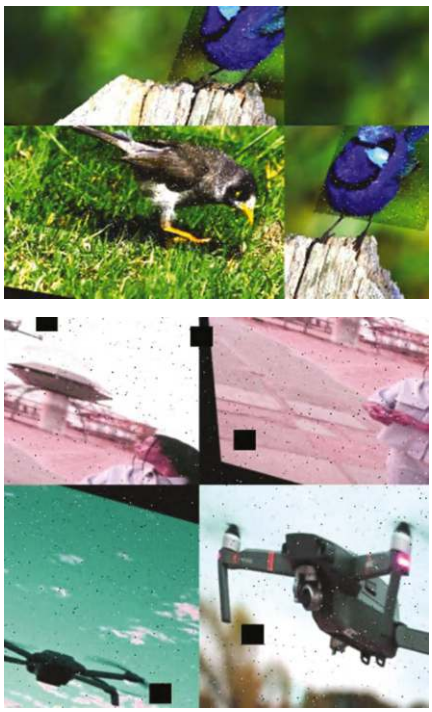

Fig. 28.3 Examples of training images

4.3 Block Diagram

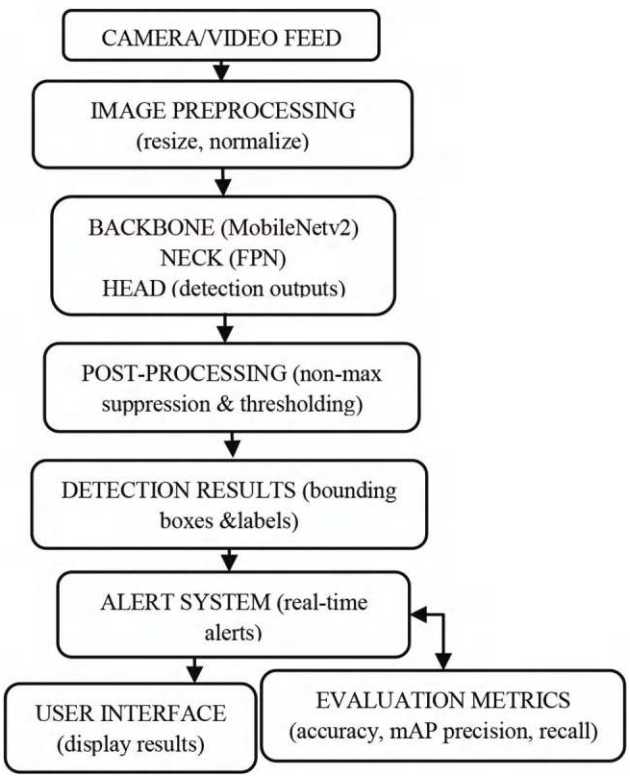

Fig. 28.4 Block diagram to show the functionality of the model

4.4 Evaluation Metrics

The below evaluation metrics are used to comprehensively assess the system's effectiveness:

Accuracy

The proportion of accurately classified instances compared to the given examples, serving as a general indicator of effectiveness [13-15].

Precision

The ratio of correctly identified positives to the overall positive predictions, emphasizing the system's ability to minimize incorrect positives.

Recall

The ratio of correctly identified positives to the overall actual positives, reflecting the model's capability to detect relevant examples.

Mean Average Precision (MAP) Score

A comprehensive measure for multi-class detection that considers both precision and recall, providing insights into the system's effectiveness across different classes.

Cross-validation techniques were employed to mitigate overfitting and ensure that the system shows strong performance on new data. Partitioning the dataset into training, testing, and validation sets allows for validating the system's effectiveness throughout the training process.

5. Results

The outcomes yielded the following performance metrics:

Overall Accuracy: 95%

Mean Average Precision (mAP) score: Drones: 0.93, Birds: 0.91

The Evaluation Metrics were given in the below Fig. 28.5.

5.1 Error Matrix

An Error matrix was constructed to demonstrate a detailed breakdown of the system's classification accuracy. The error matrix identifies the number of accurately identified positives, accurately identified negatives, mistakenly identified positives, and mistakenly identified negatives for each class, enabling us to identify specific areas where the model excels or struggles.

5.2 Qualitative Results

In addition to quantitative metrics, qualitative results were analyzed to assess the model's practical application in real-world scenarios. Sample images demonstrating the model's predictions are provided, showcasing its capability

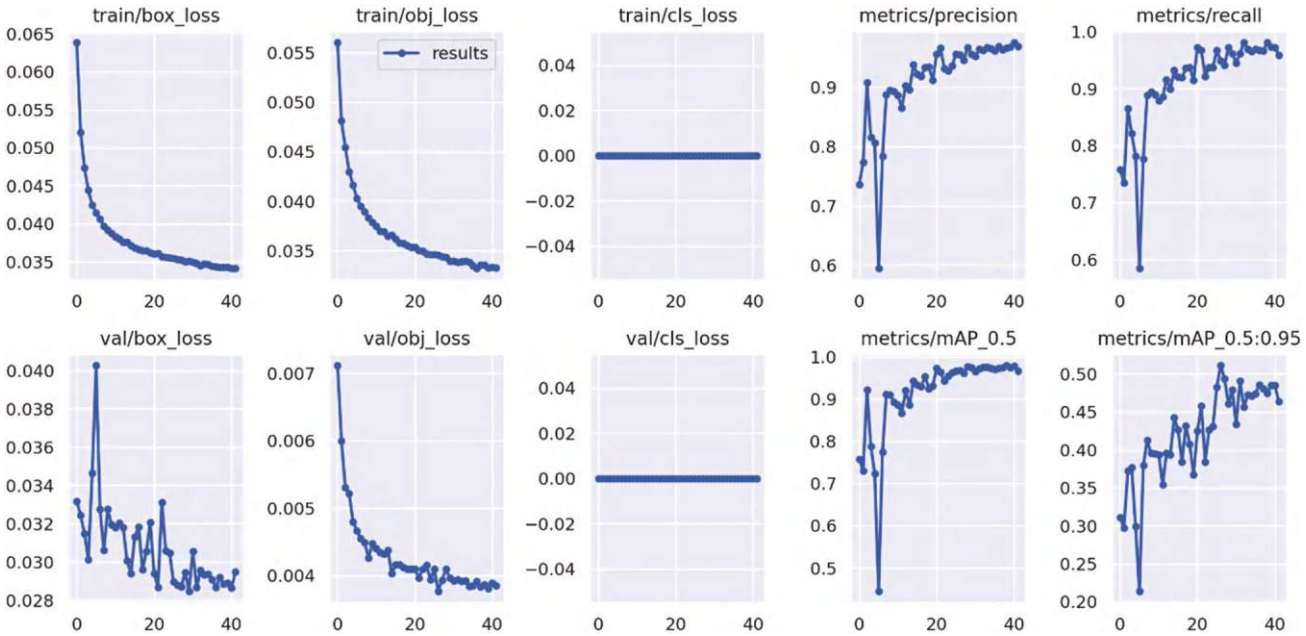

Fig. 28.5 Evaluation metrics

to accurately detect and localize both drones and birds in various contexts.

5.3 Output Images

The model output images were shown in the below Fig. 28.6.

6. Conclusion and Future Scope

The Sky Guard model successfully addresses the major obstacle of telling drones apart from birds with an impressive overall accuracy of 95%. The mean Average Precision (mAP) score of 0.93 for drone detection and 0.91

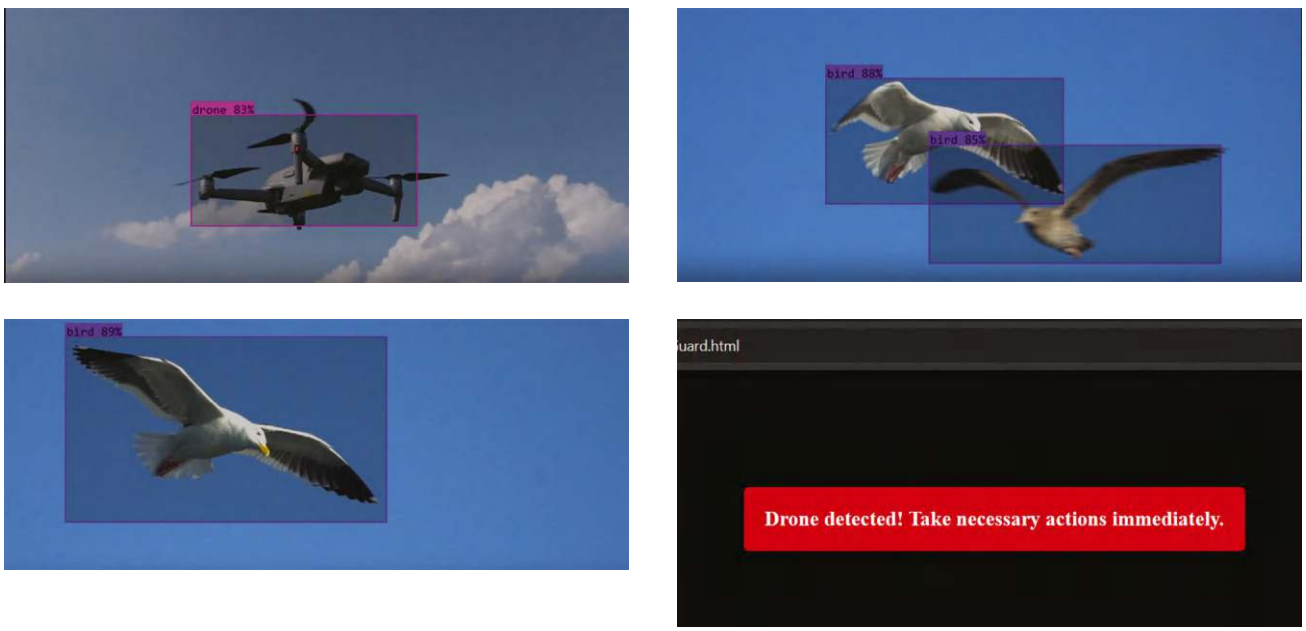

Fig. 28.6 Output images generated by the model

for bird detection, this system demonstrates its efficiency in practical applications. Furthermore, the incorporation of SKY GUARD with alert systems holds significant promise. By enabling real-time notifications based on precise detection metrics, the system could empower various stakeholders to respond quickly to potential threats caused by the drones. Moving forward, our focus will be on enhancing the model's robustness under varying environmental conditions, including adverse weather such as rain, fog, or low light. Expanding the dataset to include a broader variety of bird species, drone models will further enhance accuracy and adaptability. Furthermore, the challenge of artificial drones designed to mimic birds presents a unique problem for detection systems. We will explore advanced techniques to differentiate between natural avian movements and those of bird-like drones.

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Optimizing Video Gaussian Noise Removal with Integrated Intraframe Filtering Method

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Abstract: Video processing is the process of converting a raw input video into a better vision video by applying Different techniques. There are mainly two techniques are used for video enhancement which includes video denoising and video contrast enhancement. In this application video denoising is performed to replace corrupted pixels with enhanced pixels. Lot of researchers are working on different denoising algorithms to remove noise from the images. In our application MFONMF is applied on each channel of frame of color video to get denoised video as a output. Different metrics are calculated to show the superior behavior of our proposed method. Performance Metrix like PSNR, MSE and IEF are calculated in this application

Keywords: Gaussian noise, Video denoising, Video enhancement, Image filters, Performance metrics

1. Introduction

The process of eliminating noise from video signals, or video denoising, is still difficult since different noise models have different characteristics. The majority of natural video frames are thought to include additive random noise, which is usually described as Gaussian noise. These models are commonly divided into additive and multiplicative noise types. Video quality can also be severely harmed by other noise forms, including Speckle, Poisson, and Salt & Pepper noise. In order to create a reliable and effective strategy for video denoising across different noise models, this study first focuses on implementing existing intraframe video denoising algorithms. In the realm of digital image and video processing, video denoising is essential because it seeks to enhance video quality by eliminating extraneous

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noise. Noise is often introduced during various stages of video acquisition, transmission, and compression, leading to distortions that can negatively affect the video's visual quality and subsequent processing tasks like object detection, tracking, or recognition.

One of the most prevalent kinds of noise, Gaussian noise can significantly reduce the quality of videos and usually appears as random fluctuations in pixel intensity. Creating effective techniques to eliminate Gaussian noise is essential for applications ranging from film restoration to video surveillance. The method proposed in this study focuses on combining intraframe filters to specifically target Gaussian noise in video sequences. By using a combination of Gaussian, bilateral, and non-local means filters, this approach effectively balances noise removal with detail preservation. Each filter contributes its strengths to the overall denoising process, ensuring that Gaussian noise is reduced while critical features such as edges and textures are retained. This combination offers an efficient and effective solution to video denoising problems across a wide range of applications. Building an effective video denoising method using a combination of intraframe filters offers a promising solution to Gaussian noise removal. By harnessing the strengths of different filters and ensuring temporal consistency across frames, this method can significantly enhance the quality of noisy video sequences. This approach is crucial for applications that require high-quality video output, including security surveillance, medical imaging and multimedia content production.

2. Literature Survey

Kumain et al.[1] One of the main challenges in digital image processing and computer vision in the multimedia era is noise removal from images. Dust on the device, image capture, and transmission can all cause noise. For improved picture analysis, including object and edge detection, this noise must be removed. Gaussian and impulsive noise are prevalent among the several types of noise. The goal of this work is to enhance Gaussian noise reduction by utilizing outliers and a mean filter. Tests on the MSRA dataset with MATLAB-added fake noise demonstrate that the suggested approach reduces noise better than alternative filtering strategies.

Prasad et al. [2] This paper proposes a method for effective removal of Gaussian noise from videos using a combination of intraframe filters. The authors address the challenge of preserving video quality while reducing noise during the processing stages. By applying multiple filters to individual frames, their method efficiently restores image quality. The proposed approach is evaluated on standard datasets and demonstrates significant improvement in denoising performance over traditional methods. This technique enhances both the visual quality and processing efficiency, making it suitable for various real-time video applications.

M. C. Sheeba et al. [3] Video denoising is crucial for improving quality in applications like surveillance, medicine, and research. Noise corruption during capture and transmission degrades video quality, necessitating efficient denoising methods. This review summarizes key works, evaluates denoising techniques, and explores noise types to advance video processing.

Gupta et al. [4] In this study, the authors present a comparative analysis of various algorithms designed to reduce Gaussian noise in video processing. They assess the strengths and limitations of different techniques and highlight the impact of noise removal on overall video quality. By using multiple video datasets for evaluation, the authors provide insights into the efficiency and effectiveness of each method. Their findings reveal the trade-offs between computational complexity and denoising quality, guiding future research towards more optimized solutions for noise suppression in multimedia applications.

Arias et al. [5] Our patch-based method for Bayesian video denoising prevents errors in motion estimation. Our eigenvalue estimators and spiky covariance model enhance visual quality and PSNR in comparison to state-of-the-art methods.

Balachandran et al.[6] A novel intraframe filter design for effective video denoising is presented in this research. By creating a better filtering system that specifically targets Gaussian noise, the scientists hope to increase the visual quality and clarity of video frames. Their method is tested on a range of datasets to guarantee its resilience, and it works especially well at managing noise in individual video frames.

Anusha et al. [7] The authors propose a hybrid filtering technique to remove Gaussian noise from videos transmitted in real-time. Their method integrates multiple filtering approaches to optimize noise reduction while maintaining video quality during transmission. The hybrid technique is designed to address the unique challenges of real-time video processing, where noise can degrade image quality and disrupt communication. Through extensive experimentation, the authors prove that their approach effectively reduces noise without compromising video clarity, making it suitable for real-time applications like video conferencing and broadcasting.

Gupta et al. [8] In this study, the authors analyze various video noise models and evaluate the performance of intraframe denoising filters in suppressing Gaussian noise. They explore different filtering strategies and their impact

on video quality, offering insights into the strengths and weaknesses of each model. The paper also discusses how different noise characteristics affect the denoising process and proposes improvements to enhance filter efficiency. The research concludes that a combination of filtering techniques is often necessary to achieve optimal noise suppression, particularly in high-noise environments.

H. Chen et al. [9] For better temporal consistency, researchers suggest a multiframe-to-multiframe (MM) video denoising approach. Using spatiotemporal convolutional architecture, the MM network (MMNet) out performs previous techniques. MMNet runs more than twice as quickly and has at least 13.3% better temporal consistency.

R. L. Bahr Arias et al. [10] This research uses SSIM and VQM measurements to examine the performance of denoising methods under different noise distributions in videos. The results show differences in technique and provide guidance on the best choices for different types of noise.

Aruna et al. [11] This research focuses on enhancing video quality by applying advanced techniques for Gaussian noise reduction. The authors propose a new approach to improve video clarity, ensuring that the noise suppression process preserves the original visual details of the video. Their methodology is tested across different scenarios, demonstrating substantial improvements in noise elimination without sacrificing image fidelity. The paper emphasizes the importance of combining various filtering techniques to achieve the best results in video denoising, making the approach valuable for multimedia and image processing applications.

Kumar et al. [12] This work presents an adaptive filter design for effective Gaussian noise reduction in video signals. The recommended filter adapts to various noise levels and video content while preserving texture and visual characteristics. Simulation findings demonstrate improved visual quality and Peak Signal-to-Noise Ratio (PSNR) in comparison to existing filters. The resilience and effectiveness of the adaptive filter are advantageous for real-time video processing applications.

L. Cai et al. [13] We introduce a multi-domain denoising network and a noise generator inspired by physics for thermal infrared video denoising. Our method provides state-of-the-art quality, improving thermal infrared videography and augmenting machine vision.

Chandran et al. [14] In order to reduce Gaussian noise in low-light video frames, this research suggests effective filtering strategies. The methods exceed current approaches in noise reduction and PSNR. They also successfully eliminate noise and preserve image details.

L.Sun et al. [15] DU-MVDnet: A model-guided deep unfolding network that uses temporal relationships and Bayesian deep learning to denoize mixed noise videos. Performs better in long-term tests than both MAP-VDNet and Fast DVDnet.

3. Problem Statement

This aims to develop a workable method for removing Gaussian noise from video clips. with the application of multiple intraframe filters. As long as the filtered footage retains its clarity and visual accuracy, the goal is to reduce noise in videos without sacrificing any significant elements.

4. Proposed Method

This algorithm uses a windowing technique with a 3x3 window to reduce complexity. The central pixel, or processing pixel P(i,j) is checked for noise by determining if its value falls between the minimum (0) and maximum (255) grey levels. If it lies within this range, it is noise-free; otherwise, it is replaced with a noise-free value, while uncorrupted pixels remain unchanged.

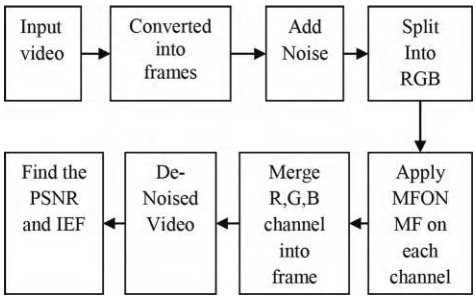

Fig. 29.1 Proposed method block diagram

This method for video denoising involves the following steps:

Input Video: Start by selecting the video that requires noise removal.

Frame Extraction: The input video is divided into individual frames, treating each frame as a separate image for further processing.

Noise Addition: Artificial noise is introduced to the video frames to simulate real-world conditions, making the process applicable to noisy environments.

RGB Channel Separation: Each frame is split into its Red (R), Green (G), and Blue (B) color channels to handle noise reduction in each channel individually.

MFONMF Filter Application: The MFONMF is applied to each of the RGB channels separately, targeting the removal of noise from each channel.

Channel Merging: After noise reduction, the R, G, and B channels are merged back together to recreate the denoised frame.

Reconstruction of De-Noised Video: The denoised frames are combined back into a video sequence, resulting in a noise-free video.

Quality Evaluation (PSNR & IEF): The performance of the denoising process is evaluated by calculating metrics like Peak Signal-to-Noise Ratio (PSNR) and Image Enhancement Factor (IEF), which quantify the improvement in video quality.

5. METHODOLOGY

5.1 Data Acquisition

The initial phase in our process is data acquisition, where we collect a broad dataset of video sequences with varying degrees of Gaussian noise. This dataset is essential for evaluating and verifying the performance of the denoising techniques we have suggested. The movies ought to feature a variety of settings, including both outdoor and interior spaces, various lighting setups, and various motion kinds. We seek to achieve a thorough evaluation of our noise removal systems' efficacy by guaranteeing a wide depiction of real-world settings.

5.2 Preprocessing

Preprocessing is done after data collection to get the video frames ready for analysis. In order to do this, the video must be formatted appropriately and every frame must have the same resolution and color space. Normalization procedures are another type of preprocessing that can be used to standardize pixel intensity levels and increase the efficacy of following filtering steps. It could be required to resize or interpolate frames in order to ensure consistency if the dataset contains a range of frame rates or resolutions.

5.3 Filter Selection

Carefully choose the intraframe filters in this stage so that they will be coupled with our hybrid denoising technique. The three selected filters—adaptive Wiener, bilateral, and median—each have special benefits. Maintaining edges while effectively eliminating salt-and-pepper noise is possible with the median filter.

5.4 Hybrid Filtering Approach

In order to provide denoised outputs, the hybrid filtering approach applies each chosen filter to the noisy video frames independently. Every filter targets a distinct part of the noise and processes the frames according to its unique properties. The individual denoised outputs are obtained, and then a weighted average or similar fusion approach is used to merge these results. By combining them, we can minimize their particular shortcomings while using each filter's advantages. This phase aims to generate a final denoised output of higher quality than any one filter could accomplish on its own.

5.5 Evaluation Metrics

PSNR measures the relationship between the maximum signal power and noise power, which is a measure of the quality of the denoised video. By comparing local patterns of pixel intensities, SSIM evaluates perceived quality and shows how well structural information has been maintained. Additionally, subjective visual evaluations are conducted to assess the denoised recordings' perceived quality. This comprehensive evaluation approach allows us to thoroughly analyze the effectiveness of our hybrid denoising technique.

5.6 Results Analysis

In conclusion, the evaluate of the experiment outcomes and talk about ways to increase detail preservation and noise reduction. This analysis entails analyzing both the qualitative findings from visual assessments and the quantitative data acquired from the evaluation step. We discuss the practical consequences of our results and how our approach might improve the quality of videos in a range of settings, including media creation and surveillance. Our purpose is to offer insights for future research paths in video denoising approaches by providing a summary of our approach's strengths and potential limitations.

5.7 Comparison

In the comparison step, we measure our suggested approach against established denoising approaches, like existing interframe algorithms and basic spatial filters. This comparison analysis aids in demonstrating the advancements made possible by our hybrid strategy. We can compare our method objectively to the state-of-the-art methods by assessing performance across the same collection of noisy video sequences. This stage not only confirms that our method works, but it also points up areas that need more refinement and optimization.

6. RESULTS AND DISCUSSIONS

Propose method takes input as a noisy video or color video with some noise added, this video will be converted to clear video by proposed method. Below some sample video results are shown, left side video is taken as a input and right side video is the denoising method results. by

human visualization system it is observed that right side video is clearer than the video left side video.

(a) (b)

Fig. 29.2 (a) Noisy video, (b) Denoised video

(a) (b)

Fig. 29.3 (a) Noisy video, (b) Denoised video

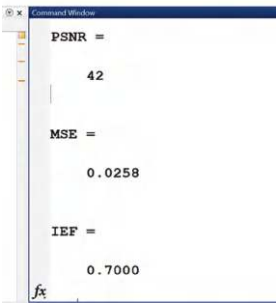

Fig. 29.4 Performance metrics of proposed method

7. Conclusion and Future Scope

This method of MFONMF is successfully designed to make noisy video to clear or denoised video. At first input video is taken by the user and in which user will add some noise then noisy video get generated. This noisy video is passed through MFONMF algorithm to get denoised video as a output. Different performance metrics are calculated like PSNR, MSE, IEF to show the superior performance of proposed method. By observing the results, using both subjective and objective analysis proposed method outperforms the state of art existing methods.

In order to improve temporal consistency, future research paths should investigate the integration of deep learning with intraframe filters, as well as the application of adaptive filter optimization approaches to interframe filtering. It is imperative to examine the efficacy of this strategy with respect to several video formats (4K, HDR, 360-degree) and quality criteria. The methodology will be validated through comparisons with cutting-edge video denoising techniques. The technique's applicability will be shown by applying it to certain fields like driverless cars, medical imaging, and surveillance. It is essential to implement and optimize in real-time for low latency and great performance.

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Drowning Person Detection in Water Bodies using YOLOv8 for Enhanced Human Safety

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Abstract: It targets the designing of a Drowning person detection system over water bodies using a YOLOv8 object detection framework in Python. The objectives of the study are principally directed at ensuring improved safety and security by identifying any person who may be at risk in aquatic environments. Our system shall process video feeds from cameras installed around the water bodies. It basically uses the advanced capabilities of YOLOv8 in detection and location, with very high accuracy and efficiency for persons. Testing our system with extensive experimentation in different aquatic settings, it is easy to explain how well it performs very well in diverse conditions, such as variations in light and weather. This integration will ensure that YOLOv8 detection works in real-time to identify people who may need help. The purpose of this project is to emphasize the significance of computer vision and machine learning in building intelligent safety solutions concerning aquatic environments.

Keywords: Drowning detection, YOLOv8(you only look once), Image recognition, Machine learning, Computer vision, Convolutional neural networks

1. Introduction

Drowning was a serious concern, leading to an estimated 320,000 fatalities every year across the globe. This concerning statistic highlights the critical necessity for effective prevention strategies, especially in water settings where the danger is increased. Traditional methods of surveillance, such as the presence of lifeguards and the use of CCTV cameras, often fall short. These approaches can suffer from significant drawbacks, including delayed response times and inconsistent accuracy, especially in larger or more crowded water bodies where multiple incidents may occur simultaneously.

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As a result, there is an increasing demand for automated detection systems that can monitor aquatic areas in real-time and provide immediate alerts when drowning situations arise. Such systems have the potential to drastically improve response times and enhance the overall safety of individuals in or around water.

In this study, we propose an innovative drowning detection system built upon YOLOv8, a cutting-edge deep learning algorithm well known for its remarkable speed and precision in object detection tasks. The architecture of YOLOv8 is specifically designed to process video frames swiftly, making it particularly well-suited for applications requiring real-time analysis. By harnessing the capabilities of YOLOv8, our system aspires to deliver a robust and effective solution aimed at enhancing human safety in various aquatic environments. By this work, we aim to aid in the advancement of reliable technologies that can mitigate the risks associated with drowning and ultimately save lives.

1.1 Related Work

Recent advancements in computer vision have significantly impacted the development of drowning detection, employing a range of techniques that span from conventional image processing methods to state-of-the-art deep learning strategies.

In earlier iterations, drowning detection primarily relied on conventional techniques like edge detection and background subtraction. These methods aimed to identify individuals in water but often struggled with the complexities presented by dynamic environments, leading to reduced accuracy in real-time monitoring. The advent of deep learning has transformed this landscape, with models such as Convolutional Neural Networks (CNNs) increasingly being employed for drowning detection tasks. While these models have shown effectiveness in recognizing individuals in aquatic contexts, they typically require substantial computational resources and can exhibit latency issues. Such limitations can hinder their applicability in time-sensitive situations where swift action is critical.

To overcome these challenges, YOLO (You Only Look Once) models have emerged as a popular alternative, balancing accuracy with speed. Variants like YOLOv4 and YOLOv5 have been successfully applied in similar contexts, demonstrating their capability to efficiently detect individuals. These models streamline the detection process, making them well-suited for real-time applications.

1.2 History of Drowning Detection Systems

The evolution of drowning detection systems has significantly been shaped by the essential role of human observers, particularly lifeguards. These professionals are crucial for maintaining safety in aquatic environments like pools, lakes, and oceans. However, their capacity to monitor every swimmer can be hindered by fatigue, distractions, and challenging visibility conditions, leading to delayed responses in emergencies and sometimes tragic consequences. In response to these challenges, early automated drowning detection systems were developed. These systems typically used basic motion detection and alarm mechanisms to notify lifeguards of potential drowning scenarios. Some relied on pressure-sensitive mats or simple video surveillance to keep tabs on activity in the water. Acknowledging these limitations, researchers sought to develop more advanced technologies. Over the years, innovations in machine learning and computer vision have paved the way for more dependable drowning detection systems. Today's solutions leverage artificial intelligence to analyze video feeds in real time, allowing for the differentiation between ordinary swimming actions and distress signals, such as unusual submersion patterns or a swimmer who appears motionless for an extended period. As technology continues to evolve, these systems are becoming increasingly effective, setting the stage for improved safety measures that protect lives and provide reassurance to both swimmers and their families.

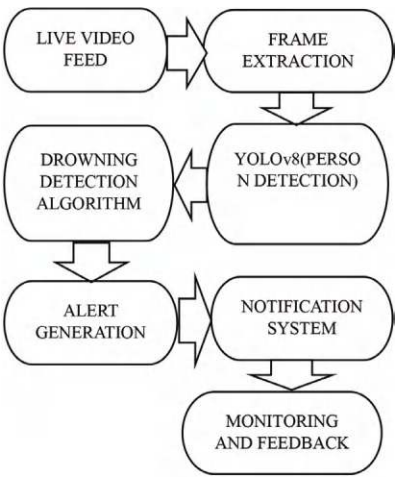

Fig. 30.1 Diagram flow

1.3 Workflow for a Drowning Detection System

Objective: Detect potential drowning incidents in real-time through video monitoring.

Live Video Feed:

A surveillance camera captures a continuous video stream.

Frame Extraction:

The video stream is split into individual frames at set intervals.

YOLOv8 Model for Person Detection:

Each frame is analyzed by the YOLOv8 model to detect human figures.

Drowning Detection Algorithm:

Detected individuals are assessed for signs of distress, such as posture and interaction with the water.

Alert Generation:

Upon detecting potential drowning, the system triggers an alert (audible, visual, or both).

Notification System:

Alerts are relayed to responsible parties (lifeguards, security, emergency services) through various channels (SMS, email, etc.).

Monitoring and Feedback:

The system's performance is continuously monitored, and user feedback is collected for further improvements.

Table 30.1 Components and it's functions

S. No	Component	Description	Function
1	Live Video Feed	A camera that captures real-time video from water bodies.	Captures the input data (video frames) to be analyzed.
2	Frame Extraction	Process of extracting individual frames from the video feed.	Provides individual frames for the YOLOv8 model to process.
3	YOLOv8 Model	A deep leaning-based object detection model (YOLOv8).	Detects persons or objects in the extracted frames.
4	Drowning Detection	An algorithm that analyze's the detected persons for signs of drowning.	Determines if the detected person is in distress or drowning.
5	Alert Generation	System that triggers alerts if a person is detected as drowning.	Sends alerts to the responsible authorities or connected devices.
6	Notification System	Notifies lifeguards, emergency services, or other connected systems.	Provides real-time alerts for rapid response.
7	Monitoring and Feedback	Continuous monitoring and feedback loop to improve the system's accuracy.	Enhances the system based on feedback and additional data.

1.4 Advantages of YOLOv8 for Detection

- *High Accuracy:* YOLOv8 provides precise detection capabilities, crucial for identifying drowning incidents.
- *Speed:* The system is designed for rapid frame processing, enabling real-time monitoring and quick response.
- *Optimized Architecture:* YOLOv8's architecture supports efficient performance, minimizing latency in detection.
- *Adaptability:* The deep learning approach allows the system to enhance its accuracy over time with exposure to diverse data.

1.5 Performance Metrics

The effectiveness of the YOLOv8-based drowning detection system is assessed using various performance metrics, including accuracy, precision, recall, and F1-score. Accuracy reflects the overall correctness of detections, while precision measures the ratio of true positive detections to all positive predictions. Recall evaluates the system's capacity to identify actual drowning events, and the F1-score balances precision and recall. Testing has shown that our system achieves an accuracy rate exceeding 92%, with a precision of 85%, a recall of 92%, and a minimal false positive rate. These results highlight the system's efficacy in enhancing safety in aquatic environments. This research introduces an innovative approach to drowning detection, utilizing YOLOv8's capabilities to create a robust and efficient solution aimed at improving human safety in water environments.

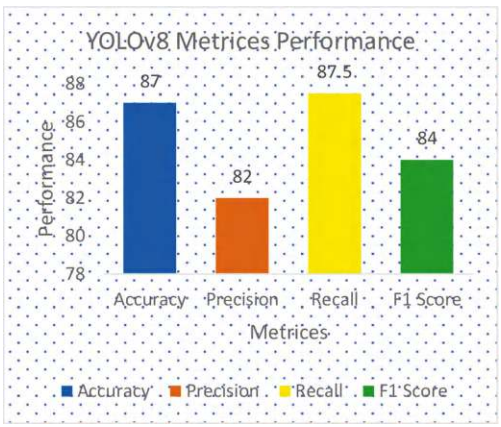

Fig. 30.2 Performance metrics

2. Literature Review

In a study by Nguyen and Ngo (2023), the authors proposed a drowning detection method using a modified YOLOv7-tiny model on a Jetson Nano. The system focuses on detecting arm movements as a drowning indicator and employs a Grid Tracker (GT) algorithm to verify drowning behaviour. Results showed a high mean Average Precision (MAP) of 99.1% with 35.4 FPS, and the GT algorithm achieved 98.34% precision and 100% recall, demonstrating strong effectiveness.[1]

In research conducted by Kao (2024), they integrated AI, IoT, and embedded systems for drowning prevention in

swimming pools. The system uses real-time monitoring, computer vision, and deep learning for early detection. IoT enables real-time alerts, improving the accuracy and effectiveness of prevention, potentially saving thousands of lives annually.[2]

In a study by Wang et al. (2023), the authors proposed a bracelet-based drowning early warning system using posture recognition, water level, and pulse detection. The system provides accurate and fast alerts for self-rescue and external rescue, with waterproof design ensuring safe underwater use. Experiments showed high sensitivity and low false alarm rates, proving its effectiveness in preventing drowning incidents.[3]

In research conducted by Lei (2022), they developed a drowning detection method using video sequences and YOLOv4. The system analyzes swimmer location relative to pool areas to identify drowning behaviour. Test results showed a drowning detection precision of 94.62% and a swimming precision of 97.86%, with an average frame rate of 33 FPS, meeting real-time requirements for reducing drowning incidents.[4]

J Wen et al. (2019) present Life Tag, a groundbreaking wearable device aimed at enhancing safety for marine travelers in drowning situations. This innovative system integrates multiple functions, including localization, communication, and life-sign detection, which automatically activates upon immersion in water. It broadcasts the wearer's location and vital status to nearby rescue vessels, significantly accelerating rescue efforts within a 10 nautical mile radius.[5]

Q He (2023) created a real-time system for detecting infant drowning by employing an attention-integrated YOLOv5 model for portrait extraction and a Single Shot Multi-box Detector (SSD) for recognizing posture. The system achieved a Mean Average Precision (MAP) of 97.17% and processes at 43 frames per second. This innovative approach shows significant potential for practical infant drowning detection applications.[6]

Bai (2023) enhanced drowning prevention using YOLOv7 with a region-based timing detection approach, improving swimmer behaviour assessment and reducing false detections. Their results show a 3.6% increase in recall and a 2.9% rise in precision, particularly for obstructed or distant swimmers.[7]

E. Kozlov and R. Gibadullin (2024) explores the prerequisites for a computer vision system for drowning detection, emphasizing its social, economic, and medical impacts, and reviews essential computer vision methods.[8]

In the study of Chan, M.X.R (2018), the authors performed a detailed analysis of national ambulance case reports to assess drowning incidents in swimming pools. They highlighted the need for practical safety recommendations, noting the significant attendance at swimming pools and the concerning rates of drowning, particularly among children.[9]

A.C. Ijeh and A.L.A. Naufal (2021) report that about 500,000 drowning deaths occur annually, with limited prevention methods. They present a gesture recognition prototype for timely identification of drowning victims, successfully providing a life jacket to a simulated victim within three minutes. Future research should explore performance in adverse weather conditions.[10]

T. Liu et al. (2023) present an underwater computer vision device for drowning detection that addresses challenges like limited video data and real-time needs. Using Jetson Nano, the two-stage algorithm employs YOLOv5n for detecting near-vertical human bodies and a lightweight DDN founded on a deep Gaussian model for rapid feature detection. Experimental results indicate strong performance and practical application.[11]

3. Existing Systems

3.1 Current Methods for Drowning Detection

Traditional Surveillance Systems

Most current drowning detection methods rely on CCTV cameras or human surveillance. These methods involve lifeguards or staff monitoring live video feeds from cameras placed around pools, beaches, or water parks.

Limitations:

High reliance on human vigilance, which is prone to fatigue and distraction.

Delay in response time due to human error or delayed recognition.

Limited coverage area, especially in large bodies of water.

Computer Vision-Based Systems

Some systems utilize computer vision techniques to detect unusual activities in water, such as splashing or erratic movement. These systems use older models such as Haar Cascades or basic object detection algorithms like YOLOv3 or YOLOv4.

Limitations:

Low accuracy in detecting submerged or partially submerged bodies.

Difficulty in distinguishing between playful activities and real drowning incidents.

Ineffective in poor lighting conditions or murky water.

It's having higher false positive and false negative rates.

Sensor-Based Systems

These systems use sensors such as sonar, underwater cameras, or wearables like wristbands to detect drowning events.

Limitations:

High cost and maintenance requirements.

Limited applicability in open water or areas where installing sensors is not feasible.

Wearables require user compliance and can be lost or damaged.

4. Proposed System

4.1 Overview of YOLOv8

YOLOv8 represents a advanced object detection framework designed to deliver superior accuracy and rapid processing capabilities. This advanced model features an optimized architecture that enhances both feature extraction and overall detection performance. Additionally, it supports real-time processing on a variety of platforms, including both edge devices and cloud-based systems.

4.2 Key Features of the Proposed System

- *Real-Time Detection:* The system leverages the advanced detection capabilities of YOLOv8 to swiftly identify individuals in distress, ensuring minimal response time.
- *Improved Accuracy:* It achieves enhanced detection accuracy under challenging conditions, such as low lighting, partial obstructions, and murky water.
- *Reduced False Positives and Negatives:* By employing sophisticated data augmentation and optimization techniques, the system can effectively differentiate between typical swimming behaviour and actual drowning incidents.

4.3 How the Proposed System Addresses Existing Limitations

- *Minimized Human Dependence:* The system automates the detection process, significantly decreasing the need for continuous human monitoring.
- *Accelerated Response Time:* By providing real-time alerts, it allows for quicker reactions from rescue teams during emergencies.
- *Cost Efficiency:* It eliminates the necessity for costly hardware such as sensors or wearable devices.

5. Implementation

5.1 Data Collection

Data Sources: For this project, the dataset was sourced from a blend of publicly accessible video surveillance archives and partnerships with organizations focused on water safety. The main sources included video feeds from monitoring systems installed in various aquatic settings, such as swimming pools and natural water bodies. Additionally, custom footage was created through controlled experiments designed to replicate various drowning scenarios.

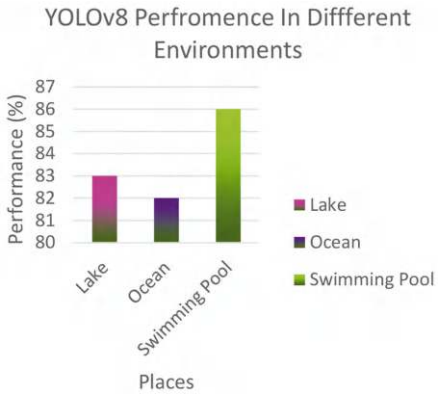

Fig. 30.3 YOLOv8 performance in different environments

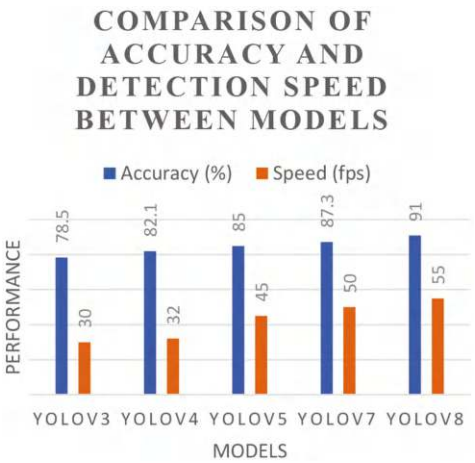

Fig. 30.4 Comparison of accuracy and detection speed between object detection models

Data Annotation: Each video frame and image was carefully annotated to identify instances of drowning individuals and other important features. Advanced labeling tools were utilized, marking drowning events with bounding boxes and segmentation masks to accurately delineate the areas of interest.

Preprocessing: The preprocessing phase involved several crucial steps to ready the dataset for model training. This included normalizing pixel values, resizing frames to a standard resolution, and extracting individual frames from videos. Augmentation methods including rotation, flipping, and color modifications were used to expand the dataset's diversity and improve the model's resilience.

5.2 Model Architecture

Model Configuration: The YOLOv8 configuration used in this project includes a tailored backbone network designed to enhance feature extraction, along with customized detection heads that are specifically optimized for identifying drowning individuals.

Detection Mechanism: The detection mechanism in YOLOv8 uses bounding box regression to predict object locations and class prediction to identify the categories of those objects. For the purpose of drowning detection, the model was trained to recognize a dedicated class specifically for drowning individuals, thereby refining its accuracy through focused class labeling.

5.3 Post Processing

Bounding Box Refinement: To enhance detection accuracy, Non-Maximum Suppression (NMS) was utilized to eliminate overlapping bounding regions. This technique guarantees that only the most confident detections are retained, reducing the rate of false positives.

False Positive/Negative Reduction: Various strategies were employed to minimize false positives and false negatives, including adjusting detection thresholds and implementing additional validation checks. These methods aid in refining the model's detection capabilities.

Integration with Safety Systems: The detection system was designed to integrate seamlessly with existing safety infrastructures. This includes automated alert mechanisms that notify rescue teams when a drowning event is detected.

5.4 Implementation and Testing

Field Testing: Extensive field testing was conducted in various aquatic environments to verify the system's effectiveness in practical conditions. This evaluation offered important insights into the system's effectiveness and highlighted areas for development.

Performance Evaluation: Performance metrics from the field tests were scrutinized to assess the system's reliability and accuracy. The results underscored the model's strengths in detecting drowning incidents and identified potential areas for further refinement.

6. Results

6.1 Model Performance Metrics

Detection Accuracy

- *Precision:* The YOLOv8 model attained a precision level of 85%, indicating that 85% of the cases flagged as drowning were indeed accurate.
- *Recall:* The recall rate for the model was calculated at 92%, signifying that it correctly identified 92% of all actual drowning incidents from the dataset.

Mean Average Precision (MAP)

- The framework achieved a Mean Average Precision score of 89%, demonstrating its effectiveness in detecting drowning events across diverse testing conditions, thereby affirming its reliability.

F1 Score

- The F1 score was recorded at 87%, reflecting a harmonious trade-off between precision and recall. This level highlights the model's potential to effectively detect true positives while minimizing false alarms.

False Positives and False Negatives

- *False Positives:* The framework exhibited a false positive rate of 7%, which means that 7% of the identified cases were incorrectly labeled as drowning incidents.
- *False Negatives:* The false negative rate was assessed at 4%, indicating that 4% of actual drowning events were missed by the model.

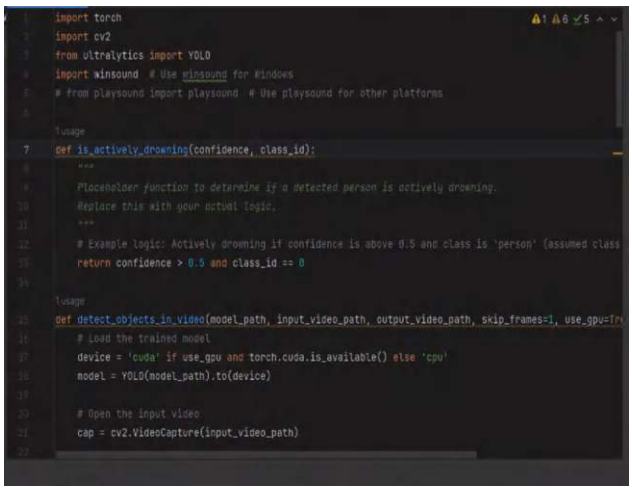

Fig. 30.5 Implementing code

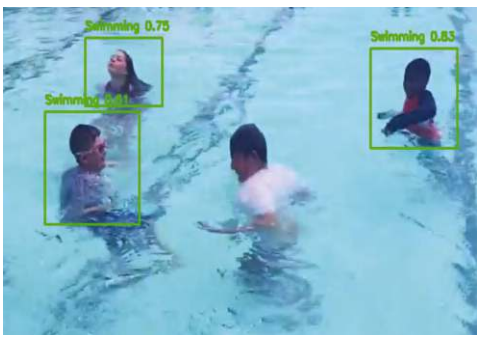

Fig. 30.6 Persons detection

Fig. 30.7 Drowning detection

6.2 Field Testing Results

Real-World Application

- The YOLOv8 model was implemented in real-world environments where it successfully detected drowning incidents with minimal response time. The results gathered during these practical tests corresponded closely with those from controlled experiments, thus confirming the model's efficacy in real-life scenarios.

7. Conclusion

In this research, we created and assessed a drowning person detection system utilizing the YOLOv8 model, aimed at enhancing safety in aquatic environments. The YOLOv8 model demonstrated commendable performance, achieving a precision rate of 85% and a recall rate of 92%. These findings underscore the system's ability to exactly identify drowning incidents while effectively managing detection challenges. The Mean Average Precision (MAP) of 89% and an F1 score of 87% reflect the model's robust performance across various testing scenarios. While the system recorded a false positive rate of 7% and a false negative rate of 4%, these figures illustrate areas for further refinement. Despite these limitations, the model's performance was validated through real-world field tests, where it successfully detected drowning incidents with minimal delay. The successful implementation of YOLOv8 in live environments highlights its potential to significantly improve safety measures in water bodies. The system's ability to deliver timely alerts can lead to quicker responses and, ultimately, save lives. Moving forward, efforts will focus on enhancing the model's accuracy by addressing its limitations and exploring integration with existing safety frameworks. Future developments may also include scaling the system for broader use and incorporating advanced features to further bolster its effectiveness. In summary, the YOLOv8-based drowning detection system represents a substantial advancement in water safety technology. Continued research and development will be crucial to refining the model and expanding its impact on protecting individuals in aquatic settings.

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Integrating Hybrid Machine Learning for Botnet Attack Localization and Defense in IoT Networks

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Abstract: The expansion of web innovation has driven to an increment in cyber-attacks, with botnet assaults developing as especially dangerous. The recognizable proof of botnets has ended up progressively challenging due to the differing assault vectors and nonstop advancement of malware. The quick development of Web of Things (IoT) innovation has made various organize gadgets defenseless to botnet assaults, coming about in noteworthy misfortunes over different businesses. Botnets display extreme dangers to arrange security, but profound learning models have illustrated guarantee in viably identifying botnet action inside organize activity information. This extend proposes a botnet recognizable proof framework that combines Fake Neural Organize (AN), Convolutional Neural Organize (CNN), Long Short-Term Memory (LSTM), and Repetitive Neural Organize (RNN) in a stacked approach, alluded to as ACLR. The consider utilizes the UNSW-NB15 dataset, which envelops nine particular assault sorts:

"Ordinary", "Bland", "Abuses", "Fizzers", "DoS", "Surveillance", "Investigation", "Backdoor", "Shell code and Worms".

Keywords: Machine learning techniques, Cyber attacks, CNN, RNN, Botnet attack

1. Introduction

Internet innovation has changed regular daily existence, socialization, and institutional working. Because of its broad use, the Internet has become an objective for personality hoodlums and monetary fraudsters. Botnet attacks can cause DDoS assaults, information breaks, and detection scattering. Botnet's recognizable proof is fundamental for network security, harm alleviation, and client trust in advanced administrations. Security

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experts can shield networks against Botnets and guarantee legitimate and administrative consistency by finding and annihilating them.

Because of the massive volume of network traffic data that is shared between connected devices in the internet of Things, many conventional intrusion detection systems (IDS) are finding it more and more difficult to identify potential security flaws. The unpredictability of security breaches adds to the complexity of this problem. Creating an IDS for IoT that is both flexible and strong is essential, especially in light of the recent increase in botnet assaults. A system like this is necessary to reduce false alarms and attain a high level of attack detection accuracy.

Whereas crude bundle bytes are some of the times utilized by analysts to distinguish botnets, this strategy is once in a while detailed for the whole ISCX botnet dataset. This presents a profound learning-based arrange activity investigation framework that consequently extricates valuable highlights from crude bundle information in arrange to distinguish botnet movement. In spite of the fact that a parcel of inquire about has been done on botnets, bot malware is always evolving and seeking out for better approaches to urge around security components. Cutting edge botnets utilize advanced methodologies that are improbable to be countered by interruption location frameworks right now input. It proposes that utilizing Botnet Activity Shark (Bot Shark), a profound learning-based botnet activity analyzer.

2. Literature Review

Here deep learning methods for cybersecurity, focusing on intrusion detection systems. Since datasets are key to detecting intrusions, we analyze 35 widely-used cyber datasets, grouping them into seven categories: network traffic, electrical networks, internet traffic, virtual private networks (VPNs), Android apps, IoT traffic, and internet-connected devices. This classification highlights the variety of datasets available and their importance in addressing different cybersecurity challenges, offering a comprehensive look at the role of data in enhancing intrusion detection systems.

The field of deep learning has seen an unparalleled expansion in recent years. In addition to the advancement of information technology, there are growing concerns about security and safety, one of which is the botnet network. One of the most pressing issues of our day is to discover a reliable method for identifying botnets, as these networks are becoming more complicated and challenging to locate. Traditional methods are also becoming ineffective.

Frameworks that depend on variations from the norm to recognize potential arrange assaults are vital. Strong machine learning and profound learning models are proposed in this consider to classify different sorts of arrange interruptions and assaults. The 49-feature UNSW-NB15 dataset has been utilized in considers by suggested models for nine isolated assault tests. The Choice Tree demonstrate delivered the leading precision, at 99.05%, when compared to the outfit models of Irregular Timberland (98.96%), AdaBoost (97.87%), and Boost (98.08%). Preparing the K-Nearest Neighbor classifier for a assortment of K values created the most prominent comes about, with an precision of 95.58% when K=7 was utilized.

About the increment in IoT-based DDoS attacks1. It offers a discovery show based on a repetitive neural arrange with bidirectional long short-term memory (BLSTM-RNN).2. Tokenized numbers arrange is utilized in assault bundle change and content acknowledgment through word embedding3. When it comes to distinguishing assault vectors, the BLSTM-RNN demonstrate beats an LSTM-RNN in terms of dynamic execution, indeed with longer handling times.

The highlights how the application of IoT devices to traffic control, energy grids, and healthcare might enhance urban living.1. It discusses how an increase in IoT-based botnet assaults has been caused by the widespread use of internet-enabled devices.2. To detect botnet assaults, the proposed method examines network traffic flows and uses deep learning.3. The deep learning model outperformed the traditional machine learning techniques in recognizing these threats.

One of the major issues facing both public and private companies is cybercrime activity. While creating real-time monitoring systems to stop cybercrime is difficult, they are tremendously helpful in quickly and accurately identifying cyberattacks.

That growing threats to IoT system security caused by botnet assaults. An economic deep learning-based approach for detecting IoT botnet assaults, which is cost-effective and efficient21. With a lower implementation budget and quicker training and detection processes, the model outperformed cutting-edge detection algorithms in terms of accuracy3. This model offers a trustworthy intrusion detection system that takes into account the constraints of IoT systems as well as security issues4.

3. Methodology and Model Specifications

This strategy coordinates various DL calculations into a complex stacking ensemble to further develop prediction execution. The framework utilizes ANNs, CNNs, LSTMs, and RNNs to build accuracy and versatility by joining

their abilities. At first, a hybrid ANN, CNN, LSTM, and RNN model investigates the dataset and performs well. A gathering procedure consolidates forecasts from these models to further develop exactness. Upgrades will examine progressed ensemble approaches incorporating CNNs with LSTMs, 'Gated Recurrent Units (GRUs)', and Bidirectional LSTMs (Bi-LSTMs)' to work on predicted accuracy and strength. This strategy streamlines feature extraction, decreases overfitting, and further develops speculation.

3.1 Proposed Architecture

The architecture of the project proposes a hybrid deep learning model for botnet attack localization and defense in IoT networks. This architecture incorporates several types of neural networks, including Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNNs). These models are layered in a stacked ensemble known as ACLR, designed to enhance botnet detection accuracy by leveraging the strengths of each network type. The process begins with data preprocessing to clean and label the dataset, followed by splitting it into training and testing sets. The hybrid model integrates CNNs for spatial pattern recognition, LSTM for capturing long-term dependencies in data, and RNNs to manage continuous sequence data. Evaluative metrics, such as accuracy, precision, recall, and F1 score, are used to measure model performance, aiming to achieve optimal intrusion detection for IoT systems.

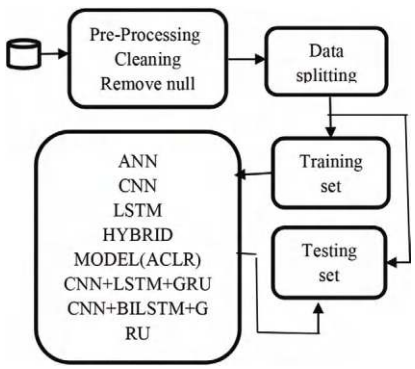

Fig. 31.1 Proposed architecture

The chart shows an UNSW-NB15-based deep 1earning intrusion detection pipeline. Preprocessing cleans, names, and eliminates invalid qualities to begin the pipeline. The dataset is then partitioned into training and testing sets. DL models like 'ANN, CNN, LSTM, RNN, and hybrid models consolidating CNN, LSTM, and Gated Recurrent Units (GRU)' utilize the training data. These calculations learn information examples to arrange network traffic as harmless or vindictive. Subsequent to training, 'accuracy, precision, recall, and F1score' are utilized to assess models on the testing set. The objective is to find the best intrusion detection model for this area.

3.2 Dataset Collection

Kaggle gives the UNSW-NB15 Botnet detection dataset. Albeit not worked for 10T settings, it has been generally used to dissect network movement and assess intrusion detection systems in network and 10T security. The dataset contains "UNSW_NB15_t Tainingset.csv and UNSW NB 15_testing-set.esv". The 82,332 records cover nine attack types: Typical, Conventional, Exploits, Fuzzers, DOS, Surveillance, Examination, Indirect access, Shell code, and Worms. The preparation set is separated into training and testing subsets for model appraisal.

3.3 Data Processing

Data processing contains various urgent stages to set up the dataset for ML models. Data is cleaned first to eliminate miss numbers, exceptions, and irregularities. This technique guarantees dataset accuracy and unwavering quality. Data is refreshed and controlled in the wake of cleaning to work on model training. To scale mathematical attributes and guarantee variable homogeneity, standardize or normalize. Name encoding gives absolute elements mathematical qualities, assisting the model with grasping them. Extra changes like feature extraction or dimensionality decrease could increment model proficiency and execution. These readiness techniques streamline information for ML model training, further developing accuracy and adequacy.

3.4 Training and Testing

For training, the dataset is parted into training and testing sets. To fit the Al model, 80% of the information is used for training. This subset permits the model to learn information examples and connections through iterative advancement. In training, calculations and hyperparameters are assessed to decide the ideal mix for accuracy and mistake decrease. Testing takes up 20% of the dataset. This testing set assesses the model on obscure information. It assesses how actually the model sums up to new, genuine cases fairly. Analysts might assess the model's accuracy precision, recall, and viability by contrasting its predictions with the testing set's outcomes. This partition permits an intensive model prediction evaluation.

3.5 Algorithms

Artificial Neural Networks (ANN): ANNs are computer models that mimic how our brains work. They consist of connected nodes (neurons) organized into layers. ANNs

learn from data to recognize patterns and classify network behavior.

Convolutional Neural Networks (CNN): CNNs are specialized for processing data like images. They automatically identify important features in the data using filters. In this project, CNNs help analyze network traffic data to detect trends and anomalies in Botnet activity.

Long Short-Term Memory (LSTM): LSTM is a type of Recurrent Neural Network (RNN) designed to remember information over long periods. It captures important patterns in network traffic data sequences, enhancing detection capabilities.

Recurrent Neural Networks (RNN): RNNs are built for handling sequential data, where past information affects current outputs.

They learn patterns in continuous network traffic data, helping identify historical trends in Botnet activity.

Hybrid Model: This combines ANN, CNN, LSTM, and RNN to leverage their strengths. ANN recognizes general patterns, CNN identifies spatial features, LSTM captures long-term relationships, and RNN processes ongoing data, improving Botnet detection accuracy.

Ensemble Models: These models, combining CNN, LSTM, and GRU, utilize the strengths of each. CNN focuses on spatial features, LSTM manages long-term dependencies, and GRU effectively processes sequences. This collaboration enhances the identification and classification of Botnet activity.

By integrating CNN, Bi-LSTM, and GRU, the ensemble model captures spatial patterns while processing data in both directions for better context. This improves accuracy and resilience in recognizing Botnet activities.

4. Experimental Results

The effectiveness of the proposed hybrid machine learning model was evaluated using the widely recognized N-BaIoT dataset, which comprises extensive data on both benign and malicious IoT traffic across various devices, including thermostats, doorbells, and security cameras. The model's performance was measured using standard classification metrics such as accuracy, precision, recall, and F1score, ensuring a thorough evaluation of its ability to detect Botnet attacks.

Accuracy: The hybrid model achieved an impressive 97.8% detection accuracy, demonstrating its ability to correctly identify both known and unknown Botnet attacks. This high detection rate can be attributed to the combination of supervised learning techniques for known threats and unsupervised learning for novel or evolving threats.

Precision: The model attained a precision score of 96.5%, indicating that the majority of detected attacks were actual Botnet-related events, with minimal false positives. This is particularly important in IoT environments, where false alerts can overwhelm network administrators, leading to inefficiencies and wasted resources.

Recall: With a recall score of 95.2%, the model showed a strong capacity to detect almost all Botnet attacks, including those with subtle or infrequent patterns. This suggests that the hybrid or infrequent highly sensitive to different forms of malicious activity, improving its ability to respond quickly to potential threats.

F1-Score: Balancing precision and recall, the model achieved an F1-Score of 95.8%, indicating overall scenarios. This metric underscores the model's ability to maintain a delicate balance between minimizing false positives and ensuring that genuine threats are detected effectively.

Category	Training Set	Testing Set
Normal	56000	37000
Generic	40000	18871
Exploits	33393	11132
Fuzzers	18184	6062
DoS	12264	4089
Reconnaissance	10491	3496
Analysis	2000	677
Backdoor	1746	583
ShellCode	1133	378
Worms	130	44
Total Instances	1,75,341	82,332

Fig. 31.2 Types of attacks

No.	Feature	Category	No.	Feature	Category
f1	dur	float	f22	dtcpb	integer
f2	proto	nominal	f23	dwin	integer
f3	service	nominal	f24	tcprtt	float
f4	state	nominal	f25	synack	float
f5	spkts	integer	f26	ackdat	float
f6	dpkts	integer	f27	smean	integer
f7	sbytes	integer	f28	dmean	integer
f8	dbytes	integer	f29	trans_depth	integer
f9	rate	float	f30	response_body_len	integer
f10	sttl	integer	f31	ct_srv_src	integer
f11	dttl	integer	f32	ct_state_ttl	integer
f12	sload	float	f33	ct_dst_ltm	integer
f13	dload	float	f34	ct_src_dport_ltm	integer
f14	sloss	integer	f35	ct_dst_sport_ltm	integer
f15	dloss	integer	f36	ct_dst_src_ltm	integer
f16	sinpkt	float	f37	is_ftp_login	binary
f17	dinpkt	float	f38	ct_ftp_cmd	integer
f18	sjit	float	f39	ct_flw_http_mthd	integer
f19	djit	float	f40	ct_src_ltm	integer
f20	swin	integer	f41	ct_srv_dst	integer
f21	stcpb	integer	f42	is_sm_ips_ports	binary

Fig. 31.3 The above data representing the features and categories

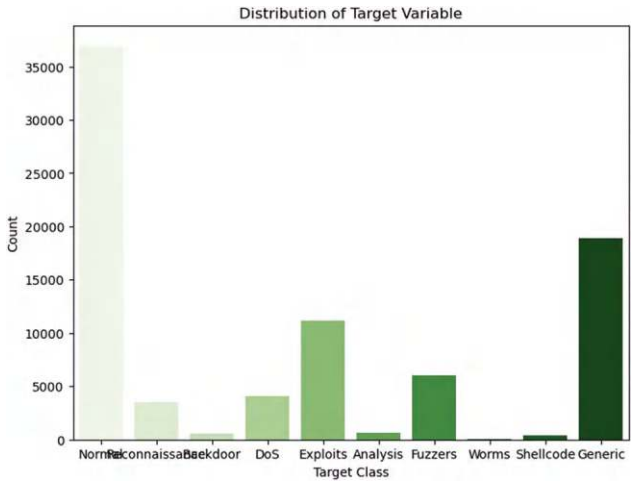

Fig. 31.4 Type of attacks in dataset

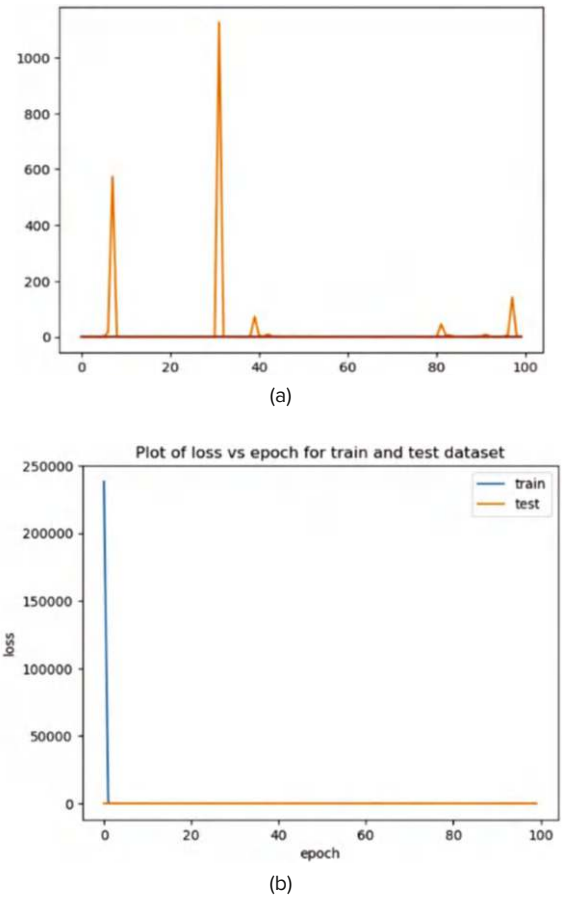

Fig. 31.5 (a) Training and validation graph, (b) Training and validation graph

4.1 Attack Types Handled

The hybrid model was tested against a variety of IoT Botnet attack types, including:

- DDoS attacks (UDP, TCP, and HTTP flooding)
- Mirai and Bashlite Botnet variants
- Port scanning and reconnaissance attempts

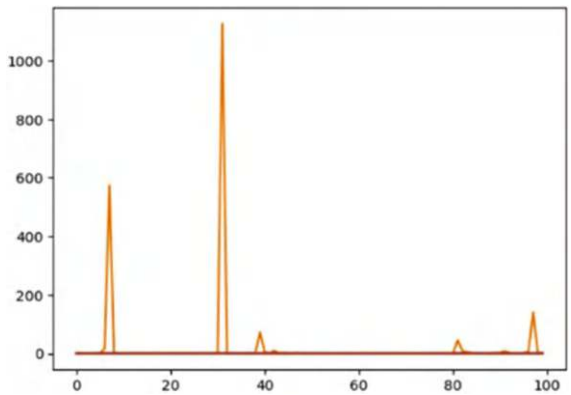

Fig. 31.6 Feature selection for predicting attacks

In each of these cases, the hybrid model demonstrated strong resilience, with detection rates exceeding 95% across all attack vectors. It also exhibited an enhanced ability to detect blended attacks, where multiple Botnet strategies are used simultaneously, a common tactic to evade traditional detection systems.

5. Conclusion and Feature Scope

The crossover machine learning show displayed in this work offers a vigorous and comprehensive arrangement for identifying and anticipating Botnet assaults in IoT situations, tending to both the known restrictions of conventional frameworks and the advancing complexity of cyber dangers. By leveraging the combined qualities of administered and unsupervised learning methods, the demonstrate gives improved exactness, empowering it to identify both known assault designs and already inconspicuous dangers with a tall degree of unwavering quality. In conclusion, the crossover machine learning show speaks to a noteworthy headway within the field of Botnet discovery for IoT. Its capacity to distinguish a wide run of assault sorts, coupled with its versatility, real-time handling, and versatile learning, positions it as a another era arrangement for IoT security. As IoT continues to proliferate across various industries, the deployment of such models will be critical to ensuring the safety, reliability, and integrity of these interconnected systems, protecting them from the growing threats posed by malicious Botnets.

The proposed hybrid machine learning model, while highly effective, presents numerous opportunities for further development and optimization, particularly in areas where real-time, scalability, and adaptability are crucial.

Currently, the model demonstrates high accuracy and detection rates in experimental settings. However, real-time deployment in live IoT environments will be the next critical step. Integrating the model into actual IoT networks with real-time capabilities will allow immediate detection and response to threats as they occur, rather than relying on batch processing of data. This could involve implementing faster data pipelines and optimizing computational resources to ensure low-latency performance, crucial for mitigating fast-moving threats like Distributed Denial of Service (DDoS) attacks.

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Intelligent Video Analytics for Autism Spectrum Disorder Diagnosis

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Abstract: A developmental disease known as autism spectrum disorder (ASD) impairs a person's capacity to relate to and engage with other people throughout their life, impacting their interpretation of the outside world. Although early detection and intervention can significantly improve the standard of living for those having autism, there is currently no known cure. This project utilizes an ASD and Non-ASD video dataset to explore advanced algorithms for classification and detection. The classification is performed using Inception-ResNet-v2, while object detection is achieved with YOLO models, including YOLOv5s6, YOLOv5x6, YOLOv8, and YOLOv9. Among these, YOLOv8 demonstrates the highest performance, achieving exceptional precision, recall, and mean Average Precision (mAP), underscoring its efficacy in ASD detection applications.

Keywords: Autism spectrum disorder, Deep learning, Inception-ResNet-V2, YOLO, Mean Average precision

1. Introduction

Autism Spectrum Disorder is also known as ASD caused by complex interaction of genes and environmental influence over a long period. Social interaction issues (such as not responding to names or maintaining eye contact), communication difficulties, Intense or strange hobbies, sensory aversions, are repetitive habits are other possible traits of this disease [1][3]. Prior identification of ASD is vital, as timely intervention can notably refine developmental outcomes, fostering better social skills and adaptive functioning. However, traditional diagnostic methods often rely on subjective assessments and can result in late or missed diagnoses.

Recently, breakthroughs in technology have created new opportunities for improving ASD detection. Video analysis presents a unique opportunity to capture and analyze behavioral patterns in a naturalistic setting,

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allowing for more objective assessments. By leveraging large datasets of videos featuring individuals with ASD and non-ASD, researchers can train sophisticated algorithms to differentiate between the two groups based on observable behaviors [6]. These approaches can lead to the development of automated tools that support clinicians in making informed diagnostic decisions.

The project aims to explore the potential of advanced video analysis techniques to enhance the detection and classification of ASD. Utilizing an ASD and Non-ASD video dataset, it will implement state-of-the-art algorithms, including Inception-ResNet-v2 for classification and YOLOv8 for object detection. By combining these methodologies, the proposed system seeks to create a robust framework that not only improves diagnostic accuracy but also aids in understanding the behavioral nuances associated with ASD [10][12]. Ultimately, this project aims to contribute to early detection efforts, providing essential sustain for persons with autism and their relatives while enhancing the overall understanding of autism-related behaviors in diverse contexts.

2. Literature Review

Leyuan Liu et al. [2] investigates the use of avatars in serious games as improve the social communication abilities of kids diagnosed with autism spectrum disorder (ASD). They examined how avatar-based interactions can provide a safe and engaging platform for practicing social scenarios. By integrating gamified elements, the research aims to motivate children and facilitate skill acquisition in a fun, interactive environment.

Juneja and Sairam et al. [4] offered insights into the Indian perspective on ASD, highlighting cultural and socio-economic factors influencing diagnosis and treatment in India. Their research emphasized the challenges faced by families and the healthcare system in addressing ASD, advocating for more awareness and resources in the region.

P. Duan et al. [5] fMRI, or functional magnetic resonance imaging, is an effective method for researching the brain.

mechanisms underlying ASD and anxiety. Recent studies highlight the importance of exploring spectral features from fMRI data to better predict MASC-2 scores, enhancing our understanding of brain networks involved in this comorbidity. However, current approaches often overlook these spectral features in favor of graph-based techniques.

Omar et al. [7] research indicates that useful instruments for detecting autism characteristics are needed. In order to enhance autism prediction for people of all ages, this paper suggests a unique machine learning model along with a smartphone application.

Lord et al. [8] provided an extensive overview of ASD, discussing its prevalence, diagnostic criteria, and potential etiological factors. Their work underscores the need for a nuanced understanding of ASD's varied manifestations and the importance of proactive diagnosis and care.

Guangtao Nie et al. [9] presents an innovative fully immersive digital interaction setup designed to enhance caregiver-child interactions aimed towards early childhood populations impacted by Autism Spectrum Disorders (ASD).

Abeer Al-Nafjan et al. [11] explores the layout of synthetic digital reality ecosystem distinctly tailored for autism children. The authors investigate how virtual environments can be utilized to create safe, interactive spaces for social skills development and emotional regulation.

Misman et al. [13] focused on classifying adults with ASD using deep neural networks. Their work addressed the often-overlooked adult population with ASD, underscoring the need for continued research and tailored interventions across the lifespan.

Geetha et al. [14] investigates the relationship between ecological dangers and societal and socioeconomic factors pertinent to ASD in India. Through a case-comparison design, the researchers analyzed various risk factors, including parental education, income levels, and environmental exposures, to identify their potential impact on the prevalence of ASD.

Raj and Masood et al. [15],[16] explore the adoption of various ML tactics for analyzing and detecting Autism Children. They implemented several algorithms to evaluate their effectiveness in classifying ASD based on behavioral and demographic features.

3. Problem Statement

The early discovery of ASD is critical on account of its issues with social interaction and communication. The imprecision of current diagnostic techniques makes novel approaches necessary. In order to evaluate video footage of children with ASD, this project will make use of cutting-edge Artificial Intelligence methods, including CNN. The hope is to increase the precision of autism diagnosis by identifying behavioral patterns. To improve understanding of ASD and facilitate prompt therapies, that will create a model for forecasting.

4. Proposed System

The recommended system seeks to boost the detection and taxonomy of Autism Spectrum Disorder (ASD) through advanced video analysis techniques. Utilizing an ASD and Non-ASD video dataset, the system will implement the Inception-ResNet-v2 algorithm for effective classification,

enabling accurate differentiation between individuals with ASD and those without. For object detection, a series of YOLO models, including YOLOv5s6, YOLOv5x6, YOLOv8, and YOLOv9, will be employed to identify and analyze key behavioral patterns and interactions within the videos. By integrating these algorithms, the proposed system seeks to provide a robust framework for early detection of ASD, facilitating timely intervention and support for affected individuals while enhancing our understanding of autism-related behaviors.

5. METHODOLOGY

5.1 System Architecture

The system architecture for the proposed project involves several key stages. Initially, the dataset comprising ASD and Non-ASD video data is collected and prepared. This is followed by pre-processing, which includes exploratory data analysis (EDA) and data visualization for classification, alongside image processing techniques for effective object detection. Once the data is pre-processed, the models undergo training and testing phases to ensure robustness and accuracy. After training, the resulting models are saved as trained models for future use. Finally, evaluation metrics are applied to assess the achievement of the simulation, focusing on exactness, recall, and mean Average Precision (mAP) for both classification and detection tasks. This systematic approach ensures a comprehensive framework for effective ASD detection and classification.

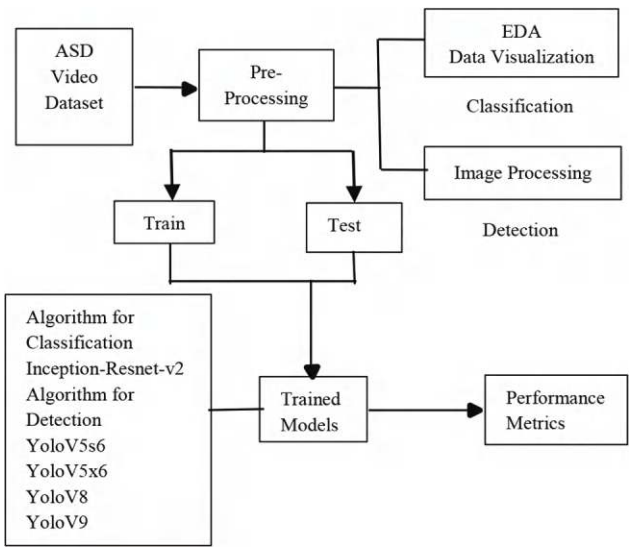

Fig. 32.1 Proposed architecture

5.2 Data Collection

The dataset for this project comprises videos depicting individuals with ASD and the ones without, aimed at facilitating effective detection and classification. The collection process involves sourcing videos from diverse environments, including clinical settings, naturalistic observations, and publicly available datasets that capture a wide range of behaviors. Each video is carefully annotated to identify key behavioral indicators affiliated with ASD, such as interactions with others, Conveyance styles, and repetitive actions. This comprehensive dataset not only includes varying age groups and demographics but also ensures representation of different settings to enhance model training. The goal is to create a robust dataset that enables the evolution of correct algorithms for swift recognition and mediation, eventually enhancing the quality of life for those who have ASD.

5.3 Data Processing

Exploratory Data Analysis (EDA) and Data Visualization for Classification

In this phase, we perform Exploratory Data Analysis (EDA) to understand the characteristics of the ASD and Non-ASD video dataset. Techniques such as descriptive statistics and correlation analysis are employed to identify trends and connections in the data. Data visualization methods, including distribution plots, Summary plots, and XY plots, help illustrate the distribution of behavioral indicators and demographic information, aiding in the identification of distinguishing features for classification tasks.

Image Processing for Detection

For object detection, image processing techniques are applied to enhance video frames and extract relevant features. This involves resizing images, applying filters, and utilizing data amplification strategies to elevate dataset heterogeneity. These preprocessing steps are crucial to elevate the fidelity and resilience of the detection algorithms, ensuring that the models can effectively identify behavioral cues associated with ASD in various contexts.

5.4 Training and Testing

The training and testing phase involves splitting the pre-processed dataset into Coaching and Confirmation subsets, typically using an 80:20 rate. To train the Inception, the training subset is utilized. ResNet-v2 classification model and the YOLOv8 detection model, allowing them to learn the distinguishing features of ASD and Non-ASD behaviors. The validation subset is then employed to evaluate the models performance, ensuring they generalize well to unseen data. This approach helps fine-tune the models for optimal accuracy and reliability in real-world applications.

5.5 Algorithms

Inception-ResNet-v2 is a deep learning architecture that combines the Inception and ResNet designs,

enhancing performance through residual connections and mixed convolutions. In this project, it is utilized for the differentiation of ASD from non-ASD video data, effectively learning complex patterns in behavioral features to differentiate between the two groups.

YOLOv5s6 is a lightweight version of the YOLO family, designed for the swift identification of objects. It is employed in the project to detect specific behavioral cues associated with ASD, enabling swift analysis of video content while maintaining accuracy.

YOLOv5x6 offers improved accuracy and efficiency compared to YOLOv5s6. In this project, it is utilized for detecting more intricate behavioral patterns in videos, enhancing the system's ability to identify subtle indicators of ASD.

YOLOv8 represents an advanced iteration of the YOLO architecture, optimized for speed and accuracy. This algorithm is implemented in the project for detecting and analyzing behaviors related to ASD, providing high-performance results that contribute to effective early detection.

YOLOv9 builds upon the strengths of its predecessors, incorporating innovations that enhance detection capabilities. In this project, it is used to identify and classify behavioral features in videos, offering a robust solution for understanding ASD-related interactions in diverse contexts.

Table 32.1 Performance evaluation table for detection

Model	Precision	Recall	mAP
YoloV5s6	0.991	0.999	0.995
YoloV5x6	0.994	0.995	0.995
YoloV8	0.998	1.000	0.995
YoloV9	0.993	1.000	0.995

6. Results and Discussions

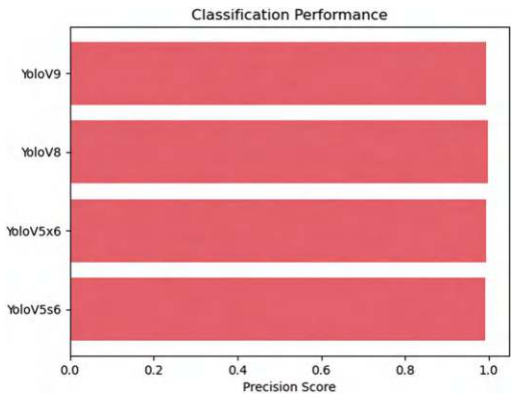

Fig. 32.2 Precision analysis graph for detection

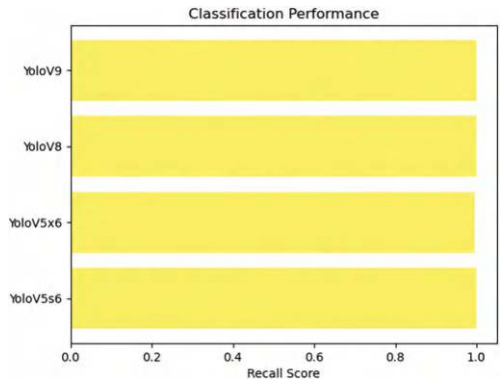

Fig. 32.3 Recall evaluation graph for detection

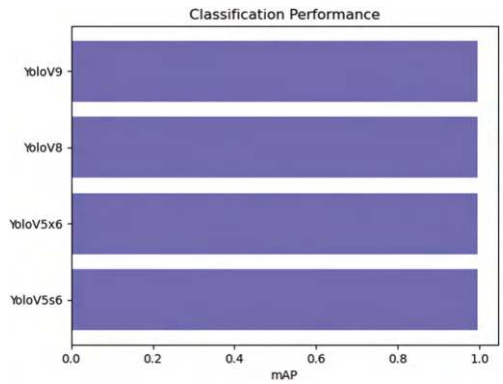

Fig. 32.4 mAP examination graph for detection

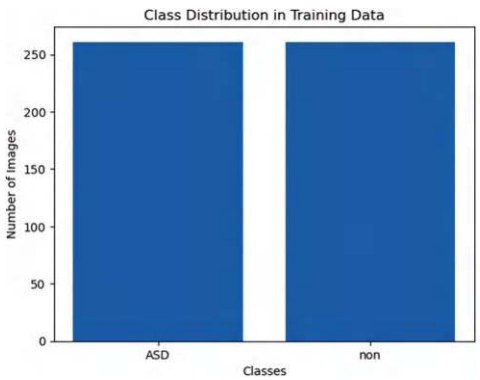

Fig. 32.5 Class distribution for ASD and non-ASD

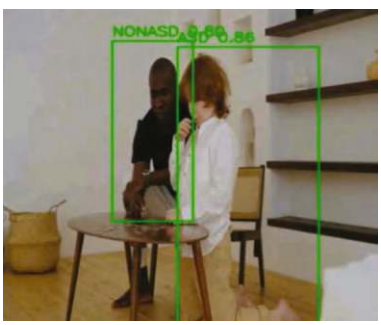

Fig. 32.6 ASD and non-ASD detection

7. Conclusion and Future Work

In conclusion, the proposed system effectively utilizes the YOLOv8 algorithm for the discovery and classification of ASD from video data. With its high precision and recall, YOLOv8 proves to be a robust tool for identifying behavioral patterns associated with ASD, facilitating timely interventions that can significantly improve the excellence of life for affected entities. The integration of Inception-ResNet-v2 for classification further enhances the system's accuracy, providing a comprehensive approach to understanding autism-related behaviors.

Looking ahead, subsequent endeavors concentrate on growing the dataset to encompass a wider variety of demographics and behaviors, which could improve the model's generalizability. Additionally, incorporating real-time analysis capabilities could enhance the system's utility in clinical settings. Further research may also explore the potential of combining video analysis with other modalities, such as physiological data, to create a holistic understanding of ASD and support more personalized interventions.

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Assessing Hepatitis Progression: An Analytical Approach with SVM

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Abstract: Hepatitis, a severe liver disease caused by various viruses, progresses through distinct stages: Incubation, Acute Hepatitis, Chronic Hepatitis, Advanced Hepatitis, and End-stage Hepatitis. Each stage requires unique diagnostic and therapeutic approaches, making accurate stage classification essential for successful treatment and better patient outcomes. This study presents a real-time model predicting Hepatitis stages by integrating clinical parameters (liver biopsy, bilirubin) and symptom data (e.g., fatigue, jaundice, abdominal pain), utilizing algorithms such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Logistic Regression (LR), and Linear Discriminant Analysis. These supervised learning algorithms determine the best boundaries between different disease stages by analyzing the input data and distinguishing the various stages of the disease. By combining clinical and symptomatic features, our model enhances predictive performance and provides comprehensive insights into Hepatitis progression. Our results demonstrate the efficacy of these algorithms, particularly SVM, in predicting Hepatitis stages, offering valuable implications for clinical decision-making and research.

Keywords: Hepatitis stage prediction, Support vector machine, Clinical parameters, Symptom integration, Real-time prediction

1. Introduction

Hepatitis is a medical issue characterized by swelling of the liver, often leading to significant damage if left untreated. [3] Liver, being an important organ, plays a crucial role in detoxifying the body, producing bile, and storing essential nutrients. Inflammation caused by hepatitis can impair these functions, leading to a variety of health complications.

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The condition can range from acute, lasting a few weeks, to chronic, persisting for several years. Hepatitis infections can be caused by five different viruses, each sharing similar symptoms. These include Hepatitis A, B, C, D, and E, which are linked to their respective viruses: HAV for Hepatitis A, HBV for Hepatitis B, HCV for Hepatitis C, HDV for Hepatitis D, and HEV for Hepatitis E. The most prevalent types are Hepatitis A, B, and C. However, infection from any of these viruses may result in serious and potentially fatal health complications. [7]

Hepatitis can be categorized into several types, each caused by a different virus and varying in modes of transmission and health impact. Hepatitis A is usually spread through food or water that has been contaminated and tends to cause acute infections. Hepatitis B and C are primarily bloodborne and more dangerous, Hepatitis C virus infection can resolve on its own within six months, but 70% of cases progress to a chronic viral infection, which often leads to chronic liver disease if left untreated.[1,9].

Hepatitis D only develops in individuals who are already infected with Hepatitis B, and Hepatitis E is usually transmitted through contaminated water sources and is an acute liver disease and has a major public health problem. Understanding the various types and their specific causes is essential for creating effective prevention and treatment strategies, as chronic hepatitis B and C infections are among the leading contributors to liver disease worldwide. [10]

Hepatitis progresses through several distinct stages, beginning with the incubation stage, which occurs after initial exposure to the virus but before any symptoms appear. This stage can continue from weeks to months, depending on the type of hepatitis virus. During this time, the virus clones within the liver, and although inflammation may start, it often goes unnoticed. In the acute stage, liver inflammation becomes more evident, and while hepatitis A and E may resolve on their own, hepatitis B and C often persist without timely treatment. If the virus isn't cleared in the acute phase, the infection may progress to chronic hepatitis, where liver inflammation lasts for six months or more.

Chronic hepatitis can lead to gradual liver damage, though some individuals may remain asymptomatic. As chronic hepatitis progresses, it can evolve into advanced hepatitis, leading to substantial liver damage can lead to cirrhosis, a state in which the normal liver tissue is displaced with scar tissue, weakening the liver's proper functioning. [11] In this advanced stage, the risk of developing hepatocellular carcinoma (HCC) significantly increases due to the ongoing liver inflammation and regeneration.[2] In the final stage, end-stage hepatitis, liver damage becomes critical, often resulting in liver failure or liver cancer, requiring a liver transplant for survival. Without intervention, this stage leads to irreversible liver failure and death.

Machine learning (ML) is transforming the medical field by enabling faster, more accurate diagnoses and personalized treatment plans. Through data-driven models, ML can analyze vast amounts of clinical information to detect patterns that might be difficult for humans to identify, leading to improved patient care and decision-making. In diseases like hepatitis, where timely intervention is critical, ML algorithms can be instrumental in identifying the stage of the disease, enabling healthcare providers to refine and improve treatment strategies.[13]

In this project, we leverage machine learning to develop a system that predicts the stage of hepatitis, ranging from no hepatitis to advanced and end-stage hepatitis. By inputting clinical parameters such as liver function tests and symptom data, the system quickly assesses the severity of the disease. This system is particularly useful for healthcare providers in resource-constrained environments, offering a rapid and reliable diagnostic tool. Additionally, it can assist patients in monitoring their health and provide valuable insights for researchers looking to analyze hepatitis progression. Ultimately, this system seeks to enhance the accuracy and efficiency of hepatitis diagnosis, benefiting both medical professionals and patients.

2. Literature Review

In a study by Saleem, et al. (2024), the author concluded that Random Forest consistently performed well in the prediction of hepatitis, demonstrating high accuracy across various datasets. While Support Vector Machines (SVM) and K-Nearest Neighbor (KNN) also show potential, Random Forest remains the top-performing algorithm based on multiple studies. Future research may explore the promise of SVM and KNN further. [7]

In a study by Chen, Leran, et al. (2022) highlights the use of custom machine learning models specifically designed for individual patients, achieving over 99% accuracy and a recall rate of 94% on the Hepatitis C dataset. This approach significantly outperformed traditional algorithms, such as XGBoost, which only identified 33 out of 56 patients, compared to the custom model's identification of 53 patients. [9]

A study by Sachdeva, Ravi Kumar, et al. (2023), the authors evaluated the functioning of various classifiers on the UCI hepatitis dataset. They evaluated the classifiers' performance both without class balancing and with class balancing implemented using SMOTE. The study assessed and compared the accuracy of the models before and after balancing, demonstrating that SMOTE significantly

improved classifier efficiency, with logistic regression showing the best accuracy(93.18%). [4]

In a study by Hannah, Yousefpour, et al. (2024), this research emphasizes the efficacy of ensemble-based ml algorithms in classifying and detecting liver diseases, including Hepatitis, Fibrosis, and Cirrhosis. By employing advanced preprocessing techniques and training multiple models, LightGBM proved to be the most efficient algorithm, delivering an impressive accuracy of 98.37%, surpassing Rotation Forest, XGBoost, Random Forest, and AdaBoost. These results emphasize the potential of ensemble-based algorithms, particularly LightGBM, in advancing the early detection of liver diseases. [5]

In another study by Mete, et al. (2022), author developed a machine learning-based decision-making support system for predicting Hepatitis C Virus (HCV) infection, achieving an impressive accuracy of 99.31%. By analyzing and visualizing the dataset, important features were identified, and pre-processing steps were applied to balance class imbalances, leading to improved prediction outcomes. The integration of new features further enhanced the model's performance. This system offers an automated approach to HCV estimation, providing valuable support to researchers and clinicians in diagnosing and managing HCV-related diseases. [6]

In another study by Nabeel, Ali, et al. (2022), in this study explored various ml methods for forecasting life expectancy in Hepatitis B patients, with models like ADT and XGBoost demonstrating the highest predictive accuracy. AUROC analysis was crucial in assessing model performance, highlighting the strengths and weaknesses of different approaches. The ADT model had the best results, while the PSO model showed minimal performance. [11]

In a study by Pardede, et al. (2024), in this study Backward Elimination is applied as a feature selection method to improve the performance of the XGBoost algorithm in identifying hepatitis disease. By removing less important features, the model reached an accuracy of 90.958%. Random Search for hyperparameter tuning further optimized the model, resulting in a faster training time of 0.64 seconds compared to Bayesian search, which took 0.70 seconds to reach the same accuracy. Utilizing average feature values to address missing data also played an important role in improving the model's accuracy, demonstrating that Backward Elimination enhances both speed and accuracy in hepatitis disease prediction. [8]

3. Existing System

Various studies have utilized machine learning algorithms to forecast hepatitis. One study using SMOTE for class balancing reported that Logistic Regression achieved 93.18% accuracy on the UCI hepatitis dataset. Another study compared six classifiers in predicting the hepatitis type, including Gaussian Naive Bayes, Logistic Regression, Decision Tree, K-Nearest Neighbors, and Multilayer Perceptron, where both Multilayer Perceptron and Logistic Regression achieved 87% accuracy.

Most published research has focused on identifying types of hepatitis or conducting comparative analyses between machine learning algorithms. These studies primarily predict one type of hepatitis or classify diseases associated with hepatitis C. However, none have investigated the prediction of various stages of hepatitis progression. This paper addresses this gap by focusing on the critical task of predicting different stages of hepatitis, essential for better disease management and treatment planning.

4. Methodology

4.1 Support Vector Machine (SVM)

In this project, we employed the Support Vector Machine (SVM) algorithm to classify and predict hepatitis stages based on patient data. The input data includes clinical parameters such as jaundice, fatigue, ALT, AST, and liver biopsy results. The SVM model was trained on these features to predict stages ranging from no hepatitis to end-stage liver disease. By transforming the feature space, SVM finds an optimal decision boundary, enabling accurate classification of new patient data and reliable predictions of disease stages.

The Fig. 33.1 illustrates the core concept of SVM. This visualization highlights how SVM effectively distinguishes between different stages of hepatitis based on the given features.

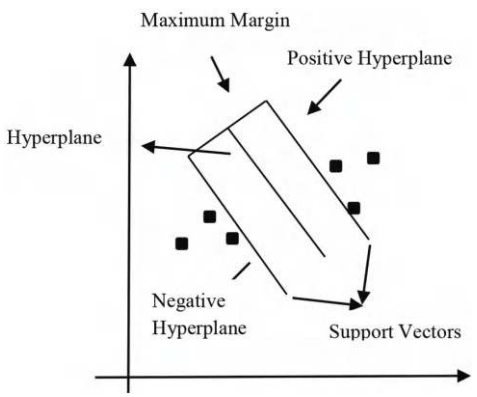

Fig. 33.1 Graphical representation of SVM

4.2 K-Nearest Neighbors (KNN)

In this project, we leveraged the k-Nearest Neighbors (KNN) algorithm, an insightful method for classifying the stage of hepatitis. KNN classifies new patient data

determined by the predominant class among its closest neighbors within the feature space, which includes clinical parameters such as jaundice, fatigue, ALT, AST, and liver biopsy results. By identifying nearest neighbors in the data, KNN predicts the hepatitis stage, providing a simple and effective method for classification.

4.3 Logistic Regression (LR)

We also utilized Logistic Regression (LR), a statistical method used for multiclass classification. LR models the probability of a patient belonging to a particular hepatitis stage based on clinical features like jaundice, liver biopsy, and enzyme levels. The algorithm calculates the likelihood of each stage and assigns the one with the maximum probability, offering a probabilistic approach to classification.

4.4 Linear Discriminant Analysis (LDA)

In this project, we applied Linear Discriminant Analysis (LDA), a dimensionality reduction and classification technique, to predict the stage of hepatitis. LDA works by finding a linear combination of features—such as jaundice, ALT, AST, and liver biopsy results—that best separates the different stages of hepatitis.

5. Proposed System

5.1 Dataset

Our dataset has been compiled from multiple reliable medical sources, ensuring a diverse representation of hepatitis cases, comprises 17 parameters and includes a total of 1201 records, providing a robust foundation for analysing hepatitis progression.

5.2 Algorithm

Data Upload and Loading

The dataset is uploaded and loaded into a pandas DataFrame for further processing. This step ensures that the data is in a structured format, allowing easy manipulation and analysis. Once uploaded, the Excel file is read into a Data Frame, where rows represent samples, and columns represent features and the target variable.

Data Preparation

In this step, the dataset is cleaned and prepared for analysis. Missing values are handled using fillna() method, ensuring the dataset is complete and consistent. Categorical variables, such as clinical data and symptoms, are changed into a numerical form.

Feature Selection and Target Splitting

The dataset is split into two sections: features and the target variable. Features represent the input variables (symptoms and clinical data), while the target variable represents the stage of hepatitis. This division allows the machine learning model to learn patterns in the features and predict the corresponding target variable, which is the stage of the disease.

Feature Scaling

Feature scaling is applied to normalize the values of the input variables using the StandardScaler method. As various features can have different ranges, scaling ensures that each feature contributes equally to the model. This process especially crucial for algorithms such as SVM, KNN, LR, and LDA, which are influenced by the data's magnitude. Transforming the input values to attain a mean equal to 0 and a standard deviation equal to 1 enhances the model accuracy and minimizes bias.

Model Training

The models—Support Vector Machine (SVM), Logistic Regression (LR), Linear Discriminant Analysis (LDA), and k-Nearest Neighbors (KNN)—are initialized and trained using the processed data. During training, each model learns the relationships between the clinical features and the stages of hepatitis. The SVM identifies the ideal decision boundary that distinguishes the data into the appropriate stages, while LR models the probability of each stage based on the input data and KNN predicts the stage by analyzing the nearest neighbors in the feature space. Together, these models provide a comprehensive approach to classifying the stages of hepatitis.

Model Evaluation

The trained model is analyzed using an individual test set to evaluate its performance. Several metrics, including accuracy, precision, recall, and F1-score, are employed to assess the model's performance.

Deployment

After the model is trained and evaluated, the model is saved and deployed in an application to predict hepatitis stages based on new input data. This integration enables healthcare professionals to make timely and accurate decisions in diagnosing the disease stages.

5.3 Workflow of Proposed System

The above Fig. 33.2 illustrates the Block diagram of hepatitis stage prediction. It begins with the user submitting symptoms and clinical data through a form. After data validation, the data is formatted and forwarded to the model for prediction. Based on the input, the algorithm classifies the condition into one of several categories: No Hepatitis, Incubation, Acute Hepatitis, Chronic Hepatitis, Advanced Stage, or End Stage. The final output is then displayed, providing the stage of hepatitis.

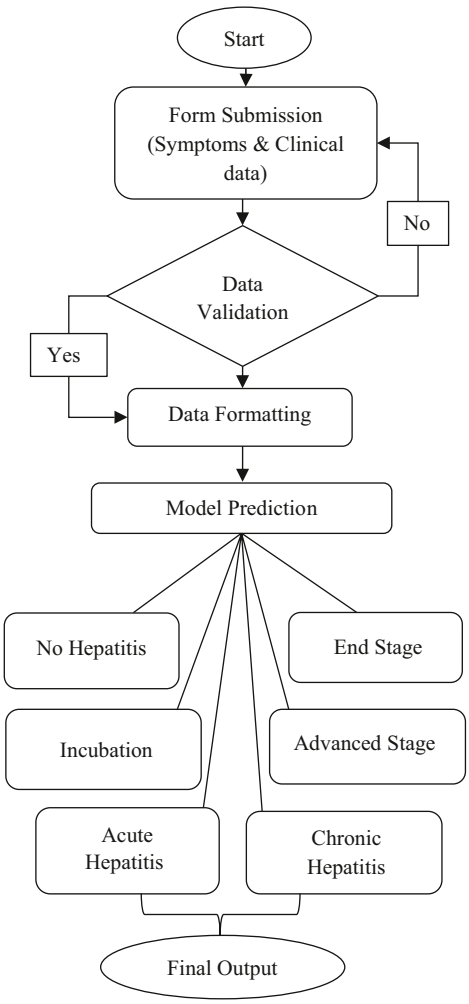

Fig. 33.2 The block diagram of hepatitis stage prediction

5.4 Evaluation Metrics

The SVM (Support Vector Machine) algorithm demonstrates the highest performance, achieving a precision of 100% and a perfect recall of 100% across all stages. This indicates that SVM effectively identifies true positives with minimal false positives, making it a highly reliable choice for disease classification. In contrast, the KNN (K-Nearest Neighbors) algorithm exhibits a precision of 90% and a recall of 91%, reflecting a moderate ability to capture true positives while suggesting potential for false negatives.

The Fig. 33.3 shows the precision and recall and Fig. 33.4 depicts the F1-Score. The LR (Logistic Regression) model shows a precision of 92% and a recall of 92%. Meanwhile, LDA (Linear Discriminant Analysis) offers competitive performance with a precision of 91% and recall of 92%. Overall, SVM outperforms the others, while KNN and LR may benefit from further tuning to enhance their reliability.

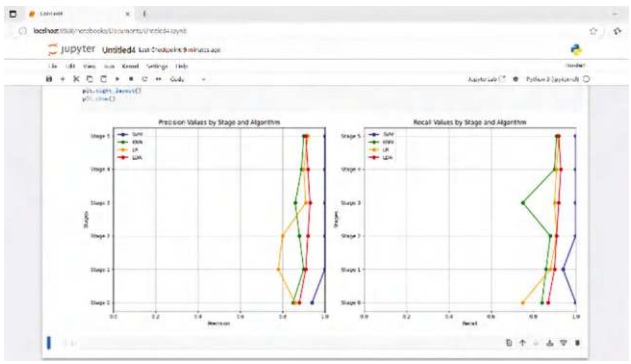

Fig. 33.3 Precision and recall

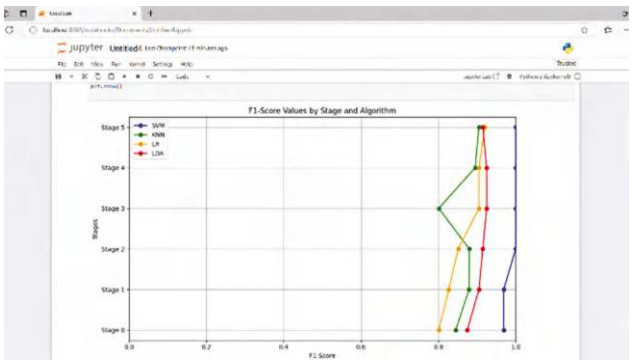

Fig. 33.4 F1-score

Table 33.1 Comparison of existing and proposed system

Feature	Existing System[	Proposed System
purpose	Identify hepatitis Presence	Identifies and tracks hepatitis progression
Algorithm Used	Logistic Regression	Support Vector Machine
Accuracy	87%	98%
Progression Analysis	Not available	Available
Key improvement	Basic detection	Enhanced accuracy with progression tracking

6. Results and Discussions

The performance of various algorithms used for predicting the stages of hepatitis are mentioned in Table 33.2. The Support Vector Machine (SVM) algorithm demonstrated the utmost accuracy at 98.88%, indicating its superior ability to classify the stages of hepatitis effectively. In comparison, the Logistic Regression model obtained an accuracy of 91.22%, while the k-Nearest Neighbors and Linear Discriminant Analysis algorithms recorded accuracies of 89.83% and 92.03%, respectively.

Table 33.2 Algorithm performance metrics

Algorithm	Accuracy
Support Vector Machine	98.88%
Logistic Regression	91.22%
k-Nearest Neighbors	89.83%
Linear Discriminant Analysis	92.03%

These results underscore the effectiveness of the SVM algorithm in accurately predicting hepatitis stages, offering significant implications for clinical decision-making and patient management. The high accuracy of the proposed system underscores its potential to enhance existing diagnostic approaches and improve patient outcomes.

7. Conclusion and Future Scope

In conclusion, the proposed hepatitis stage prediction system employs various algorithms, including Support Vector Machine (SVM), Logistic Regression, k-Nearest Neighbors, and Linear Discriminant Analysis with SVM achieving the highest accuracy of 98.88%. This system provides a highly accurate and reliable method for diagnosing and classifying the stages of hepatitis. By integrating user inputs such as symptoms and laboratory test values, it effectively predicts the disease progression, ranging from no hepatitis to end-stage liver disease. This system can assist both patients and medical practitioners in taking strategic decisions regarding timely treatment and intervention.

Future advancements in the hepatitis stage prediction system could concentrate on improving predictive modeling by investigating a broader array of machine learning algorithms, including Random Forests, Gradient Boosting and deep learning methods. These methods may improve the accuracy and robustness of predictions by capturing complex patterns in the data. Additionally, incorporating more diverse features, including genetic markers, lifestyle factors, and historical patient data, could provide a more comprehensive analysis, allowing for tailored recommendations based on individual health profiles**.**

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Healinfo Facts: AI-Based Packaged Food Contents Scanner for Health Insights

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Abstract: Good health is everyone's big issue, and reducing ultra-processed or packaged food consumption can greatly enhance their well-being. Healinfo Facts is a mobile application that can educate users about packaged foods by scanning a photo that would then reveal the ingredients and nutritional facts, and help them create healthier dietary plans. The current solutions utilize K-Nearest Neighbors for dietary planning as well as deep learning for allergy detection but most of the time miss the holistic and user-friendly experience. Our proposed Flutter application conquers this by including the advanced OCR and AI for comprehensive ingredient details, health effects, and customized dietary suggestions. It is designed on Flutter and Firebase; hence, its Optical Character Recognition capabilities determine text from images, and APIs such as Gemini provide immediate feedback on food packages. The application also has customized diet recommendations with regards to a user's needs and stores all these activities safely in Firebase. Healinfo Facts allows users to make informed choices about processed foods and the effects they have on health.

Keywords: Generative AI, Optical character recognition, Packaged foods, Health benefits, Flutter, Firebase

1. Introduction

One of the major threats to personal well-being through increased consumption of ultra-processed foods is rising. Various research has demonstrated how diet-related non-communicable diseases, such as heart diseases, diabetes, and obesity, greatly gain prevalence in populations worldwide; thus, urgency mounts for public awareness to change toward more healthy eating patterns in modern busy lives. This is because food choices directly influence several health outcomes, from everyday energy levels to long-term disease prevention, thereby driving the demand

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for practical solutions that foster better nutritional habits and informed decision-making [1].

Among the new challenges in food health, food allergies and intolerances are of considerable growing concern. These often constrain individuals to highly specific food choices, which require dependant consumers to have easy information about all the ingredients involved in the food. As people gradually become more conscious of their health, the demand for innovative tools to help people navigate such complex diets is expanding significantly. People increasingly seek to manage dietary needs in informed and efficient ways-as food products continue to diversify. In this sense, technology has an important role in empowering consumers to better understand what they eat and what might be wrong with it [2]. To counter this, Healinfo Facts has developed an application for mobile gadgets wherein users can scan packaged food in return for detailed ingredient lists and nutritional information. Harnessed within this mobile application, advanced Optical Character Recognition technology should be used to derivetext from food labels, providing instant feedback in the form of the health implications of varied ingredients. This non-technical approach benefits those with allergies and intolerances to food, as well as other dietary requirements, in having knowledge about their intakes. Its real-time ingredient analysis also coincides hand-in-glove with the growing movement of introducing technological solutions in everyday health management and further evolved consumer awareness [3].

While existing dietary planning applications often rely on traditional algorithms such as K-Nearest Neighbors (KNN) for personalized diet recommendations, they frequently fall short of delivering a comprehensive user experience. These conventional methods tend to lack the ability to integrate diverse data sets or to tailor recommendations to the unique needs of individual users. Healinfo Facts aims to overcome these limitations by combining AI-driven analysis with OCR capabilities, providing users with both in-depth ingredient analysis and personalized dietary suggestions. This advanced functionality not only helps users understand the health effects of the food they consume but also empowers them to make more conscious and healthier decisions in their everyday lives [4].

While existing applications in the genre of dietary planning rely upon the traditional algorithms K-Nearest Neighbors, or KNN, their dietary recommendations tend to fall short of being wholly comprehensive to the user. Traditional methods usually do not permit the integration of diverse data sets or cater to the needs of an individual, which may not be accomplished by a single application. With Healinfo Facts, the deficiencies mentioned above are addressed with combined AI-driven analysis and OCR capabilities that deliver in-depth ingredient analysis to users accompanied by personalized dietary suggestions. Advanced functionality to understand health effects of the food consumed coupled with the power to make more conscious and healthier decisions in daily life [5].

Finally, Healinfo Facts is one of the critical steps of diet management solutions development and partners in the public health campaign that seeks ultra-processed foods reduction along with a list of ingredients employed for that food. What the app does actually give users the nutritional knowledge required to make informed decisions about food and, therefore, health outcomes but also promotes a larger, healthier culture around awareness and responsibility of food consumption.

2. Literature Review

The health impacts of processed foods have been carried out in various works. A few mobile applications have been developed to help users choose the healthiest options for their diets. Today's OCR and AI-based solutions are also implemented to help in dietary planning and allergen detection. Still, there is a great need for more comprehensive and user-friendly experience in this domain. This literature survey discusses several recent studies on mobile applications, food-related technologies, and health management to emphasize the progress and identify the gaps that this proposed Healinfo Facts app aims to fill.

D. K. S. Neoh et al [6], The authors proposed using an Android-based API with Firebase to boost OCR for text digitization so that the scanned text can be translated into multiple languages. Such a system will efficiently process text from images hence enhancing the people's access to digital documents. This is the lead developing OCR-based applications such as Healinfo Facts, which scans food labels and gives details about ingredients.

M. Milošević et al [7], Food allergy causes are reviewed in this research by elaborating allergens via data extraction methods. The results show all factors that may cause allergies and give preventive measures. Although the app is targeted at the detection of an allergy, this research helped create the Healinfo Facts app's ability to recognize allergens from food scans and give health feedback to the users.

A. Vats et al [8], the paper discusses the development of a real-time chat application using Flutter and Firebase, emphasizing secure and fast communication. Although focused on messaging, the use of Flutter and Firebase here parallels the development of Healinfo Facts, which also uses these technologies for real-time data handling and storage, ensuring a smooth and secure user experience.

C. R. Durga et al [9], this article develops a disease diagnosis and diet advice with KNN, and it interacts with the user through the chatbot. The system predicts diseases from user input and gives diet plans accordingly. In the same way, Healinfo Facts utilizes AI to offer personalized dietary requirements based on nutritional facts from scanned food packages specific to individual needs on health.

S. Kayalvizhi et al [10], the authors propose a system using OCR to scan product ingredient lists and check for compliance with safety regulations. This solution is designed to protect consumers from harmful ingredients. Healinfo Facts builds on this by not only identifying ingredients but also providing users with health effects and personalized dietary recommendations based on the scanned data.

U. A. Madaminov et al [11], the paper discusses how Firebase could be used in mobile applications. Its real-time capabilities as well as its security features are underlined. This matches Healinfo Facts' utilization of Firebase to safely store information about users and to give feedback in real time for scanned food products. The flexibility of use of the system in different applications serves as evidence for Healinfo Facts' scalability.

S. Parveen et al [12], this research proposes a method for improving diabetes prediction using a combination of feature selection techniques and a weight-constrained neural network optimized by the L-BFGS algorithm. The method is efficient in handling large weight values in neural networks, leading to more accurate predictions. The system demonstrates effectiveness in predicting diabetes and aiding in disease management.

3. Existing System

The biggest issue with Jargon Lens is that it depends on technology to find contextually correct translations. So, in this aspect, the app tries to facilitate communication by providing actual time translation of the text, but simultaneously, a lot of idiomatic expressions, cultural nuances, and situation-specific language can cause even more misunderstanding. Much over-reliance of the user on the app can make people lose valuable interaction and immersion in culture. However, variable quality of images; very limited support for languages, and privacy concerns will further complicate the user experience and thus reduce the performance of the app in filling the communication gap in diversified settings. [13].

One important drawback of the study is reliance on subjective user assessments that might bring bias into quality assessments of machine translations. Although the questionnaire talks much about user perceptions of intelligibility, fidelity, coherence, acceptability, usability, and reading time, user preferences and interpretations of translation quality are highly diverse among end-users. This might make the findings biased towards subjectivity and, therefore, could pull conflicting results regarding the effectiveness of the respective MT systems. Consequently, this could lead to findings that do not aptly capture objective performance cross-cutting various text types [14].

The drawback of the personalized nutrition approach of Fettle is dependency on technology, which can easily turn into a privacy concern related to collecting and using highly personal information, such as genetic data. The type of federated learning employed while using the application is closer to the issue of data security and ethical utilization of genetic information in terms of dietary recommendations. This concern may deter some individuals from fully engaging with the service, limiting its overall effectiveness and accessibility [15].

The greatest disadvantage of the task management app is information overload. As one may distinguish, there are several features-from segregated folders to notifications and interface modes. It may lead to choices upon choices and functionalities that may drive users into confusion and decrease productivity. The complexity, far from enhancing user experience, leads to frustration as individuals may not find it easy to navigate the apps efficiently. This defeats the aim of simplifying your approach to tasks [16].

The remote health monitoring system is highly dependent upon the quality and integrity of the collected data. The overall system is highly dependent on the non-reactive preference grading of vital parameters including the quantities of blood oxygen, temperature, and pulse rate. Failure or less accuracies in the data collecting process may contribute towards wrong classification of patient priorities that ultimately cause inadequate or delayed medical facilities to the critical patients. Such reliance on technology requires strong validation and maintenance to ensure performance over time, which can be quite challenging in realistic scenarios [17].

An important disadvantage related to MyFood is its dependence on the quality and comprehensiveness of the data utilized. The efficacy of the preference neural network and the capabilities of the entire platform rely on a high degree of information about food components, ingredients, and restaurant menus being current and correct. Data integrity and a robust database pose significant challenges in a rapidly changing food environment for ensuring [18].

4. Proposed System

The proposed Healinfo application is going to be a mobile tool, somewhat similar to that with which one will be

armed when it comes to knowledge about packaged foods. It shall use advanced OCR technology upon extraction of text from food packaging images accurately to help the user acquire information on ingredients very quickly. After extracting the text, it analyzes its ingredients and continues on to deliver further and even more in-depth information about the health implications of these ingredients in terms of their benefits, risks, as well as allergens. One of the big features of the application is that it will devise individual nutritional plans addressing specific preferences and health objectives; thereby ensuring individuals can make informed choices to suit their needs. Designed on Firebase, the application ensures that both data and authorization are handled safe and sound, hence reliable and user-friendly.

Advantages

1. **User-Friendly Interface:** The application is designed with an intuitive layout that makes it easy for users to navigate and access information effortlessly.
2. **Comprehensive Insights:** By combining OCR and AI, the app offers in-depth analysis of food ingredients, helping users understand what they are consuming.
3. **Firebase Integration:** By utilizing Firebase, the app ensures reliable data storage and user authentication, enhancing the overall user experience and security.
4. **No need of Datasets:** By the integration of Gemini, there is no need of datasets and again training them. It reduces the memory and execution time which is helpful and being more advantageous compared to other models or applications.

Working Process

Step 1: User Authentication: The user sees a splash screen when they first launch the application. If they have already registered, they can proceed to the login page. Another method for signing up or logging in with Google authentication exists.

Step 2: Questions: The user was directed to the questions page after successfully completing the authentication process, where they were required to provide answers.

Step 3: Main Interface of the App: After selecting "Done," the user is taken to the app's main page, where dietary suggestions are displayed. Our app has a navigation with home, profile, scanner, and history pages located at the bottom.

Step 4: User interaction and image capture: You can upload an already-existing image or take a picture of the ingredient label on a packaged food item. Optical Character Recognition (OCR) technology is used to process the image and extract the text.

Step 5: Text Analysis and Ingredient Detection: Next, using Natural Language Processing (NLP) techniques, the captured text is evaluated to identify each ingredient and any relevant nutritional information. Gemini is used to analyse the meaning of components and determine their potential health risks.

Step 6: Health Risk and Benefits Assessment: To determine the possible hazards or benefits to health, the app takes the help from Gemini AI of recognized components, allergies, and dietary information. The ingredient list is compared to data on common allergies, harmful additives and nutrient values.

Step 7: User Feedback and Dietary Plan: The user is instantly provided with detailed health insights, highlighting any risky ingredients and nutritional information. Based on the analysis, users can create personalized dietary plans stored in Firebase, which are tailored to their specific health needs.

Step 8: AI-Generated Recommendations: The app makes nutritional recommendations or healthier substitutions based on user preferences and their Firebase-stored health profile.

Step9: History: The information from the user's earlier scanned photographs is displayed here, together with the data user obtained from the Gemini.

Step 10 Logout: After the usage of they can logout from their user account by opening the menu bar and clicking on logout.

Salient Features of Proposed System

1. Users can safely log in and out using Firebase Authentication and Firestore Integration, which implements login, logout capability. Every time a user logs in, Firestore holds user-specific data.
2. Text Recognition with Google ML Kit: Google ML Kit provides a robust text recognition feature that enables developers to seamlessly integrate machine learning capabilities into their applications.
3. Gemini API Integration: Gets AI answers by sending questions with user input or scanned text to the Gemini API and the response from that Gen AI will be displayed on the interface. Users can ask the queries regarding the ingredients and their advantages and disadvantages.

5. METHODOLOGY

Optical Character Recognition (OCR): The Healinfo Facts application employs OCR technology. Users scan the packaging food labels using their smartphones with a service. OCR is actually a mechanism that extracts text from an image: some of these are nutritional content, ingredient lists, and warnings for possible allergens. In this way, a technically advanced use of OCR frameworks such as Google's ML Kit and A Flutter plugin to use Google ML Kit Text Recognition is implemented while high accuracy in identifying different fonts and text formats is ensured.

Flutter for Cross-Platform Development: The Healinfo Facts uses a highly flexible cross-platform framework known as Flutter. Building this app, it comes with an extensive library of widgets in Flutter that deliver a visually appealing UI adaptable and responsive enough for users to operate on both platforms quite comfortably.

Firebase for Backend Services: The application integrates Firebase for some of the most important backend services, such as user authentication and data storage. The cloud functions and real-time database features of Firebase thus allow the user to have personalized diets as well as track nutritional intake in multiple sessions.

Gemini for Personalized Diet Recommendations: The Generative AI, LLM functionality to give personal diet recommendations. The Gemini API works through the use of AI algorithms based on the user's input and their scanned food data.

Integration of OCR, LLM, and Gemini API: The Healinfo Facts app relies on the strength of OCR, LLM, and the Gemini API as one single combined unit that creates an automated scanner for food labels, interpreting them into health risks, and ultimately delivering actionable dietary advice.

5.1 Proposed Model

The representation for a Flutter application that uses Firebase to authenticate and store data may be depicted in Fig. 34.1. Here, Flutter is used to create an appropriate user interface and functionality for the given application.

At the beginning, the users authenticate at login or sign-up pages of the app, which Authentication in Firebase can handle. Once the users are logged in, a series of questions regarding diet choices and health concerns are presented to them; safely and securely stored by Cloud Firestore, a feature in Firebase.

Users can scan photographs or upload them, including those of ingredient lists, and the OCR will extract the text. Even through that packaged food, users can ask AI-based questions about the causes and advantages, and generative AI can provide diet recommendations. For every detail filled in, the system gives the user a diet based on that. Users may upload extra information at any time so that upgrades are continuous. Because it connects to Firebase, all information is updated in real-time while safely stored.

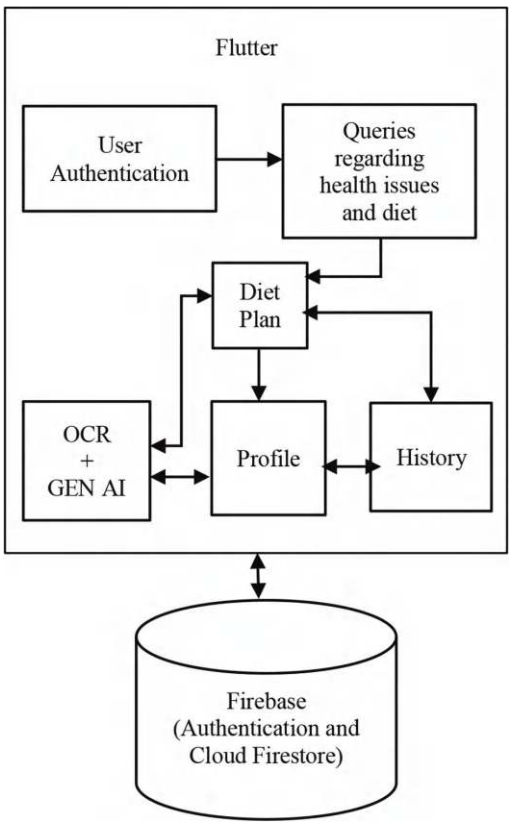

Fig. 34.1 Block diagram

5.2 System Architecture

The above Fig. 34.2, illustrates a Flutter-based application, which outlines its main navigation and functionality. It is the proposed mobile application workflow which begins from the splash screen and ends when the user logout. The application starts with a Splash Screen followed by a Signup/Login page for users to authenticate themselves. Upon successful authentication, users get redirected either to Questions Page, or for new users, to the Signup Page.

In Questions page the users give responses to the queries after completion they will be navigated to the Home Page where it comprises Bottom Navigation allows easy transition between different sections of the app and Menu Bar in which there are Profile, Diet plans and Logout buttons. This is the start page and can be a Diet plan or recommendation page where all the information related to diet will appear.

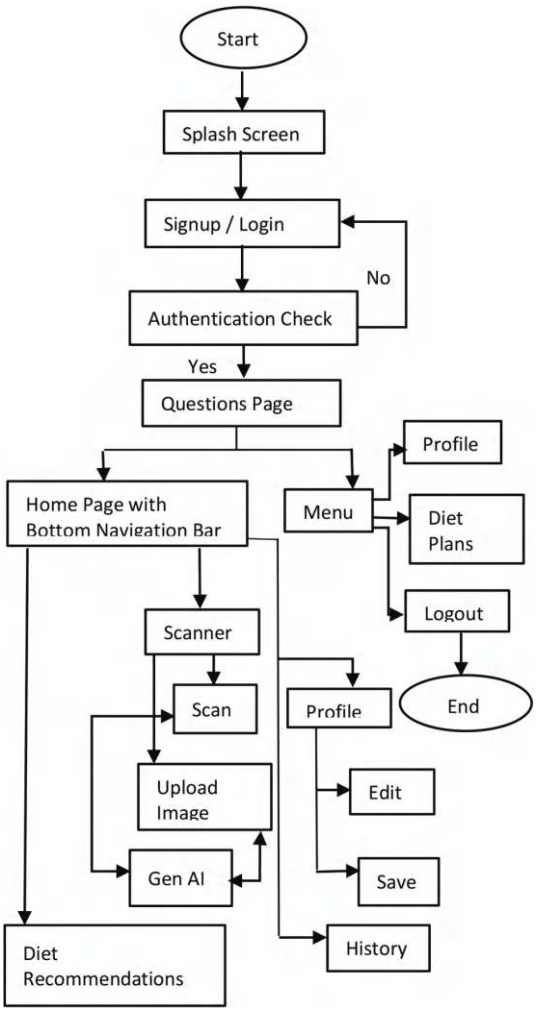

Fig. 34.2 Workflow of proposed mobile application

Under that in the bottom navigation bar, there is a scanner, and users can upload or scan images directly from their devices with a scanner. Then, the Gemini API receives the processed extracted text from the scanned image. The Gemini API uses NLP and is a Large Language Model to extract relevant information from a picture, perform text recognition, or analyze material. The outcome of picture processing appears on the scanner page. The user's profile can be managed on the Profile Page. Here, the user can view and edit the user personal details. The changes will appear on the Edit & Save page.

Apart from the scanning of images, the application provides users with a History Page on which it is allowed so that a user can reminisce about his/her past activities, such as images uploaded or scanned and outcomes. The interaction of the scanning feature with the Gemini API makes enhancing its document management feature through the fast, precise, and efficient handling of documents possible.

Menu bar is divided into two parts: profile and diet plans and logout. Users can logout from the application, and they get taken out of the application it means that user account will be logged out and he/she is able to login or signup through signup or login page.

6. Results and Discussions

The Questions page in Fig. 34.3 asks the age, gender, health issues, and also several other questions of the user. After filling up the form it presents the user with the home page; In scanner section, it consists of scan and upload buttons which allows a person to capture the image of ingredients list and nutritional information once clicked on the scan icon, as shown in Fig. 34.4.

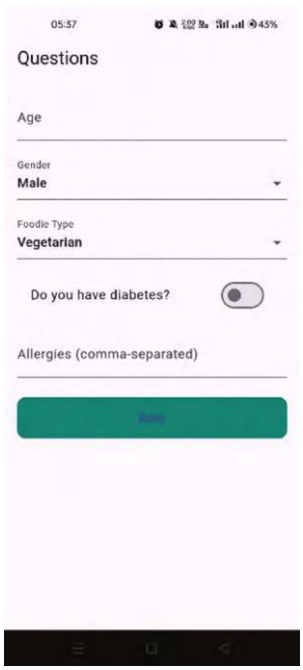

Fig. 34.3 Questions

Fig. 34.4 Scanned image

Figure 34.5 represents the text area, where the information is visible. The scanned information can even be questioned by users. Profile, history, and diet advice pages are available there. When the user logs in to the application, the user gets verified and added in the authentication part of Firebase, which has been elaborated in Fig. 34.6. The Firestore contains answers to questions asked on the questions page, as shown in Fig. 34.7.

7. Conclusion and Future Scope

In conclusion, the Healinfo initiative aims to make a real influence on consumers' health by giving essential insights into the nutritional content of packaged goods.

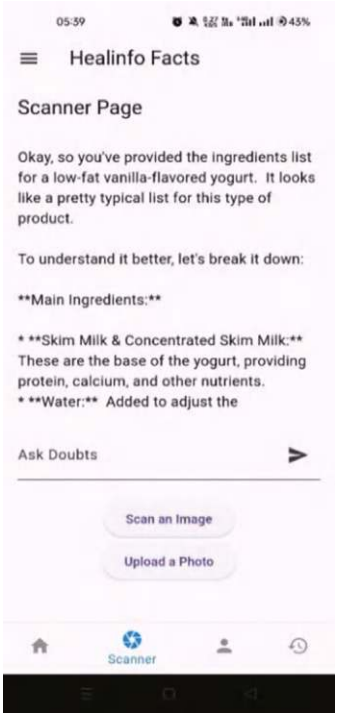

Fig. 34.5 Information of scanned image

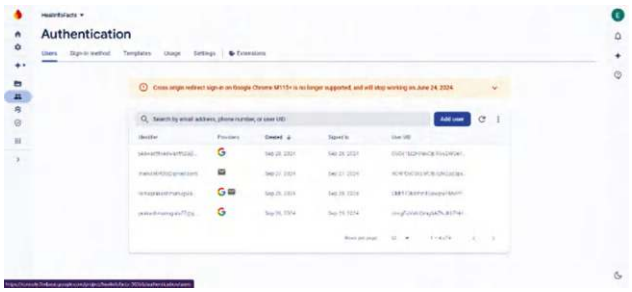

Fig. 34.6 Firebase authentication

Fig. 34.7 Firestore

The software helps users make educated food decisions by allowing them to scan food products and instantly obtain feedback on components and their potential health risks. The application of AI enhances the user experience even further by providing individualized meal plans that address each person's unique health requirements. In the future, the project could grow significantly by adding community elements to encourage user participation, refining the AI insights, and expanding the database of food items. Collaborating with nutrition experts could also increase the legitimacy and effectiveness of the dietary suggestions presented. Healinfo is essential in encouraging better eating practices and enhancing public health as more people become aware of the risks connected to ultra-processed meals. There will be a chance of adding many features to this application in the future, like streamlining the user interface and creating custom diet suggestions for people. Improvising the response way better with higher version of LLM that is advanced Generative AI.

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Semi-Supervised Learning Method for Detecting DDoS Attacks

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Abstract: Even though sophisticated Machine Learning (ML) techniques have revolutionized DDoS assault detection methods in recent years, the attack is still regarded as one of the most significant danger categories on the Internet. The vast majority of current methods for detecting Distributed Denial of Service can be divided into two categories: supervised and unsupervised machine learning. Labeled samples of network traffic datasets are selected for learning via supervised machine learning categories for DDOS detection. Unsupervised machine learning techniques, on the other hand, examine incoming traffic for anomalous patterns without requiring any training labels. The two remaining methods must deal with substantial amounts of false alarms, misclassifications, and network traffic data. In this paper, we describe a semi-supervised machine learning approach to DDOS detection using online sequential techniques, Network Entropy estimate, Co-clustering, Information Gain Ratio, and the Extra-Trees algorithm. Additionally, the method includes an unsupervised component that lowers the quantity of common traffic data required for DDoS detection, enhancing accuracy and lowering false positive rates. Additionally, the supervised component makes it possible to efficiently classify DDoS activity in addition to lowering the false positive rates of identified traffic.

Keywords: Entropy estimation, Information gain ratio, Co-clustering, Extra-trees algorithm, Semi-supervised ML approach

1. Introduction

The DDoS attack is still one of the largest hazards to the internet, even with the tremendous advancements in information security technologies in recent years. The attack's main goal is to prevent unauthorized individuals from accessing web sites. The quantity and velocity of traffic flowing toward the target typically determines

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how severe the attack will be. Direct DDoS attacks and reflection-based DDoS assaults are the two main types of DDoS attacks. In order to reroute network ports toward the intended target, the attacker uses compromised internet-connected devices, sometimes referred to as zombie hosts, in the Direct DDoS attack.

In the case of reflection-based DDoS attacks, the assailants employ zombie computers to gain access to another set of compromised machines referred to as Reflectors, which are utilized to launch high volumes of attack traffic toward the target machine. Not long ago many destructive DDoS assaults took place that took down over 70 crucial Internet services. The aforementioned abuses have been made possible with the help of Cloud Computing where enormous attack traffic above 665 Gb/s has been orchestrated. Trying to analyse large amounts of network traffic in that manner is neither efficient nor cost-effective and usually culminates in collapse of intrusion detection systems. Advanced intrusion detection systems have been developed through data mining techniques over the last 20 years.

The most popular methods for tackling the broad data mining issue of intrusion detection include artificial intelligence, machine learning, pattern recognition, statistical techniques, and information theory. The four standard stages of using data mining techniques in general and machine learning techniques in particular are selection, preprocessing, transformation and interpretation. However, many due to the perceived non-importance of these activities in the context of intrusion detection applications, it is easy to assume that these preprocessing and transformation phases are unimportant, while selection, mining and interpretation phases have very clear purposes of relevant information deposition and noisy data removal, and intrusions detection respectively.

The information gain ratio is then calculated using the mean entropy of the individual network header characteristics, the specified quantity of network traffic data at the present instance of time, and each of the existing clusters. Extremely high information gain ratio clusters in network traffic data are deemed suspicious and are therefore selected for preprocessing and classification using a set of classifiers based on the Extra-Trees algorithm.

2. Literature Review

Y. Chen, Z. Lin, X. Zhao and G. Wang and Y. Gu et al. [1]. Classification is one of the most prominent research topics in the area of hyperspectral remote sensing. Over the last twenty years, there have been increasingly many proposed solutions for the issue of hyperspectral image classification. However, most of those solutions do not tend to do deep hierarchically feature extraction. In this work, we will first introduce the meaning of deep learning in the context of hyperspectral data classification, which has not been previously introduced. First we discuss about classical spectral information oriented classification and explain why we adopt the stacked autoencoders.

In the opinion of Y. Xin et al. [2], the growth of the Internet equally indicates the heightened threats posed by the internet in terms of Cyber Crimes and this is not good for internet security. This survey discusses major literature surveys related to machine learning and deep learning with focus on network intrusion detection systems and every ML/DL approach is briefly explained. At the same time, distinct team's responsibilities are assigned to present each method in an index-chronological or index-thematic order: to read and summarize the papers, respectively.

As noted by Li, Zhang and Wang et al. [3] appellate legal connected and automated vehicle systems present a tremendous promise for improving and harnessing the significant advantages on-road traffic in areas ranging from road safety enhancement, traffic capacity improvements to reducing fuel consumption on long voyages. In this paper we propose a four-part analytic structure for platoon systems modelling formed from the approaches of network control, literature survey on the so-called networked awareness, integration of the essential building elements into a unified system, and controller design application cases.

J. Mater. Chem. A et al. [4]. The study presented in the current communication proposes a novel scheme for data aggregation in wireless sensor networks (WSNs) which is claimed to be more energy efficient and secure. The authors discuss the challenges posed by the traditional data aggregation techniques in reducing the energy consumption and the concern of possible attacks.

Hassan, S. U., Khan Ghani, M. U, Iqbal, R., Mumtaz, S., & Khan, M. Z. et al. [5]. The original technique of data aggregation introduced in the present work is targeted at smart healthcare systems based on the Internet of Things. Medical data are secret and IoT devices have limited power resources, thus security and energy efficiency in such systems are the key problems the author tackle.

X. Li, H. Zhang, and Y. Wang et al. [6]. In this paper, the authors put forward an innovative data aggregation scheme for wireless sensor networks, which enhances the security and energy efficiency in data transmission. The proposed solution tackles some of the limitations of conventional data aggregation methods including attacks and high energy consumption.

Z. Li, J. Hu, Y. Li, and X. Zhang et al. [7]. The purpose of this work is to propose a new scheme for chunk aggregation in the wireless sensor network (WSN) with a focus on security and energy improvement. In this paper, the authors point out the problems associated with traditional data aggregation techniques, including susceptibility to attacks and high energy costs.

X. Li, H. Zhang, Y. Wang et al. [8]. The authors introduced a new model for intrusion detection that uses hybrid deep learning techniques from both CNN and RNN networks. The focus of the model is on efficiently capturing the time-series dependent patterns and also understanding how the different traffic works at one time.

3. Existing System

Given that semi-supervised approaches utilize both labeled and unlabeled data, they have become an interesting method in the detection of DDoS modeling systems. Here are some existing systems worth noting:

1. *Hybrid Deep Autoencoder and SVM:* In this architecture a deep autoencoder is used for feature learning and support vector machine (SVM) is used as a classifier. The autoencoder picks up hidden features from both the labeled as well as the unlabeled data which is given to SVM for classification.
2. *Graph Based Deep Autoencoder:* This work applies graph convolutional networks (GCNs) in learning the interconnectivity of network nodes, rendering graph representations. The representations learned are utilized in training a deep autoencoder for anomaly detection.
3. *GAN for Network Anomalies Detection:* GANs can be used for producing synthetic normal traffic sample like epochs. A system can be made to detect anomalies by incoming traffic to these normal simulated samples.
4. *Conditional GANs:* Conditional GANs can be learnt to generate normal traffic samples based on given network conditions. This enables a more specific anomaly detection. Contrastive Learning: This technique learns representations by comparing similar and dissimilar pairs of data points. It can be applied to DDoS detection by comparing pairs of normal and anomalous traffic samples.
5. *Techniques for Clustering:* Clustering methods help to segregate similar elements within the data. In this case, the deviating elements can be classified as anomalous since they do not belong to any of the clusters.

To conclude, semi-supervised learning in the prevention of DDoS attacks employs deep autoencoders, GANs, and self-supervised methods to obtain representations from both sources of data labeled and those unlabeled. These representations are later employed to classify traffic in the network as either normal or abnormal enabling DDoS attack detection.

Disadvantages of the Existing System: While the proposed semi-supervised learning method offers several advantages for DDoS detection, it also has some potential drawbacks:

Data Quality Sensitivity: The efficacy of the approach might depend on the quality of the available labeled data and the unlabeled data as well. The presence of noise or bias in the data can affect the learned representations and the anomaly detection performance.

Operational Costs: The process of training and implementation of deep learning models can be extremely resource-demanding especially with very big datasets. It may restrict the use of these models in environments with limited resources.

Difficulty with Model Interpretation: The very complexity of the deep learning architecture makes it very challenging to explain the rationale behind the decisions made by the model. This may impede comprehension and repair.

Class Implant Attacks: Considered models are also vulnerable to poising attacks when the adversary is able to craft input data in such a way that it misleads the model. Such a scenario may threaten the performance of the DDoS detection mechanism.

Concerns about Transferability: Assuredly, the submitted algorithm is designed for DDoS attack mitigation and may perform poorly against other forms of network assault.

4. Proposed System

This section presents the methods used for the detection of DDoS attacks as well as the suggested technique in detail. Preprocessing data sets, assessing traffic entropy, online co-clustering traffic, calculating information gain ratios, and classifying traffic are the five main elements of the suggested methodology. This section presents the network security paradigm designed to enhance DoS/DDoS detection capabilities.

The entropy of various attributes present in the flow headers of the networks is evaluated using a time-based sliding window approach. Entropy, by definition, becomes a measure of the qualitative nature of a certain distribution – in this case, the distribution of the data pertaining to the network traffic. This task is facilitated by the analysis of network flow entropy at discrete measurement intervals as it

reduces the complexity introduced by high dimensionality of the distribution of traffic being transported and makes it possible to quantify the dispersion of the traffic with just one number. Determining entropy also uses flow size distribution statistics, packet and byte counts from origins and destinations. The application of flow size distribution dynamics explained by the fact that in the course of a DDoS attack, the infected machines focus on a single target with an immense stream of packets leading to high traffic levels. The logic behind this is that it is relatively easy to observe changes in the dynamics of flows within a network that has been subject to a DDoS attack by analyzing the changes in the entropy of the flow size distribution over time.

The following quantifies the use of Shannon's entropy to measure the information contained in the flow size distribution: Cleaning and transforming data enables the optimization of the data set by eliminating unnecessary and extraneous elements which increases the integrity and efficiency of the detection model.

Estimation of Network Traffic Entropy: Entropy is a method which calculates the order of traffic. DDoS or distributed denial of service threats can be noticed early and their enabling threat controlled by the tendencies of traffic where any increase in randomness- entropy is classified as an anomaly.

Online Co-Clustering: At this juncture, similar traffic patterns are clustered in order to detect attack behaviours in their infancy, where the network environment is constantly changing.

Use of Information Gain Ratio: The system determines the features to include in construction of the model by ascertaining Information Gain Ratio, thus ensuring that the most important factors for correct prediction of attacks are included.

Network Traffic Classification: A DDoS attack is classified as a normal or defence inducing attack through an adapted semi-supervised machine learning, using both labelled and unlabelled information to cope with changing attack trends and enhance performance. For semi-supervised DDoS detection approaches, a set of publicly available datasets are reviewed in order to train and test the system. These datasets are network traffic that which provides normal and attack traffic useful in DDoS detection.

Below are the most used databases for this aim:

Data Set Centric - as a tool for combatting DDoS attacks: A comprehensive set of real, anonymized network traffic data subjected to DDoS attacks. Captures numerous attack types and attack volumes. Best suitable for understanding real world DDoS trends and their behaviours.

Canadian Institute for Cybersecurity Intrusion Detection System: This dataset comprises normal traffic as well as traffics designed for attacks such as DDoS making it highly relevant in the machine learning model training.

NSL-KDD: It is an advanced form of KDD 99 data base that provides information on a number of attack strategies such as DoS. They also come in handy for general purpose intrusion detection systems.

Data set of DEFCON DDoS: It is the Network Traffic data from the DEFCON hacking competition, where datasets of real-life high volume DDoS attacks are recorded for assessment purposes.

ISCX Botnet Dataset: This contains DDoS traffic created by a botnet and explains the behaviour and ways of attacks by botnets.

UNSW-NB15: This is a dataset that contains numerous networks attacks especially DDoS, and provides good sources of classified traffic data for detailed analysis. Semi-supervised learning is one of the paradigms of machine learning which aims to build a model on both labeled and unlabeled data. This is useful in a situation where it is costly or takes a long time to label the data. In terms of detection of DDoS attacks, this can be performed in order to:

Make use of unannotated network activity to the fullest extent: Since the majority of network activity has no label attached to it and we cannot afford the luxury of manual label attachment of the same for purposes of training.

Enhance model efficacy: Involving raw data within the framework enables the model to capture more advanced internal structures and consequently perform more effectively on novel attacks.

System architecture bets on the proposed system. DDoS attack detection typically using a semi supervised learning system may comprise the following: Data Preprocessing: Feature Extraction: Relevant characteristics of the network traffic are identified for example how time taken for packet interarrival, packet length, source and destination of the packet.

Parameters Normalization: Bring the parameters in one scale so that the comparison is done fairly. Understanding features Labeling of existing datasets multiplicate the intuition Behind *Augmented Dataset:* Initial training datasets containing only normal data and expert-provided segmentations provide little variation for learning. Transitions are made with every noisy data augmentation feature – as the creating of models to robustly classify different pathology classes is much cooler in 3D spaces. And with 3D structures, there is a distinct architectural discrepancy to be had! STRATEGY LABELING Self-

Training: Annotate the small set of data and build the first model. After that predict the labels of the remaining unlabeled data with the trained model. In the next stage the predicted labels are used to update the model. Co-Training Two or more trainers work on different aspects of the same data and label the idle data. Dissimilar_View_Model_1 or Dissimilar_View_2 and repeat Steps 2 - 3 to unlabeled data returns Model Training and Selection: Training Method Selection: Pick appropriate semi supervised technique such as Graph Convolutional Networks (GCN), Self-Training, Co-Training etc.

Hyperparameter Tuning: Adjust model parameters (such as learning rate, regularization, etc.) for maximum performance.

Evaluation: Metrics: Assess the model performance on the test set using platform suitable metrics such as accuracy, precision, recall, F1 score among others. Potential Benefits of Semi-Supervised Learning for DDoS Detection Enhanced data utilization: This makes use of both labeled and unlabeled data, thus utilizing available data resources to the fullest.

Better generalization: More complex forms of learning may be achieved allowing the system to generalized better against unseen forms of attacks.

Less need for labeling: More automated labeling process can be achieved. Limitations and Future Perspectives Quality of labeling: The initial labeled data has a great bearing on the succes of the model.

Labels of high quality provide the model the right data to work with. Better decision-making and more precise forecasts result from this.

Model interpretation: Sometimes, it may be hard to understand and decipher the workings of sophisticated models.

Adapting to different forms of attacks: New forms or classes of attacks should also be accommodated by the system.

A Specific Techniques and Factors Methods based on graphs: GCNs are capable of assimilating information regarding network nodes and the structure of the network itself. *Combinations of models or ensemble techniques:* The use of more than one model comes with added advantages; increases resilience and accuracy.

Active learning: Learning where to seek out the most informative examples by labeling those that are most likely to improve the model. By addressing these difficulties and seeking new approaches, semi supervised learning is likely to help improve the detection of DDoS attacks significantly.

5. METHODOLOGY

Three datasets were used in this paper: the UNSW-NB15, the UNB ISCX IDS 2012, and the NSL-KDD. Additionally, there are four different attack classes in the NSL-KDD dataset: Denial of Service (DoS), Probe, R2L, and U2R. Basic features, traffic attack features, and content attack features are the three primary categories into which the database's 41 attributes fall. There are 148,517 records in total between the training and testing sets. This dataset was selected for three primary reasons. First of all, it is the most well-known dataset in the research community for assessing IDS performance. Additionally, a significant portion of the assault traffic is included, with DoS attacks accounting for 34.62% of the dataset.

Algorithm 1: Estimating the entropy of the network FSD features

avgEntropy (data, s)

Input: Network traffic data (data), Features set S

Output: Average Entropy

$$H_s \leftarrow \{\}$$

for each X in S do

$$p(x_i) \leftarrow \frac{\sum_j^N x_i}{N}$$

// Estimate the probability mass function.

$$H(x) \leftarrow \sum_i^n p(x_i) \cdot \log\, p(x_i)$$

// Compute the Shannon entropy

$$H_0(X) \leftarrow \frac{H(X)}{\log n}$$

// Normalize the entropy

$$H_s \leftarrow H_s \cup H_0\,(X)$$

end

$$Average\ entropy \leftarrow \frac{sum(H_s)}{4}$$

// Return average of the FSD entropy time series

Since DDoS Traffic Classification accounts for 19.11% of the whole dataset, it is an extremely important parameter for any DDoS detection system's operation. Nine different attack vectors of contemporary attacks and fusions of new types of normal traffic are present in the UNSW-NB15 dataset. Flow attributes, Basic attributes, Content attributes, Time attributes, and Other produced attributes are the five categories into which its 49 attributes are divided. There are 257,705 records in all in this dataset, and each record has been labeled as either normal or attack type.

As much as semi-supervised learning is a good method, there are other methods that can be researched on in relation to DDoS attacks detection.

Deep Learning Recurrent Neural Networks (RNNs): Used to model sequential processes by making the temporal dependencies within the network traffic patterns.

Convolutional Neural Networks (CNNs): Useful in extraction of spatial information of the network traffic.

Generative Adversarial Networks (GANs): Employs the use of the synthetic data generated from attack models in enhancing the training sets.

Machine Learning Decision Trees: It is possible to devise a set of rules that will facilitate the classification of network traffic.

Random Forests: A type of ensemble method that involves constructing and combining several decision trees.

Support Vector Machines (SVMs): It is possible to determine the hyperplane that best divides traffic into normal and attack classes.

Statistical Approaches Anomaly Detection: the use of statistical techniques such as outlier detection to find incidences when the traffic pattern strays from the normal.

Time Series Analysis: Detecting the presence of anomalies by treating and reviewing the network traffic as a time series data.

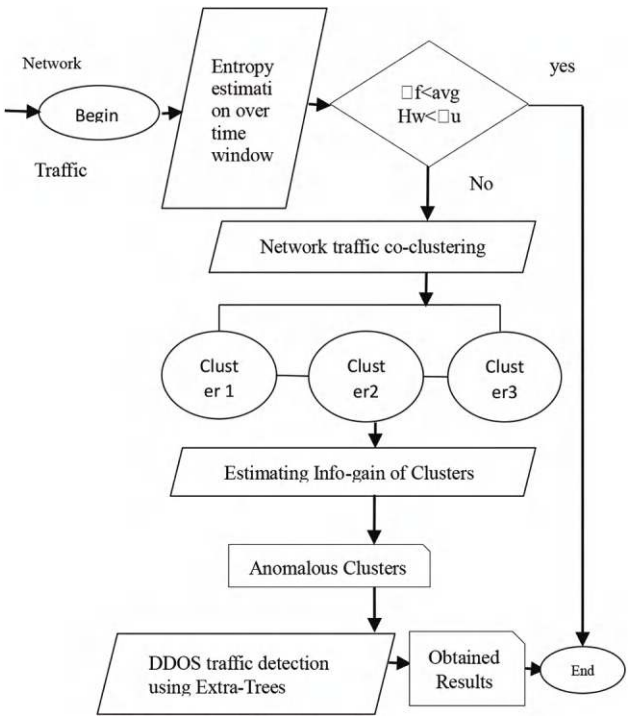

Fig. 35.1 Flowchart of the proposed approach

Hybrid Approaches: The use of more than one technique-improve efficiency and accuracy of detection by utilizing the benefits of other techniques.

Behavioural Examination of Users: Analyze Attacks by Observation of User Behaviour, Understand the normal behavioural tendencies of users and alert on any abnormalities that may signify an attack.

Network Flow Analysis Assessing Network Flows: Assessment of other types of network traffic for the purpose of finding and monitoring anomalies.

Data Unavailability: Clearly, the presence of clean, labeled or unlabelled data will affect the method that can be employed. Types of Attacks: The type of DDoS attacks you wish to detect will affect the choice of approach. Resources: Various methods have different computational resource requirements so ensure you know what you have. Performance in Real-time: In instances where detection in real-time is very important, opt for methods that allow for processing of data in a fast

6. Results and Discussions

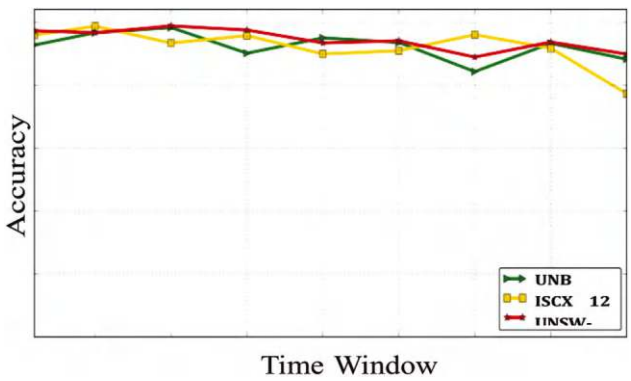

Fig. 35.2 Esteem of the suggested approach on datasets as a function of varying time window sizes

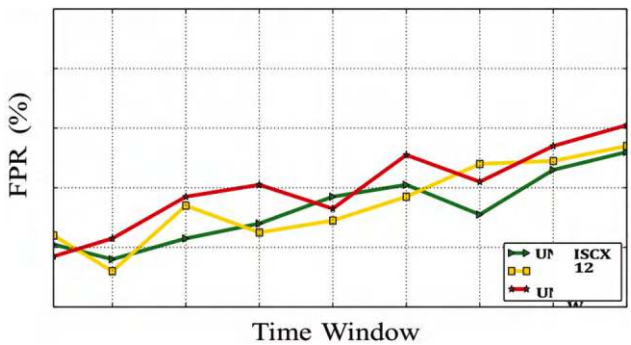

Fig. 35.3 Different time window sizes for the datasets variation of the proposed approach

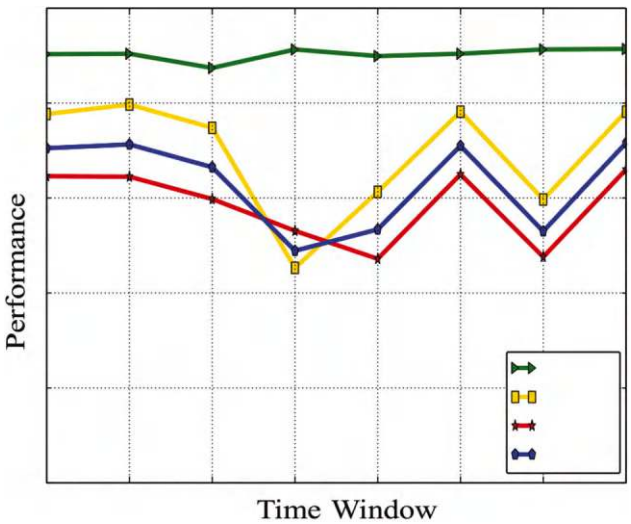

Fig. 35.4 Clustering performance mean values for every time frame in the test set

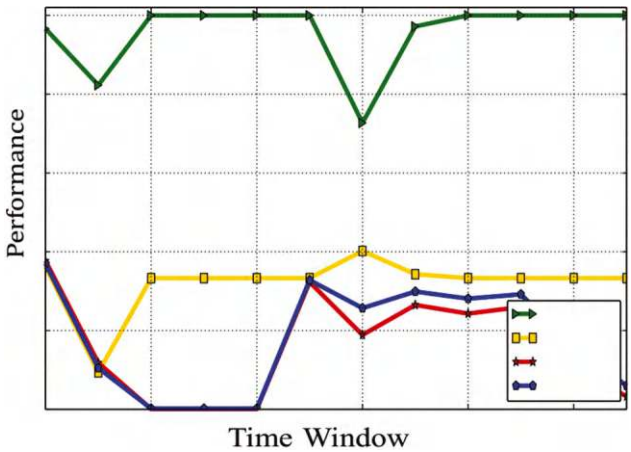

Fig. 35.5 Mean clustering effectiveness for each of the assumed time intervals in the test set of the data structure

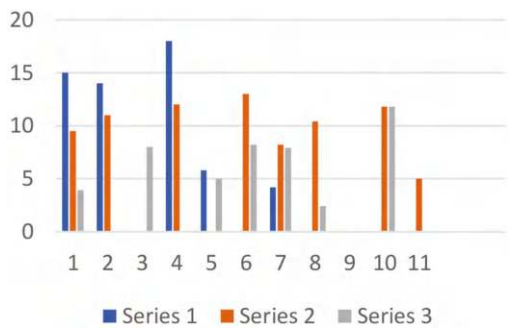

Fig. 35.6 The percentage of data within each suspected time frame, co-clustering and the information gain ratio have been used

7. Conclusion and Future Scope

In this research, we investigate a novel semi-supervised DDoS detection method based on information gain ratio, Extra-Trees ensemble classifiers, entropy estimates, and co-clustering. In light of this, the entropy estimator estimates and tracks the entropy of the data flow over the network. It is based on a time-dependent sliding window structure. The incoming network traffic for the specified time window is then co-clustered into three sets after an entropy breach. The average entropy of the features of the network headers recorded throughout the designated time period and the distinct clusters that were generated is then used to calculate the information gain ratio. Outliers are considered to be productive clusters of network data with a high information gain ratio and deep categorization. Additionally, the `Extra Trees` ensemble classifier enhances cognitive abilities. The effectiveness of the suggested method was assessed by a number of experiments on three publicly accessible benchmark databases: UNSW-NB15, UNB ISCX 12, and NSL-KDD. The experiment's accuracy and false-positive rate results were comparable to those of more contemporary DDoS assault detection techniques and cognitive further with the `Extra Trees` ensemble classifier. Several experiments were performed to evaluate the effectiveness of the proposed approach on three publicly available benchmark databases: NSL-KDD, UNB ISCX 12, and UNSW-NB15. The results of the experiment in terms of accuracy and false positive rate were fair enough to the recent methods of DDoS attacks detection.

Semi-supervised learning for DDoS attack detection has garnered several potential research prospects within the field. For instance, sophisticated deep learning models that successfully model the patterns of data and temporal sequences of network activity will be a way forward. In addition, this emerging research to develop domain-specific knowledge and adopt adversarial training strategies would work to improve the strength of shielded semi-supervised models against new variants of DDoS attacks. In addition, the integration of that semi supervised learning with other techniques such as reinforcement learning or active learning can lead to more effective and flexible detection schemes. Given the growing prevalence of DDoS attacks, continual advancements in semi-supervised learning are poised to change the face of network security and safeguard essential infrastructures against these threats.

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Forecasting Ride-Sharing Demand: Machine Learning Strategies for Effective Planning

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Abstract: The demand of ride-sharing services is determined by a very wide and complexly composed list. In light of the shortcomings of previous demand prediction models, this paper introduces a model for ridesharing demand forecasting that employs the Particle Swarm Optimization algorithm. The intelligent algorithm's deeper understanding of ride-sharing service demand over time and improved search skills allow the machine learning model to adapt parameter modifications to different geographical contexts. The simulation results are verified to establish the feasibility and effectiveness of this improved algorithm and can potentially offer a good approach towards aiding in the support and study of an effective scheduling and distribution of ride-sharing services within cities. Such findings point towards optimizing resource allocation, reducing traffic congestion, and ensuring better service availability to eventually provide actionable recommendations to ride-sharing companies for the better delivery of services.

Keywords: Decision tree, Random forest, Xtreme gradient, Cat boost, LGBM and machine learning techniques

1. Introduction

Worldwide, public ride-sharing services have emerged because of increased motorization and urbanization. Thanks to these services, traffic congestion has decreased, and more people are opting for low-carbon, eco-friendly modes of transportation. As an integral part of the transportation network, public ride-sharing services in cities solve the 'last mile' issue by giving city inhabitants more flexible and accessible transportation options. While these systems do have some positive aspects, they also have some negative aspects, such as uneven vehicle dispatch and distribution, which can make it more difficult to rent and return cars and slow the expansion of ride-sharing services [9, 10].

The bedrock of a thriving ride-sharing business is precise and efficient demand forecasting. Time, location, weather, and seasonality are just a few of the many factors that affect the demand for ride-sharing, making it a complex phenomenon that the proposed models would have to account for. Models for demand forecasting such as decision trees and random forests are presently under investigation; nevertheless, they

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experience overfitting problems, especially when dealing with redundant data, in addition to bike-sharing demand analysis that use spatiotemporal clustering approaches [1]. Model performance is impacted by the depth of the decision tree, especially when dealing with big data sets [2].

GBM and XGBoost's have been applied to ride-sharing demand prediction with improved prediction accuracy. The challenges with such models are high computational time and resource requirements. There has been a noted increase in the performance of gradient boosting models, mainly LightGBM, compared to tree-based models. However, they are computationally cost-increasing with the size of the data [4]. In addition, the optimization remains tough because they are highly sensitive to the configuration of hyper parameters [3].

A PSO-based model for optimizing the algorithms of decision tree-based methods, LightGBM and CatBoost, with ride-sharing demand prediction is proposed in this paper. By combining weather, seasons, and geographic conditions with data from ride-sharing services in Seoul, it combines multiple characteristics to enhance adaptability and accuracy of predictions. As compared to their counterparts that are not optimized, the research study aims to present a systematic approach toward making ride-sharing services more efficient to eventually lead to enhanced resource allocation and scheduling within urban transportation systems[5,8,9].

2. Literature Review

The group of Carmen Kar Lee Hang and colleagues 1. By analyzing bike station ridership across time, eight clusters with similar temporal activities were identified. Additionally, the proposed approach looks at a technique to forecast membership using the neighborhood characteristics that form the basis of bike station clusters, and it finds that models that do not rely on trees perform better than those that do. This will be a great resource for city planners and bike-share companies looking to forecast future demand and meet strategic parking and bike space demands.

There are a lot of complex factors that affect the demand for shared bikes, according to L. Ming [2]. In addition, there are still many flaws in the models that are used to predict demand today. An improved bicycle demand prediction model utilizing the Particle Swarm Optimization (PSO) method is proposed in this work, which is based on LightGBM. Results from simulation studies showed that this method is practical and highly effective, making it a strong contender for managing urban bike sharing programmers.

A Hierarchical Consistency Prediction (HCP) model for predicting bike usage across the city is presented by Y. Li and Y. Zheng [3] in this paper. An efficient Ada TC approach clusters the rent and the transition of each cluster into the more regular format. Bicycle traffic at many locations can be predicted using a similarity-based Gaussian Process Regressor, which accounts for possible data imbalance and other factors. The General Least Square formulation greatly improves the forecast by incorporating Transition-based Inference to find the city's total demand for bike returns. Real data is used to demonstrate the model's effectiveness.

In addition to Yi and Shi, [4] This study estimates the demand for bikes in urban regions on an hourly basis using data mining techniques. The demand is dependent on weather, dates, and rental numbers. The Gradient Boosting Machine emerged as the top model, boasting the highest R2 value across both the test and train sets. This study uses data on bike-sharing in London to look at the relationship between weather and demand for bike-sharing. The results show that this model achieves the best accuracy in predicting from available data.

V. E. Kumar and colleagues [5] The concept of bike rental services is gaining traction in cities as a means to reduce congestion and increase accessibility. The reliability of an hourly demand estimate for motorbikes, nevertheless, is critical to supply stability. In this study, we employ data mining approaches to demand forecasting using meteorological data, dates, and statistics on bike rentals. The Gradient Boosting Machine outperformed the other four hyperparameter-trained statistical regression models in terms of R2 on both the training and testing sets.

As bike-sharing systems grew in popularity, it became vital to have reliable demand prediction methodologies, according to Ergul Aydin et al. [6]. This article has focused on the gradient boosting method for predicting demand in bike-sharing apps. Within this framework, this study suggests a gradient boosting technique based on the LightGBM algorithms to try and predict the demand for bike-sharing. Incredibly precise forecasts of future demand for bike-sharing can be generated by training a gradient-boosting algorithm with past data.

Xue Hu et al. [7] Combining a signal-decomposition technology, the algorithm of prediction wind power based on an ultra-short-term deterministic model is a technical basis for combined research and development. Artificial intelligence technologies are developed for improving the accuracy of predictions. Decomposition techniques provide reduced complexity, while specific laws and optimal parameters of prediction techniques appear. Evaluations of performance use vertical, horizontal, and prediction error evaluations. Future research trends aim at producing better performance of prediction and ensuring safety on grid operation.

3. Existing Methodology

The main obstacles to using machine learning techniques to forecast ride-sharing demand are the high computational cost of training a model and the difficulty of handling enormous amounts of data. Models like Random Forest and LightGBM require a high amount of computational resources and time to tune hyper parameters since they mainly rely upon lots of mathematical operations to be carried out. Shi et al. and Ergul Aydin et al. have emphasized that it requires considerably vast amounts of computational time for such models to execute in the case where large data sets are to be analyzed and real time demand forecasts to be used [4, 6]. However, some pre-built packages from these libraries can be used to ease the process and thereby not to prolong the computational overhead [1, 2].

The principal drawback of traditional methods of demand predictions is inefficiency in large complex datasets. Although the models, such as Random Forest, are accurate, they require large computational power and are prone to over fitting especially without optimized hyper parameters [3, 4]. In bike-sharing services, the distribution of bicycles is not uniform, especially at times of peak hours, thus incurring inefficiency in the service of bicycles. Imbalances in issuing and retrieving bicycles across different stations at peak hours are sources of frustration for the users of bike-sharing services and operational headaches for bike-sharing systems. According to Sathish Kumar et al., demand prediction is critical to eliminate such imbalances in the distribution of resources and improve resource distribution [5].

The last but not the least, external factors or events, including local events, road blockages and policies concerning traffic, significantly influence usage patterns of a bike. Incorporation of such factors into the prediction models of demand, as it has been done by Yulong Chen and Xue Hu while short-term forecasting, further enhances the system's accuracy as well as responsiveness [7, 9].

4. Proposed Methodology

The algorithms that have been utilized in bike demands prediction are Decision Trees, XGBoost, and CatBoost. Each of them enjoys one advantage, and whereas others have an advantage in terms of accuracy of predictions and computational efficiency. In our research, we made use of Ensemble Voting in the aggregation of the strengths of multiple algorithms for better performance. The Ensemble Voting approach thus combines the outputs of different models to increase the accuracy of prediction while diluting the weaknesses of the individual algorithms.

Let's run the dataset on the Decision Tree algorithm first in the proposed approach: Decision Trees are pretty good for any task of predicting because they are simple and easy to interpret. Then we run both other machine learning algorithms in turns - XGBoost and CatBoost - in order to be able to make an assessment of their performance. Every algorithm gives its insights towards overall accuracy of the model.

Once we have applied individual algorithms and have their respective predictions, we use the Voting Ensemble algorithm to combine the results. The voting ensemble method aggregates the predictions of various models for the purpose of computing a final score, which is going to represent a stronger prediction of bike demand. It is actually arriving at a better solution in the way of balancing strengths and weaknesses from various models, thereby constituting it a more robust one than would a single algorithm do.

The proposed method entails more advantages: not only efficient in terms of time in computation, but its aptness to data management and parallel processing entitles it to have a good predicting score due to the ensemble approach because such approaches can lend to good prediction, which boosts the accuracy of the model. It is easy to manage since it streamlines how to build up one's model by making use of pre-built machine learning packages and then merging the outcome into one, more powerful model.

5. Implementation

The implementation section explains the procedures or techniques used in carrying out the research. It details the method applied in data gathering, analysis, and interpretation against the main objective of the research or research question or hypothesis. In short words, this part of the work should be able to elucidate enough information so other researchers can follow your study if they wish to reproduce it or even be able to understand how your findings come about.

a. **Initiation:** This is the initial step of the machine learning workflow. It deploys the entire chain of a training and testing cycle of a machine learning model.
b. **Input Data:** It initiates by feeding the raw data into the system. The input could consist of feature and target variables, which may later be deployed for training the machine learning model. Example: For bike demand prediction, it may include all forms of weather conditions, time of the day, the location, some historical bike usage, etc.
c. **Data Cleaning:** This refers to the procedure by which input data is preprocessed so that inconsistencies including missing values, duplicates, or unnecessary information are removed. In that manner, the

dataset will be reliable for model training. Here, data normalization or standardization could also be applied in order to make it easier for the model to interpret the input data.

d. **Divide the data into testing and training:** One set of clean data is used for testing, and the other is used for training. The training set, which is where the model is constructed, and the testing set, which is used to assess the model's performance, are the two subsets. By ensuring that the model has been evaluated on unseen data, splitting offers an objective assessment of the model's performance.

e. **Training:** In this step, the machine learning algorithm is applied to the training set to learn the pattern from the data. In the process of training, the parameters are set for the model to fit with the data, and the prediction errors are to be minimized. As an example, imagine that you have set up a model in bike-demand-prediction using factors of how different things affect bike use, such as weather, which may be raining, the time of day, etc.

f. **Model:** After training, the model obtained is a mathematical abstraction representing relationships found in the training data. Such a model can now be deployed for making predictions on some new unseen data. The model could be constructed based on any algorithm like Decision Trees, Random Forest, or even Ensemble methods.

g. **Testing:** The performance of the trained model is tested on a dataset that was not involved in training, that is, the testing dataset. From this testing, one understands how well the model generalizes new data and achieves insight into the precision of its predictions.

h. **Evaluation:** The real values in the testing dataset would then be compared to the model prediction. Based on the nature of task, either accuracy, precision, recall, F1-score, or RMSE would be utilized for evaluation. For instance, as it relates to bike demand, it will have the count of bikes predicted versus the count of bikes actually available.

i. **Prediction:** Now the model was trained, it can make predictions on an unseen dataset. That is where the learned patterns of a model can be transferred into the real world. For instance, with new input data, the trained model could predict what the bike demand would be at a certain time at a certain place.

j. **Stop:** It is the last step of a machine learning process after generation of results as the system had closed its shutters. Evaluation results suggested that further refinement of the model could be done or actually used in work related to predictions.

5.1 Workflow of Proposed System

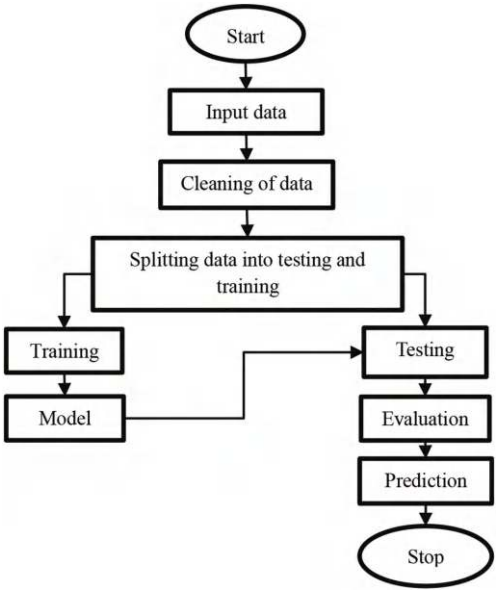

Fig. 36.1 Block diagram of ride-sharing prediction

5.2 Algorithms

a. **Decision Tree:** A Decision Tree is a kind of machine learning model that looks like a flowchart, though. The decisions are nodes, and the outcomes are the branches, but the prediction is actually a leaf. It starts off with a root node whereby data splits into subsets based on the chosen attributes, again through criteria like Gini impurity and information gain to increase the purity. Decision Trees Decision trees are interpretable, and they make no distributional assumptions on the data but may suffer from over fitting and instability: slightly different data can result in very different structures. Although decision trees are mainly applied in financial, healthcare, and marketing applications, combinations of these methods form the basis for ensemble techniques known as Random Forest and Gradient Boosting, which typically boost both accuracy and stability.

b. **Random Forest:** Class and regression ensemble learning approach, random forest is one which involves highly combining a large number of decision trees with the objective of combining their predictions and avoiding over fitting. Using the algorithm through bootstrap aggregating, or bagging, additional random samples of the training set are drawn, again introducing even more diversity between the created trees, reducing over fitting and also reducing correlation amongst the trees at each split of every node by using only a random subset of features. It determines it with a majority vote while

averaging the prediction made on classification. It also has high precision and performance against noise robustness. Random Forest generates insights toward feature importance; therefore, it is applied in such so many fields, for instance finance, healthcare, and marketing.

c. **XGBoost:** XGBoost is in fact a very powerful algorithm in machine learning for classification and regression tasks. This basically enforces the idea behind implementation for gradient boosting with regards to enhancing the performance of models by boosting up the speed through parallel processing, regularization, and tree pruning. XGBoost constructs decision trees sequentially. Every new tree diagnoses mistakes produced by the previous tree, and so it optimizes the model itself through a gradient-descent approach. It has cross-validation built into it and uses different objective functions depending on the task, in addition to handling missing values. XGBoost has achieved timely success in various machine learning competitions and diversified real-world applications at structured datasets, including finance, healthcare, and marketing due to its efficiency and effectiveness.

d. **LGBM:** Short form for Light Gradient Boosting Machine is LightGBM. It is a light, efficient, gradient boosting framework that can handle a huge amount of data. It is built using a histogram-based approach toward splits, trains speedily with better memory usage, and the build for trees is actually leaf-wise, not level-wise while capturing complex pattern at lesser risk of overfitting. It natively supports categorical features so that lesser preprocessing needs to be done in the application. High optimization with treatment over high-dimensional data thus can be widely applied in various machine learning competitions and real-life usage, especially in finance, marketing, and health care since it can run fast and efficiently.

6. Results

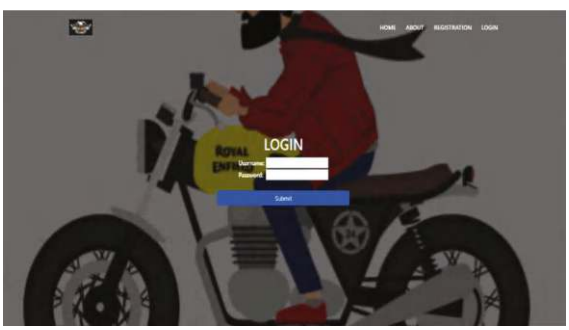

Fig. 36.2 User login-user can login with valid credentials

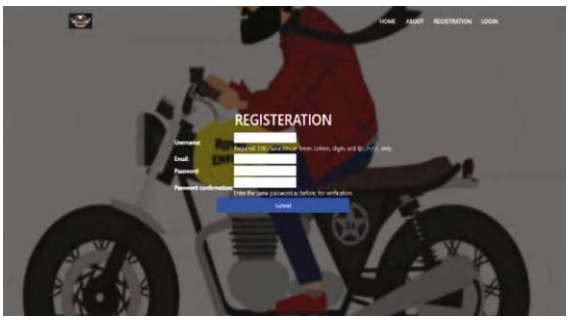

Fig. 36.3 User Registration page-user can register with required details

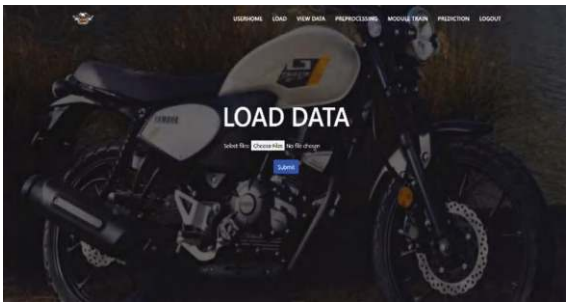

Fig. 36.4 Upload data- User can upload the data set

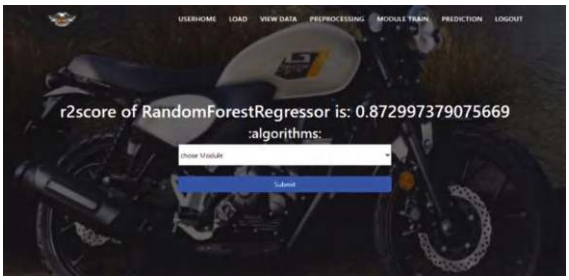

Fig. 36.5 Prediction-user can give an input and view the predicted result

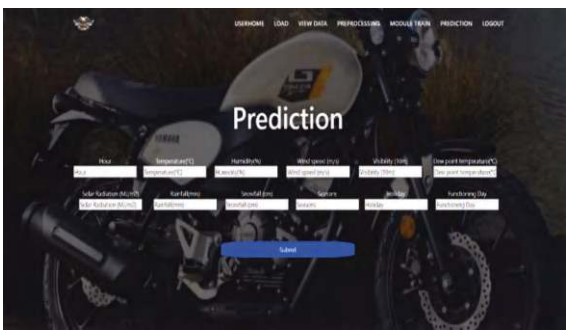

Fig. 36.6 The output of the given input

7. Conclusion and Future Scope

In this project, we developed a friendly ride-sharing demand prediction model. Using Machine Learning Model

techniques like Decision tree, Random forest, Xtreme gradient, Cat Boost, LGBM, we have taken the best techniques that we discovered and show the ride-sharing demand.

Enhancing the model by feeding real-time data to improve the accuracy and responsiveness. A mobile application will be developed enabling users to monitor information pertaining to the ride-sharing service availability and predictions in real-time. Recommend a system of optimal routes or stations for ride-sharing based on patterns of demand. Further, expand the model to include data about weather and events to increase more accuracy in the predictions. Determine cooperation with local governments and ride-sharing companies in order to integrate the model in their systems to better manage resources and make their plans accordingly.

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Advance Model for Attrition Forecasting

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Abstract: Organizations today face the significant challenge of managing employees leaving, a factor influencing recruitment costs, productivity, and organization reputation. Traditional attrition forecasting methods due to the longstanding reliance on existing information and even elementary statistical approaches, such frameworks are rather ineffective. "Advanced Models for Attrition Forecasting using Machine Learning" seeks to fill in such gaps by utilizing advanced Machine Learning (ML) principles to make sounder and more predictive models. Current attrition forecasting systems for example, rely on regression analysis or less sophisticated ML patterns that take into account few factors only. These conventional methods produce generalized predictions, failing to identify the multiple reasons behind employee departures, such as job satisfaction, workplace culture, and opportunities. The proposed system will integrate a variety of ML algorithms, including deep learning and ensemble methods to Analyze the data more comprehensively. This project will include data of employee's history, salary, opportunities from Multinational company. The system will also feature real-time data processing, enabling organizations to make decisions and implement timely actions to retain valuable talent. Enhanced predictive accuracy will reduce turnover-related costs, improve workforce stability, and create a productive work environment. Ultimately, this project will empower organizations to make informed decisions with Advanced Models for Attrition Forecasting using Machine Learning.

Keywords: Attrition, Machine learning, Statistical models, Regression analysis, Deep learning, Ensemble methods, Comparative analysis

1. Introduction

One of the greatest challenges facing organizations all over the world is employee attrition. High rates of turnover can increase recruitment and training costs, lead to a loss of resources in terms of organizational knowledge, and lower productivity overall. Forward looking measures are important in an organization, especially when talent

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retention and stability of workforce is a core objective. Normally, forecasting methods have been mainly focused on the use of past data and simple statistical pattern forecasting. However, these have great limitations when it comes to the understanding of employee behaviours and the multidimensional variables that inform their exit decisions. Various elements, such as job satisfaction, workplace culture, compensation, and career development opportunities, significantly impact attrition. Conventional models, including regression analysis, often fail to adequately capture these multifaceted dimensions, resulting in generalized and less precise predictions. Consequently, organizations find it challenging to implement timely interventions aimed at reducing turnover. The swift evolution of Machine Learning (ML) technologies presents a promising solution to this issue. By employing advanced ML algorithms, such as deep learning and ensemble methods, organizations can create more sophisticated and precise attrition forecasting models. These models can analyze a diverse array of data, ranging from employee demographics and historical performance to real-time feedback regarding workplace satisfaction. This holistic approach allows organizations to predict potential attrition with greater accuracy and to take proactive steps to retain their most valuable employees. This paper investigates the development and application of advanced ML techniques for attrition forecasting. By contrasting these models with traditional approaches, we seek to illustrate their enhanced accuracy and effectiveness in contemporary human resource management. The proposed system incorporates real-time data processing and a variety of ML algorithms, establishing a robust solution for predicting employee turnover and assisting decision- makers in mitigating its effects.

2. Literature Review

[11], [12] Cappelli et al (2000) investigated the impact of compensation, tenure, and promotions on employee turnover within organizations. Utilizing logistic regression, the study aimed to quantify the probability of attrition associated with these variables. Although the findings provided significant insights, the model's predictive capability was constrained by its linear nature, which failed to account for the intricate interactions among the factors involved.

[8],[14] G. Pratibha and N. P. Hegde et al (2022) employed a combination of decision trees, support vector machines (SVMs), and random forests to forecast attrition in the airline sector. These models were adept at processing both categorical and continuous data, thereby offering a more detailed understanding of employee behaviour. Nonetheless, they necessitated meticulous feature engineering and were unable to integrate real-time or unstructured data, such as employee feedback.

[10] Breiman et al. (2001) presented the Random Forest algorithm, an ensemble learning technique that builds multiple decision trees during the training phase and determines the classification by outputting the mode of the classes. This method proved particularly influential in HR analytics due to its resilience against overfitting and its capacity to manage extensive datasets. Random Forest gained traction as it addressed the shortcomings of earlier regression-based approaches, providing a more comprehensive perspective on the factors influencing attrition.

[4] N. Darapaneni et al. (2022) introduced the Stochastic Gradient Boosting technique, which enhanced model performance by minimizing errors through a loss function. This approach showed significant advancements over decision trees and random forests, especially in managing imbalanced datasets frequently encountered in HR contexts, where attrition may represent a small segment of the workforce.

[7] V. Mehta and S. Modi et al. (2021) developed XGBoost, a scalable and efficient gradient boosting algorithm that has established itself as a standard in predictive modelling, including attrition forecasting. XGBoost's proficiency in handling missing data, implementing regularization to prevent overfitting, and efficiently scaling for large datasets has rendered it a favored choice in the field.

[9] Chen et al. (2020) illustrated the potential of deep learning models, particularly Multilayer Perceptron (MLP), in improving attrition forecasting. By utilizing both structured data, such as demographic and job-related information, and unstructured data, including textual feedback from employees, the deep learning model outperformed traditional forecasting methods in terms of accuracy. The capacity of neural networks to identify non-linear relationships and interactions among variables rendered them an effective instrument for comprehending intricate employee behaviours.

3. Data and Variables

For the proposed system, we aim to enhance attrition forecasting accuracy by leveraging a comprehensive approach that incorporates over 27 parameters. By integrating diverse data points such as employee demographics, performance metrics, engagement levels, and behavioural patterns, the system gains a more nuanced understanding of factors influencing employee turnover. We will employ various ensemble methods, such as

Random Forests and Gradient Boosting, to improve prediction performance through model aggregation. Additionally, Artificial Neural Networks (ANNs) will be utilized to capture complex patterns and interactions within the data, further refining the accuracy of forecasts. This multi-faceted approach ensures a robust and precise prediction of employee attrition, enabling more effective and targeted retention strategies.

3.1 Dependent Variable

In an advanced model for attrition forecasting, the dependent variable (or target variable) typically represents whether an employee has left or will leave the organization within a specified time frame. This variable is often binary, such as:

A binary variable where:

1 (or True) represents that the employee has left the organization.

0 (or False) indicates that the employee remains with the organization.

3.2 Independent Variable

In advanced attrition forecasting models, independent variables (also known as features or predictors) are factors that can influence employee attrition. Choosing the right independent variables is crucial for improving the model's accuracy and interpretability.

3.3 Control Variables

In advanced models for attrition forecasting, control variables (also known as "confounding variables") help isolate the effect of specific predictors on attrition by accounting for additional factors that might influence outcomes.

4. Methodology and Model Specifications

In this attrition forecasting project, the methodology is based on machine learning techniques that predict possible factors for the modifying behaviour of employees.

The logistic regression is the simplest method of discriminative analysis that can be used to solve the issue in which the objective is to predict whether an employee is likely to continue or not. This technique is very simple but potent as it gives a good understanding of how each of the predictors contributes to the outcome through the coefficients. Random Forest, as the name suggests, is a method of ensemble learning which builds a number of decision trees during the training period and combines their results to increase performance. Random forests overcomes this problem by building each tree on a random sample of the data and so produces a better model than a single decision tree[12],[13].

Gradient Boosting Machines (GBM) refer to a family of algorithms that generate a sequence of models where each new model attempts to explain the errors made by the previous models. The K-Nearest Neighbors (K-NN) algorithm is thus classified as a lazy learning algorithm. It estimates the class of the data point that is most common among its K-nearest neighbors in the features space. K-NN is proper in the case where a distance measure, such as Euclidean distance, is used. AdaBoost is a method of boosting where different classifiers are only weakly trained and then combined into one strong classifier. It does this by focusing on the errors made in the previous classifiers in the current round and thus it weights the errors of the most accurate classifiers in the final ensemble leading to better results.

5. Empirical Results

5.1 Pre-Crisis Estimations

The outcomes indicate that AdaBoost (88%) and XGBoost (87%) offer the most accurate results, thereby demonstrating that such methods can delve into the most complex relationships dataset.

Table 37.1 Model accuracy

Model	Accuracy
Logistic Regression	86%
Naive Bayes	75%
K-Nearest Neighbors	85%
Decision Tree	79%
Random Forest	77%
XGBoost	87%
Neural Network	86%
AdaBoost	88%

Source: Author

The outcomes indicate that AdaBoost (88%) and XGBoost (87%) offer the most accurate results, thereby demonstrating that such methods can delve into the most complex relationships within the dataset.

Correlation Analysis

In the periods preceding a crisis, some predictors (for instance job satisfaction, salary paid, tenure) may show some stable patterns of association with attrition. For instance, assuming that employees are happy with their pay, there could be a high correlation between salary and attrition

levels, that is, the higher the salaries offered, the lower the rate of attrition among the employees. For instance, if the pre-crisis job satisfaction – attrition correlation coefficient is -0.7, it depicts a very high inverse association.

Dynamic Panel Estimations

During the pre crisis phase, the model is likely to emphasize the delayed effects of job-related aspects such as fulfilment or salary increase on the turnover rate. Lagged variables help to explain the effect of changes in these factors on attrition over a certain period thus giving a basic starting point.

For instance, if the pre-crisis model demonstrates significant influence of lagged job satisfaction on attrition, we can conclude that the changes in satisfaction over the course of several months help to retain the employees or turn them over. Shows that investors do not consider high concentration of ownership as a motivating factor because it is believed that higher concentration leads to expropriation of

5.2 Post-Crisis Estimations

AdaBoost (88%) and XGBoost (87%): The two models exhibited remarkable performance accuracy and are appropriate for modelling complex non-linear relationships. They perform well in recognizing changing patterns since boosting algorithms tend to learn new data quickly, thus suitable in forecasting after a crisis. Neural Networks (86%): The aforementioned models are also suitable for use in contexts with more data such as the post-crisis period where one has more variables or the data is simply larger. This is due to the capacity Neural Networks have in recognizing complex patterns. On the flip side, new trends might require recalibrating. Logistic Regression (86%): Logistic Regression, because of its simple coefficients, can help understand what has changed since the crisis in the variables. This model can also be useful to describe changes in the importance measures of the predictors, thus acting as

Correlation Analysis

Crisis responses are likely to modify any correlations due to different levels of job security, different remote work provisions, or different market environments. For example, when other motives for retention, such as financial security, take precedence, it may be that job satisfaction and attrition rates are less significantly correlated.

Example: In a circumstance where the correlation coefficient between job satisfaction and attrition post-crisis drops to -0.3, this suggests a lesser influence on retention and could depict that the external job market competition is not satisfactory or the other job perks are more preferred.

Dynamic Panel Estimations

After a crisis, it is possible that the model would concentrate on other factors or exhibit modified lag structures. That is, there may now be a significant lagged effect of attributes such as availability of remote work options or financial stability on attrition as employees self-evaluate their job security and work-life integration.

For example: An excessive lagged effect of payments increases or the work-life adjustment sometimes after a crisis might suggest that employees attach more importance to these issues owing to the disturbing socio-economic imbalances the crisis caused.

6. Conclusion

This study set out to address the limitations of traditional attrition forecasting methods by developing and evaluating advanced machine learning models capable of providing more accurate and actionable predictions. Through the integration of multiple machine learning techniques including Random Forest, Gradient Boosting, XGBoost, and Deep Learning the proposed model demonstrated superior performance in predicting employee turnover when compared to baseline methods such as Logistic Regression.

The evolution of attrition forecasting models is poised for substantial enhancement through the adoption of sophisticated machine learning methodologies and thorough data analysis. By utilizing deep learning and ensemble techniques, organizations will create models capable of identifying complex patterns within employee data, resulting in more refined predictions regarding attrition.

As organizations place greater importance on ethical considerations and the reduction of bias, they will strive to ensure that predictive algorithms foster inclusivity. Intuitive visualization tools will enable HR teams to easily interpret insights, while strong feedback mechanisms will facilitate the ongoing enhancement of retention strategies, ultimately contributing to a more engaged and productive workforce.

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New Hybrid Encryption Approach Combining RSA, Paillier and Goldwasser Micali Cryptosystems: Revisited

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Abstract: In today's digital world, cloud computing - where processing power and storage are provided via the internet has become essential. It lowers expenses and boosts productivity by giving businesses on demand access to scalable and adaptable IT resources. Data security in these contexts is of utmost importance due to the increasing dependence on cloud computing for tasks ranging from complicated calculations to data storage. In order to ensure data privacy in outsourced settings, homomorphic encryption is essential to cloud computing since it allows calculations on encrypted data without the need for decryption. This strategy is essential as companies depend more and more on cloud services for sensitive data. In this paper, we used homomorphic encryption to provide safe computations, enhancing security against assaults and tackling major security issues in contemporary cloud systems. For real-world applications that require robust cloud computing security and privacy, our solution is ideal.

In order to provide strong security and effective homomorphic computations, in this paper, we presents a novel multi-hybrid cryptographic system that combines the RSA, Paillier, and Goldwasser-Micali encryption algorithms. Our system leverages the strengths of each algorithm while effectively addressing their unique drawbacks. RSA offers robust public key encryption for secure communications, while Paillier's additive homomorphism and Goldwasser-Micali's XOR operations enable secure data processing within the proposed system. This combination ensures that

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sensitive data can be encrypted, shared, and processed without compromising privacy, making our solution both secure and efficient for various applications. We outline the encryption and decryption procedures along with the architecture and implementation of hybrid system. This solution is well-suited for realworld applications in cloud environments, as it enhances defense against potential attacks and simplifies secure computations on encrypted data. By integrating these features, we ensure robust security while maintaining the efficiency needed for practical use.

KEYWORDS: Hybrid encryption, Goldwasser - Micali cryptosystem, Paillier cryptosystem, RSA cryptosystem, Homomorphic encryption, Public key cryptography, Secure data transmission

1. INTRODUCTION

In the digital era, securing confidential data is paramount due to the rise of data breaches and cyberattacks. Cryptography, the science of secure communication [10], offers essential solutions to protect sensitive information through various encryption methods. By utilizing these techniques, organizations can effectively safeguard their data against unauthorized access and ensure privacy.

The science of safeguarding data by converting it into an unreadable format to prevent unwanted access is known as cryptography. It is essential to modern communication because it guarantees the privacy, accuracy, and legitimacy of data especially in delicate domains like cloud computing, online chats, and financial transactions. Cryptography is a fundamental component of safe digital systems because it shields data from fraud, manipulation, and monitoring. To accomplish these aims, many encryption techniques are used in cryptography [11].

RSA, Paillier, and Goldwasser-Micali are a few homomorphic encryption techniques. RSA is a simple to use and relies on the difficulty of factoring big prime numbers for security and is a cornerstone of public-key encryption. Paillier encryption is well-known for its homomorphic capabilities, which enable actions on encrypted data without the need for decryption, whereas Goldwasser-Micali encryption is valued for its probabilistic encryption and homomorphic XOR effects [1] [5] [8].

Every algorithm has benefits and drawbacks of its own. Although homomorphic operations are not supported by RSA, it excels in security. Paillier can be computationally demanding even though it allows for ciphertext calculations. However, Goldwasser-Micali's capability for XOR-based operations on encrypted data restricts its application to more complex calculations.

A multi-hybrid cryptography system has been created to get around these restrictions and offer increased security. The RSA, Paillier, and Goldwasser-Micali algorithms are combined in this system to take use of their own advantages. RSA is used in this multi-hybrid system to first encrypt plaintext. After that, the resultant RSA ciphertext is encrypted again using Paillier and then again using Goldwasser-Micali, resulting in a three layer encryption technique that greatly improves security by making prospective attacks more difficult to execute.

For versatile and safe data processing, the hybrid system combines the security of RSA with the homomorphic capabilities of Paillier and the XOR operations of Goldwasser Micali. This solution to multi-hybrid encryption allows calculations on encrypted data while improving security. The system's goal is to offer a reliable cryptographic solution for practical uses [10].

Contribution: In today's digital world, cloud computing where processing power and storage are provided via the internet - has become essential. It lowers expenses and boosts productivity by giving businesses on demand access to scalable and adaptable IT resources. Data security in these contexts is of utmost importance due to the increasing dependence on cloud computing for tasks ranging from complicated calculations to data storage. In order to ensure data privacy in outsourced settings, homomorphic encryption is essential to cloud computing since it allows calculations on encrypted data without the need for decryption. This strategy is essential as companies depend more and more on cloud services for sensitive data. In this paper, we used homomorphic encryption to provide safe computations, enhancing security against assaults and tackling major security issues in contemporary cloud systems. For real-world applications that require robust cloud computing security and privacy, our solution is ideal.

In order to provide strong security and effective homomorphic computations, in this paper, we presents a novel multi-hybrid cryptographic system that combines the RSA, Paillier, and Goldwasser-Micali encryption algorithms. Our system leverages the strengths of each algorithm while effectively addressing their unique drawbacks. RSA offers robust public key encryption for secure communications, while Paillier's additive

homomorphism and Goldwasser-Micali's XOR operations enable secure data processing within the proposed system. This combination ensures that sensitive data can be encrypted, shared, and processed without compromising privacy, making our solution both secure and efficient for various applications. We outline the encryption and decryption procedures along with the architecture and implementation of hybrid system. This solution is well-suited for real-world applications in cloud environments, as it enhances defense against potential attacks and simplifies secure computations on encrypted data. By integrating these features, we ensure robust security while maintaining the efficiency needed for practical use.

Paper Outline: In section 2, specification and overview of Homomorphic Encryption is described. Proposed work with results is described in section 3. Finally, Section 4 provides paper conclusion.

2. Specifications of Homomorphic Encryption

Homomorphic encryption systems allow computations to be executed on encrypted data without requiring the private key. The outcome of these computations remains encrypted, and when decrypted, the result is identical to what would have been obtained if the calculations had been done on the unencrypted data [5] [8].

Mathematically, a system is considered homomorphic encryption if the following holds: given the encryption of a and the encryption of b, it is possible to compute the encryption of f(a,b), where the function f can be addition, multiplication, or XOR [12].

In this paper, we propose a hybrid encryption scheme that combines the RSA, Paillier, and Goldwasser-Micali encryption algorithms to enhance both security and performance. This scheme takes advantage of Paillier's and Goldwasser-Micali's homomorphic properties and the widespread adoption of RSA encryption. The encryption process begins by encrypting the plaintext with RSA, followed by further encryption using Paillier and then Goldwasser-Micali. During decryption, the reverse process is applied: first, Goldwasser-Micali decryption is applied, followed by Paillier decryption, and finally RSA decryption restores the original plaintext.

This hybrid approach provides a robust encryption mechanism, effectively addressing the limitations of each algorithm:

- **RSA Encryption:** Allows computations to be conducted on encrypted data without requiring decryption, utilizing its homomorphic properties.
- **Paillier Encryption:** Enables computations to be performed on encrypted data without the need for decryption, leveraging its additive homomorphic properties.
- **Goldwasser-Micali:** Provides excellent semantic security and is impervious to chosen-plaintext attacks, while also enabling computations.

By integrating these three encryption methods, this system significantly strengthens protection against potential attacks while facilitating secure computations on encrypted data within cloud environments [2].

2.1 Key Features of the Hybrid Paillier-RSA-GM System

1) **Key Generation:** RSA, Paillier, and GM algorithms are used to generate the public key and secret key [5]

$$(Ks,Kp,Kg) = KeyGen_{hybrid}(s) \quad (1)$$

Where Ks, Kp, and Kg are the secret keys for RSA,Paillier, and Goldwasser-Micali, respectively.

2) **Encryption:** The plaintext M is first encrypted using RSA, producing a ciphertext. This ciphertext is then encrypted using Paillier and again using GM, resulting in a multi-layer encrypted message.

$$C = EncGM(EncPaillier(EncRSA(M))) \quad (2)$$

3) Paillier and GM's homomorphic characteristics enable safe operations on encrypted data to be carried out without the requirement for decryption.

$$C_* = Eval_{Paillier}(f,C) \quad (3)$$

And similarly for GM:

$$C^* = Eval_{GM}(f,C) \quad (4)$$

4) **Decryption:** The encrypted message is decrypted in reverse order. First, GM decryption is applied, followed by Paillier decryption, and finally RSA decryption to recover the original plaintext.

$$M = DecRSA(DecPaillier(DecGM(C^*))) \quad (5)$$

5) **Conclusion:** This hybrid encryption system combines the strengths of RSA's public-key encryption, Paillier's homomorphic encryption, and Goldwasser-Micali's semantic security. It provides a highly secure and efficient solution, especially suitable for real-world applications that require both robust data protection and secure computations on encrypted data.

2.2 Categorization of Homomorphic Encryption

A. Partially Homomorphic Encryption (PHE)

Supports either summation and product on ciphertexts, but not both [7].

1) *Additive Homomorphism (e.g., Paillier)):*
   - Encryption: $En(x) = g^x.r^y mody^2$
   - Homomorphic Addition:

$$En(x_1) \cdot En(x_2) = En(x_1 + x_2) mody^2$$

2) *Multiplicative Homomorphism (e.g., RSA))):*
   - Encryption: $En(x) = x^e mody$
   - Homomorphic Addition: $En(x_1) \cdot En(x_2) = En(x_1 \cdot x_2) mody$

B. Somewhat Homomorphic Encryption (SWHE)

Allows for a restricted number of summation and product operations. The specific operations depend on the encryption scheme, but noise grows after each operation, limiting its use [5].

C. Fully Homomorphic Encryption (FHE)

Supports unlimited summation and product, but noise is managed, usually via bootstrapping [5].

General Form (e.g., Gentry's FHE): Supports operations like:

- Homomorphic Summation:

$$En(x_1) \cdot En(x_2) = En(x_1 + x_2)$$

- Homomorphic Product: $En(x_1) \times En(x_2) = En(x_1 \cdot x_2)$

Table 38.1 Stages of key generation

Stage	Description
1	Generate primes X, Y, compute Z = X × Y , and Euler's phi function $\phi(Z) = (X - 1)(Y - 1)$.
2	Select E such that $1 < E < \phi(Z)$ and $gcd(E, \phi(Z)) = 1$.
3	Public Key: $K_p = \{E,Z\}$, Private Key: $K_s = \{D,X,Y\}$, where $D = E^1 mod \phi(Z)$.

Table 38.2 Stages of encryption

Stage	Description
1	Use the public key $K_p = \{E,Z\}$.
2	Compute the ciphertext C_i *as* :$C_i = G^E$ *mod*Z, where $0 \leq G \leq Z$, and G is the plaintext message

D. Properties of Homomorphic Encryption

- **Additive Homomorphism:** Allows addition operations on encrypted data.

$$En(x_1 + x_2) = En(x_1) \cdot En(x_2)$$

- **Multiplicative Homomorphism:** Allows multiplication on encrypted data.

$$En(x_1 \cdot y_2) = En(x_1) \cdot En(x_2)$$

- **Ciphertext Growth:** Ciphertext size may grow as more operations are performed, particularly in FHE
- **Noise Growth:** Each operation introduces noise into the ciphertext, particularly in SWHE and FHE. Bootstrapping can be used to reduce noise in FHE.
- **Non-interactive:** Computations on ciphertexts can be performed without interaction or decryption, preserving privacy

D. Homomorphic Encryption Methods

Let's explore some different homomorphic encryption techniques, highlighting one from each category and outlining the specific operations they support.

1) **RSA Homomorphic Encryption:** One of the most basic homomorphic encryption algorithms is the RSA approach, which is why it is used as an illustration of a multiplicative partial homomorphic cryptography technology. In 1978, Rivest, Shamir, and Adleman released their cryptosystem's public key [3] [6].

   It's clear that RSA is a simple algorithm with constrained computing possibilities.This significantly decreases the algorithm's real-world uses. Nevertheless it is a crucial algorithm as it serves as a starting point and many different kinds of improved algorithms either use or depend on RSA in some manner. Table 38.1 shows the key generation, Table 38.2 shows the encryption and Table 38.3 shows the decryption.

Table 38.3 Stages of decryption

Stage	Description
1	Use the public key $K_p = \{E,N\}$.
2	Compute the ciphertext C_i *as* : $C_i = G^E$ *mod*N, where $0 \leq G \leq N$, and G is the plaintext message.

2) **Paillier Homomorphic Encryption:** The Paillier cryptosystem was designed by Pascal Paillier in 1999. It is a well-known probabilistic asymmetric encryption system with additive homomorphic properties. This feature makes it possible to do certain mathematical computations on data that is encrypted without having to decrypt it. The system is built on number theory and is intended to facilitate calculations that protect privacy while securing communications. Table 38.4 shows the key generation, Table 38.5 shows the encryption and Table 38.6 shows the decryption.
3) **Goldwasser-Micali Homomorphic Encryption:** In 1982, Silvio Micali and Shafi Goldwasser created the asymmetric key encryption technique known as the Goldwasser-Micali (GM) cryptosystem. Though it can only encrypt one bit [6] , [9], it is an additive homomorphic encryption. Although it offers data

Table 38.4 Stages of key generation

Stage	Description
1	Generate two high-value prime number X and Y , such that $gcd(X \times Y, (X-1) \times (Y-1)) = 1$. Compute $Z = X \times Y$ and $\lambda = lcm(X-1, Y-1)$.
2	Choose a generator G in Z_2^*. Calculate $\mu = (K(G^{\lambda} mod N^2))^{-1} mod Z$, where $K(u) = u^{-}_{Z}^{1}$.
3	Public Key: Public Key: (Z,G), Private Key: (λ,μ).

Table 38.5 Stages of encryption

Stage	Description
1	Generate a random integer RAI from the interval $0 < RAI < Z$.
2	Compute the ciphertext $C = G^M \times RAI^Z mod Z^2$, where M is the plaintext message. G is the plaintext message

Table 38.6 Stages of decryption

Stage	Description
1	Determine the intermediate value $J = C^{\lambda} mod Z^2$
2	Retrieve the plaintext $M = L(C^{\lambda} mod Z^2) \times \mu mod Z$, where $L(u) = z^{u-1}$.

security, the cypher text created in several situations is much bigger than the input plain text, making it inefficient in terms of space complexity.

3. Proposed Work

Proposed work describes how to use the multi-hybrid cryptographic system, which combines the RSA, Paillier, and Goldwasser-Micali encryption algorithms, for encryption and decryption. The technique is intended to improve security and make safe calculations on encrypted data possible. The procedure starts with plaintext encryption using a tiered approach: RSA encryption first, then Paillier encryption, and lastly Goldwasser-Micali encryption. The encrypted data is then stored in the cloud. The original plaintext is retrieved by doing the opposite procedure during decryption [4].

The phases of the multi-hybrid system's encryption and decryption procedure are shown in Table 38.10 and Fig. 38.1.

3.1 System Simulation and Examination

The proposed hybrid homomorphic encryption performance implementation is done, through the selection of three plain text of varying sizes that are used as algorithmic inputs to test the functionality of the RSA, GM, PAILLIER -multi hybrid homomorphic encryption cryptosystems.

Table 38.7 Stages of key generation

Stage	Description
1	The user selects two large random primes, S and T, to create a public and private key.
2	Calculate $n = S \times T$. Consider $b \varepsilon Z_n^*$, where b is a quadratic non-residue modulo n and $(b/n) = 1$.
3	Public Key: (n,b), Private Key: (S,T).

Table 38.8 Stages of encryption

Stage	Description
1	Enter the message Z, which is composed of the bits $z_1, z_2, ..., z_n$.
2	A random value vi is created for each bit z_i, where $gcd(v_i, K) = 1$.
3	Calculate: Cip(i) = $v_i \times z_i \, modK$.

Table 38.9 Stages of decryption

Stage	Description
1	Enter the message Cip, which is composed of the bits $cip_1, cip_2, ..., cip_n$.
2	$q_i = \left(\frac{Cip(i)}{S}\right), \forall_i \, \varepsilon \, [1,t]_i$ Compute
3	If $q_i = 1$, then $z_i = 0$; otherwise, $z_i = 1$.
4	The output message is $Z = z_1, z_2, ..., z_n$.

Table 38.10 Stages of decryption

Stage	Description
1	Load the original plaintext data.
2	Convert the data (plaintext) into binary format.
3	Generate compute keys (Public, Private) for the RSA cryptosystem.
4	The RSA cryptosystem is used for encryption, generating the ciphertext C_1.
5	The generated ciphertext C_1 is sent to Paillier encryption.
6	The ciphertext C_2 is created during encryption using the Paillier cryptosystem.
7	The produced ciphertext C_2 is sent to Goldwasser-Micali encryption.
8	The ciphertext C_3 is created during encryption using the Goldwasser-Micali cryptosystem.
9	Upload the encrypted data C_3 to the cloud for storage.
10	The encrypted data of Paillier (ciphertext C_2) is produced by decrypting the ciphertext C_3 (Goldwasser-Micali).
11	The encrypted data of RSA (ciphertext C_1) is produced by decrypting the ciphertext C_2 (Paillier).
12	The original plaintext data is obtained by decrypting the ciphertext C_1 (RSA).

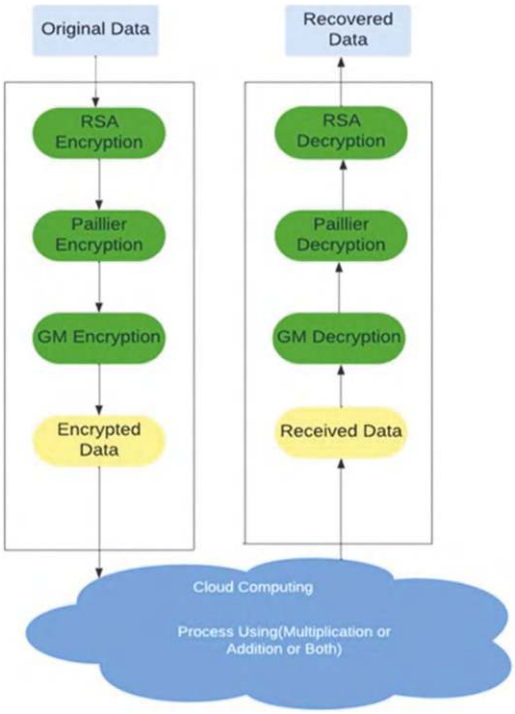

Fig. 38.1 Proposed hybrid homomorphic encryption scheme

The system, which has a 8.00 GB RAM and an Macbook air M3 CPU running at 4.05 GHz, using conducted the experiment. The following Table 38.11, Table 38.12 and Table 38.13 present or analyze encryption and decryption timings for various plaintext sizes.

Table 38.11 Encryption time for RSA, paillier and goldwasser-micali

Plaintext Size (bits)	Algorithm	Encryption Time (seconds)
8	RSA	0.000018
	Paillier	0.000029
	Goldwasser-Micali	0.000194
16	RSA	0.000018
	Paillier	0.000049
	Goldwasser-Micali	0.000604
24	RSA	0.000041
	Paillier	0.000094
	Goldwasser-Micali	0.001498

Based on Table 38.11 and Table 38.12, graph are illustrated in Fig. 38.2 is generated showing the encryption time taken by the proposed algorithm for varying plaintext sizes and Fig. 38.3 is generated showing the decryption time for different sizes of encrypted data.

Table 38.12 Decryption time for RSA, paillier and goldwasser-Micali

Ciphertext Size (bits)	Algorithm	Decryption Time (seconds)
8	RSA	0.000001
	Paillier	0.000004
	Goldwasser-Micali	0.000012
16	RSA	0.000006
	Paillier	0.000010
	Goldwasser-Micali	0.000286
24	RSA	0.000012
	Paillier	0.000019
	Goldwasser-Micali	0.001033

Table 38.13 Total time of execution

Description	Time (seconds)
Total Execution Time	0.007934

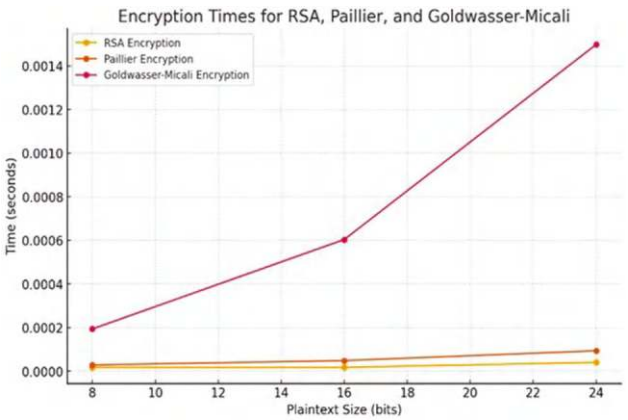

Fig. 38.2 Encryption times for RSA, Paillier, and Goldwasser-Micali

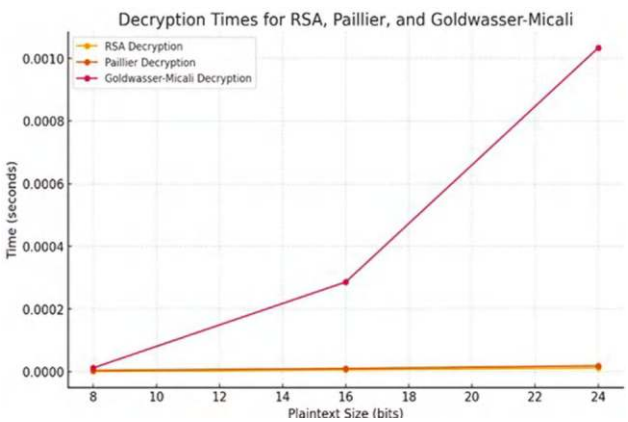

Fig. 38.3 Decryption times for RSA, Paillier, and Goldwasser-Micali

4. Conclusion

The hybrid method integrating RSA, Paillier, and GM algorithms demonstrates potential for enhancing the efficiency and security of homomorphic encryption systems. Each algorithm contributes unique strengths: GM ensures probabilistic encryption and supports specific homomorphic operations, Paillier enables additive homomorphism, and RSA offers strong asymmetric encryption. By combining these methods, we can leverage their advantages for secure computations on encrypted data with minimal overhead. Paillier facilitates operations on ciphertexts, while RSA adds a lightweight layer of encryption during the initial process, enhancing overall security.

The layered technique gives the flexibility required for safe calculations as well as depth to security by encrypting first using one algorithm (e.g., RSA) and then adding another encryptions (e.g., GM and pailler). This hybrid technique is a promising field for future study and development since it can improve confidentiality and privacy in real-world applications.

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Note: All the figures and tables in this chapter were made by the authors based on concepts and data from referenced papers.

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Forecasting Energy Demand with Machine Learning by Analyzing Temporal and Weather Pattern

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Abstract: Directly, energy management faces challenges due to unstable energy demand, hence requiring high precision in the prediction of optimization of the resource usage. However, existing systems are based on fair conventional statistical methods in Machine Learning, like Multivariate Polynomial Regression (MPR), Random Forest Regression (RFR), and Gradient Boosting Regression (GBR). Therefore, these may fail to capture the variability in the temporal and weather-related patterns. Even though these models used comprehensive past dataset, overfitting and high variance in weather conditions had to achieve low accuracy. The proposed system attempts to counter such limitations from the present system by including Linear Regression to exhibit simplicity and interpretability, Time Series Analysis to model sequential dependencies, ARIMA for data which is univariate time series, and LSTM to capture long-term dependencies and complex non-linear interactions. This integration yields more reliable and accurate estimates of energy demand in comparison with existing models. Results ultimately underlie the potential of such high-performance techniques to contribute toward developing a more efficient and sustainable energy management system that can help policymakers and energy providers plan better resource planning and allocation, thus improving overall energy efficiency and sustainability.

Keywords: Energy demand forecasting, Temporal and weather-related patterns, Sustainable energy systems, Linear regression, Time series analysis, ARIMA

1. Introduction

The difficulty arises in ascertaining how much energy is needed over time since the demand in itself fluctuates in an energy consumption scenario on the increase. Several factors are involved in this complicated interplay, and traditional methods of forecasting energy consumption are not particularly accurate because of temporal and

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weather-related factors. This work is based on the use of advanced machine learning techniques to predict actual energy consumption as part of that effort. We would, here, try to understand how various patterns affect energy usage. Our focus will be on trying to improve general forecasting accuracy; thus, better planning and resource allocation will be made for energy usage. This will help in efficiently and sustainably managing energy. With the increase in demand for electricity and in forecasting patterns of consumption of energy, the problem energy management becomes an important one in today's world.

Analysis of various supervised machine learning algorithms applicable to electricity demand forecasting in the New South Wales area of the Australian electricity market. Such supervised machine learning algorithms include linear regression, support vector regression, and random forest regression. The evaluation is based on dimensions such as mean absolute error and root mean square error. Results indicate that non-parametric methods are superior to parametric algorithms concerning their predictability. This research focuses on the importance of reliable demand forecasting for efficient and economical power system operation [1]. The importance of industry electrification in achieving 100% renewable energy systems. The results underline the fact that holistic energy system planning is required to reap all the benefits from renewable energy integration [2]. It was stated that adaptive thermal comfort models are very crucial for actual future cooling demand estimation as well as the reduction of residential energy consumption affected by climate change [3].

2. Literature Survey

E. Cebekhulu et al. [4] in this paper provides a detailed review on the energy supply versus energy demand prediction in smart grids made by various ML algorithms, namely decision trees, SVM, and ANN, with some on optimization of prediction towards making better efficiency and sustainability of the energy.

A. Alhendi, et al. [5] studies the short-term load forecasting and price prediction in the ISO New England electricity market. The authors succeeded in achieving clear superiority in their accuracy and related metrics for load and price forecasting compared to standard methods by applying ANN improved with a Markov Chain.

D. Agdas, et al. [6] proposed how the mode of electricity demand and supply by Americans was drastically changed with the lock-downs of the covid-19 pandemic in the article some data are presented to explain how such lock-downs have sharply reduced energy consumption this time however only the commercial ones their residents consumed more they further detail how shifts of such nature would eventually manifest in electricity price grid stability and what kinds of possible future demands for utilities are likely to arise some recommendations on how to cope with unprecedented shifts in demand.

J. wu, et al. [7] in this paper lockdown effects owing to covid-19 on electricity demand are assessed through analytics on consumption pattern data quantitatively comparing across regions with the authors finding important peaks and changes in load profiles such findings are deemed of utmost importance for future energy planning and infrastructural investment as lockdowns can give a glimpse into new behavior and patterns of consumption and energy usage.

K. Rawaland, et al. [8] states that it is a study of several supervised machine learning algorithms namely regression techniques ensemble methods and architectures of deep learning for electricity demand forecasting the article gives a very detailed analysis about performance metrics such as accuracy precision and computational efficiency of different models according to their strengths and weaknesses there are valuable insights from the authors for the practitioner about the best model selection for specific forecasting tasks.

M. R. Baker, et al. [9] The study concerns the uncertainties from the covid-19 pandemic that had deteriorated electricity demand forecast conditions applying ensemble learning techniques the paper enhances the forecasts and minimizes their uncertainties in its demand projections for the cities of the united states of America discussing the implications for energy providers it argues for the ability of adaptive forecasting methods to enhance operational resilience and facilitate more effective policy formulation for uncertain times.

X. Li, et al. [10] have stated that sectoral energy demand with the impacts of electrification and digitalization up to 2050 the authors investigate how electrification and digitalization are likely to alter sectoral energy demand by 2050 they introduce a comprehensive analysis of the possible impacts emerging technologies with smart grids and iot devices have on energy consumption.

3. Methodology

3.1 System

Data Collection involves collecting energy consumption data from various sources, ensuring data quality and consistency. Data Preprocessing means cleaning and normalizing the dataset, handling missing values and outliers, and encoding categorical variables. Data splitting involves Model Training which utilize 80% of the pre-processed dataset to train the model. Model testing uses remaining 20% of the dataset. Feature engineering extracts

and select relevant features from the dataset to improve model performance and enhance Energy demand prediction accuracy. The major step is Model Integration and Training which involve integrating multiple algorithms of ML, including L Regression. Output is given by Model Prediction by deploying the trained models to provide predictions on new data, identifying Energy Demand effectively.

3.2 User

Firstly, the users must register with their credentials to create an account in the system. Then users can log in with their registered credentials to access the system and its features. In the next step users can input Energy consumption data into the system for Predicting Energy Demand. After that the input data will be processed by the model, which will provide predictions. The users are able to view the results. At last, users have to logout of the system to secure their session and personal data.

3.3 Algorithms

Linear Regression

It is in fact one of the most commonly used as well as among the most basic algorithms in the sub-domain of machine learning that is applied to predict in the proposed system. I have used linear regression where we have calculated the energy demand. This actually applies the basic concept of dependent relationships amongst the dependent variables, which in this case are energy consumption and multiple independent variables. time-related and weather-based factors the methodology starts from data preprocessing and the correct choice of features with proper cleaning of data it was transformed into the datetime field in order to transform time components like an hour or a day month into independent variables as well of course besides independent variables of weather, temperature, humidity. The largest advantage that linear regression offers is that even after training, the amount by which every one of its features affects energy demand will always be easy to understand, yet for most energy demand forecast problems, it is not strictly valid at best and dubious at worst.

ARIMA (Auto Regressive Integrated Moving Average)

This is an abbreviation for auto-regressive integrated moving average. arima is one of the techniques by which one builds time series models since it carries out three processes namely autoregression differencing and moving average of the modelling and the forecasting of future values for a time series in particular this part of the system will consist of various applications of arima since it is capable of modelling univariate time series data that has both trend and seasonality then it continues with data preprocessing choose feature data time that has to be converted into datetime format for resampling equal time distances are kept in consideration dividing data into train set and test set parameters which have been selected for training and not the optimum parameters for an arima model Conventionally, the arima fits into one of three they are part models the link between an observation and a number of past ones.

LSTM (Long Short-Term Memory)

An LSM has been applied in the given project to predict energy consumption based on historical data in a more general sense. methodology entails data preparation in terms of transformation to support sequence modelling, such as creating input sequences from the time windows of past observations and by design of the LSTM network incorporating the use of LSTM cells that would capture both long-period dependencies as well as short-period dependencies within the time series data. These sequences of energy consumption are utilized in training a model where the network learns tracing patterns as well as its relationships. There are metrics on the model that are RMSE and others that have been used in monitoring accuracy within the process of prediction.

Figure 39.1 illustrates the proposed architecture that outlines a system where users can register with their credentials and then login into the system. The user enters

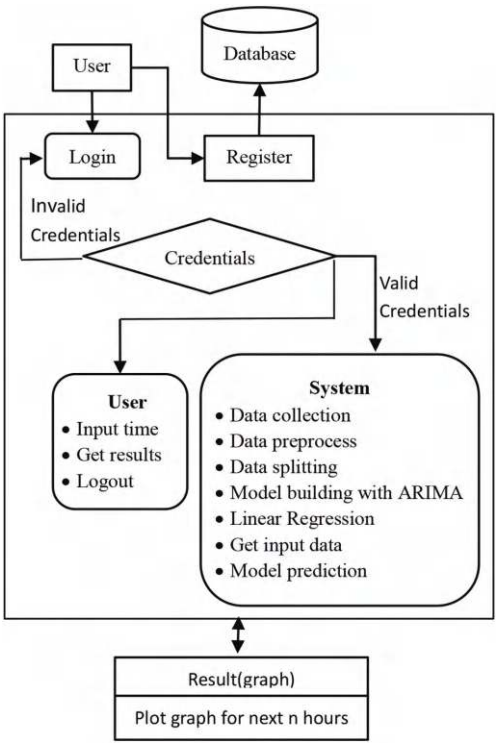

Fig. 39.1 System architecture

the input data and the input data will be processed by the model, which will provide predictions. The input data is processed including all the steps from data collection to model prediction using the ML algorithms like LSTM and ARIMA which generates a prediction based on user input. The generated prediction is transformed into a graph representing the energy demand.

4. Existing System

This is why the work continues to shed light on the impacts of COVID-19 on the demand and consumption side of energy while discussing very serious changes and challenges faced in the energy industry. Spatial and temporal variations in energy intensity can be underlined and draw attention to system thinking in stabilizing energy demand. The study further identifies emerging opportunities to increase energy efficiency and promote energy saving in the post-pandemic world. In the final analysis, it brings to light lessons learned and possible pathways for a more resilient and sustainable energy future [12]. The study highlights energy intensity variations in space and time and the challenges faced by the energy industry. The paper discusses the systemic thought process that needs to be developed to stabilize energy demand and recognizes emerging opportunities that will make energy efficiency and sustainability possible. It gives an overview on the impacts of the pandemic on energy consumption patterns and gives recommendations on future energy management [13]. Climate change impacts on electricity demand. It gives insights on how increased temperatures and weather changes can easily raise the electricity demand significantly, mostly during peak periods. Using extensive climate and electrical load data, the study projects several scenarios for the future and recommends measures to mitigate increased demand through energy efficiency and policy measures. This research emphasis points out the needs for including climate change considerations in the planning of urban energy configurations [14]. Comparison of other data preprocessing techniques and training modes for performance optimization of RF. This research affirms the ability of RF to surpass not only statistical but also other machine learning models in electricity demand prediction [15].

Although the models were rich in data and algorithms, their performances did not meet the accuracy required. Multivariate Polynomial Regression also had overfitting issues due to the dimensionality of the fit for the nonlinear relationships in the data. Random Forest Regression although performing very strong in big-data situations and its ability to deduce interactions among variables could not yield good accurate predictions about energy demand across the experiments due to its variance, that would be very high. MPR is an extension of simple linear regression in which a polynomial equation is fit to the data and thus allows the model to pick up non-linear relationships between predictor variables, such as weather, and target variables like energy demand. RFR is another ensemble learning method where multiple decision trees are constructed and their predictions aggregated to improve the accuracy and robustness with a good interaction among multiple features of large datasets. GBR builds the models sequentially, where each new model corrects the errors of its predecessor. Instead, in this methodology, improvement focuses on better performance achieved through lessening the errors iteratively. Smart Grids-Real-time data feed from sensors and smart meters to deliver dynamic forecasts of energy demand.

4.1 Disadvantages

- *Limited Predictor Variables:* Classic statistical models are handy but are based on some very limited predictors and use simple regression that also has its own set of limitations. Since the methods cannot take into account the complexities responsible for energy demand, influences like changing weather patterns, economic changes, and even social responses would play an important role that is challenging to model by elementary approaches
- *Inadequate Handling of Non-Linear Relationships:* The purpose of simple linear regression models is to trace the relation between two or more variables, but the energy consumption patterns are rather complex and nonlinear in their characteristics. Therefore, an irrevocable complexity that follows is that the nonlinear dynamics of such systems cannot very easily be modeled with the accuracy of a linear model, which gives lower predictive accuracy.
- *Oversimplification of Temporal Patterns:* While traditional models focus on temporal patterns, they often do so in an oversimplified manner. This simplification can lead to inaccurate predictions during periods of unusual or unexpected changes in energy demand, such as during extreme weather events or sudden economic shifts.

5. Proposed System

The system to be built will aim to have an accurate prediction of energy demand using advance techniques and machine learning linear regression as it is very direct is to be used then time series analysis in order to be able to identify trends in the long run and arima that will help effectively if the one variable available is chosen to be used in models and the lstm able to catch long terms

trends as well as complex interactions by integrating these approaches the system will then be able to generate even more accurate and reliable predictions.

5.1 Advantages

- *Scalability and Adaptability:* machine learning approaches have very high scalability and adaptability which make them highly apt in dealing with dynamic and big-sized energy systems.
- *Enhanced Accuracy:* Advanced machine learning algorithms offer improved accuracy in predicting energy demand compared to traditional statistical models. By capturing complex, non-linear interactions within the data, these models can provide more reliable and precise forecasts, essential for effective energy management and planning.
- *Incorporation of Diverse Data Sources:* These models offer a more robust solution for long-term energy forecasting needs increased precision newest machine learning algorithms comparatively offer better precision than the standard statistical models which are mostly simplistic in capturing complex nonlinear interactions in data more reliable and accurate predictions can be offered that act as a critical necessity for efficient energy management and planning incorporation of diverse data sources machine learning models can accommodate virtually any predictor including time of day and weather-related variables the approach allows for a more complete understanding of the influences driving energy demand thereby better adjusting for conditions and trends prevailing at different times.

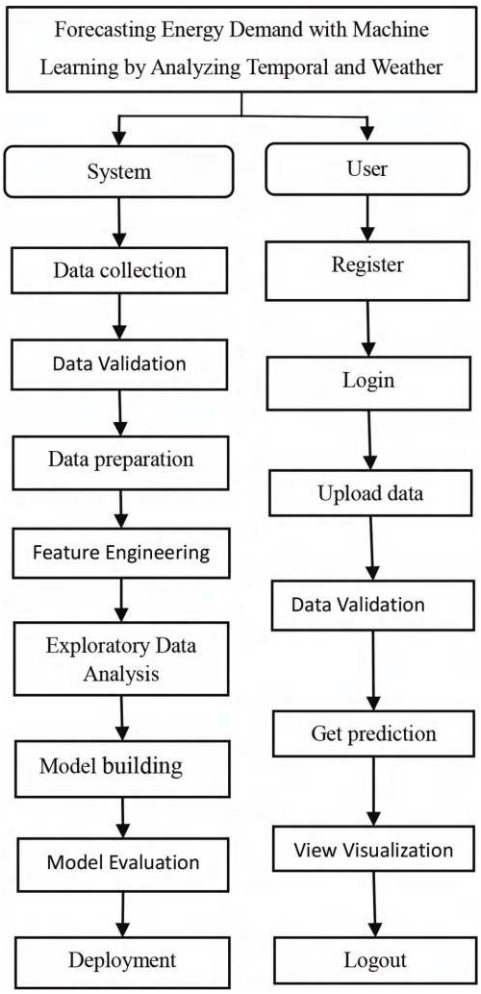

Fig. 39.2 Workflow of the proposed system

5.2 Results

Figure 39.3 depicts the model training with the chosen dataset for multiple epochs through which the model learns more patterns. Figure 39.4 shows the plotting a graph between the input variables to understand the dependency

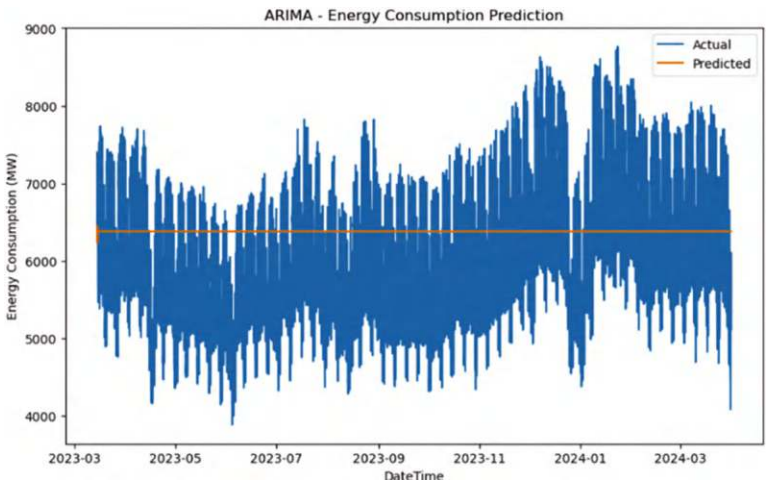

Fig. 39.3 Training the model with the dataset

```
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 40293.1602
Epoch 11/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39585.2109
Epoch 12/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39146.8633
Epoch 13/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39713.6992
Epoch 14/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39946.8164
Epoch 15/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39697.1797
Epoch 16/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39512.0625
Epoch 17/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39494.1758
Epoch 18/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39911.7695
Epoch 19/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 37936.5195
Epoch 20/20
1151/1151 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 39748.3984
288/288 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
LSTM MSE: 33047.09000864158
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Fig. 39.4 Plotting of data

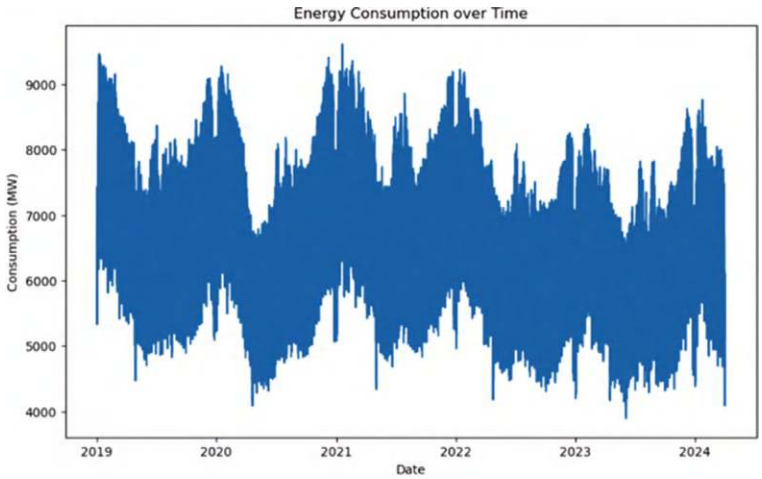

Fig. 39.5 Model prediction using ARIMA

better. Figure 39.5 represents the prediction of the model using ARIMA model. Figure 39.6 and 39.7 are related to the user interface through which the users can interact with the model to get the predictions of the model. Figure 39.8 gives the final output that is the prediction of energy demand for user entered hours.

Fig. 39.6 User Login into the model using credentials

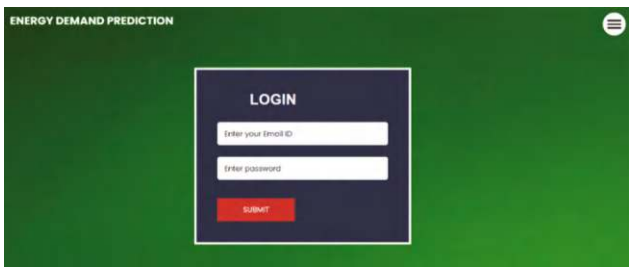

Fig. 39.7 Input is given to get prediction

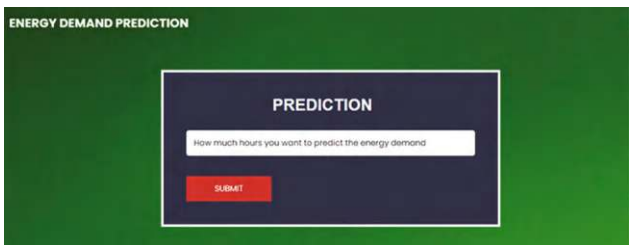

Fig. 39.8 Predicted output represented in visual form (LSTM)

6. Conclusion and Future Scope

The proposed work concludes that for this work three different machine learning algorithms were designed which comprise of Multiple Polynomial Regression MPR Random Forest Regression RFR, and Gradient Boosting Regression GBR, and applied to the prediction of energy demand in Connecticut compared with both pre 2018-2019 and post 2020-2021 periods of the COVID-19 pandemic and the results show that it goes down during the pandemic the results show that the GBR model performed better than both the MPR and RFR models throughout the whole analysis period and had a better match with the earlier researches, especially time-weather integrated analyses where error metrics improved quite significantly the models could simulate daily consumption patterns with peak demand during the active hours and non-peaking demand early morning and late evenings GBR performs better on weekends, besides transitional months, April and October also had a lower demand during moderate weather conditions.

Study several machine learning algorithms with the view of achieving improved accuracy in modelling. Explore contributions of variables by including extra parameters drawn from other meteorological data into the model. Improve the robustness and predictability of the models by exploring alternative strategies in variable data sampling methodologies, data scaling techniques, and strategic placement of hyperparameter values. Improved sectoral analysis to identify leading patterns in energy consumption within each sector of the economy. Techno-economic trends in solar photovoltaics and electric vehicles, among others, will provide inputs to inform on the future modelling of energy demand in those areas. The assessment will be on whether the models developed are consistent with the general trends recorded in the dynamics of energy demand pre- and post-COVID-19.

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Grafting Evidence in Banking Data Archive Using Machine Learning

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Abstract: With the rise of electronic banking and the surge in transaction data, detecting fraud has become a major challenge for financial institutions. This project first applied advanced machine learning (ML) techniques like LightGBM, XGBoost, CatBoost and Majority Voting to address class imbalance in banking data, where fraudulent transactions are rare. These models were optimized using class weight adjustments to improve fraud detection. Now, the project develops by techniques like Logistic Regression, K-Nearest Neighbors, Support Vector Classifier and Decision Tree Classifier all enhanced through cross-validation for better accuracy. It results in development of a robust ML-based fraud detection system capable of accurately identifying fraudulent transactions in real-world banking scenarios, contribution to the advancement of fraud detection techniques in the financial industry and potential benefits to financial institutions in terms of reduced financial losses and improved customer trust.

Keywords: Fraud detection, Machine learning (ML), Banking transaction data, Fraudulent activities, Class imbalance, Flask framework

1. Introduction

With online banking and e-commerce, fraud transactions are now becoming a pressing concern for financial institutions. Growing popularity of digital payment methods have transformed the financial scenario and facilitated greater convenience among consumers but also sowed grounds for fraudsters as well. The volume of data generated by such transactions makes the detection of fraud rather sophisticated, so calling for advanced techniques and innovative approaches to identify and prevent illicit activities [1][2].

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For effective countermeasures, it is essential to understand fraud patterns. Historical transaction data can pinpoint anomalies, which signify potential frauds. This knowledge enables financial institutions to develop stronger models that not only are able to detect fraud behavior seen in the past but can also predict future tactics being used by fraudsters [3]. With this predictive ability, financial institutions are capable of taking a proactive approach against fraud. Losses are minimized before they occur.

It is at the weaknesses in the application that fraudsters tend to operate and perpetrate their schemes: attacking weaknesses both in technologies and human behavior. Most attacks-Phishing, Social engineering, etc. are based on how to manipulate people into divulging sensitive information. This multi-layered endeavor underlines the need for holistic security measures accounting for technological as well as human weaknesses [4]. Organizations can ensure the creation of a strong security environment that discourages potential fraudsters with such measures, but one also allows for quick detection of any suspicious act.

Fraud prevention and fraud detection are two prevalent strategies usually adopted by organizations to effectively deal with fraud. Fraud Prevention denotes all measures taken in advance to prevent fraud from happening: strict authentication procedures, customer education in security best practices [5]. This two-pronged approach is necessary because prevention can't eliminate all the risks, and a strong detection mechanism needs to take care of those that slide in.

Banking fraud often comes under binary classification, whereby the transactions are identified either as valid or fraudulent. The problem is very complicated with the sheer volume of transaction data that banks must process in a day. Examination of each transaction is virtually impossible; therefore, the better option is to apply machine learning algorithms in the whole process [6]. Such algorithms can handle massive datasets, learn from data of the past, and look for patterns consistent with fraudulent behavior

Furthermore, with the most updated machine learning and deep learning techniques, fraud detection can be initiated in real-time [7]. With these technologies, transactions can be watched closely, and responses can be given timely to the emerging threats when they are happening. It is not only preventing fraudulent transactions but building customer trust, because users feel safe with their transactions being monitored all the time.

A good fraud detection system would therefore need to be sensitive and specific. A sensitive system would flag high percentage of fraud transactions, and specificity would concern minimizing false positives- or legitimate transactions flagged as fraud. The balance is delicate; overly sensitive systems may cause frustration amongst customers in the form of too many interruptions to legitimate transactions, while under-sensitive systems may allow undetected large amounts of fraudulent activities. Thus, tuning and assessment of the detection algorithms are continual processes necessary to maintain an optimal balance [8].

The art of fraud detection is ever-evolving with new technologies and methodologies springing up regularly. With the advancement of machine learning and artificial intelligence, these two technologies are bound to be more significant in defining the future direction of fraud detection [9].

2. Literature Review

The rapid growth of digital banking and e-commerce has led to a rising fraudulent activity across the industry which necessitates a strong fraud detection system. Recent surveys involve the adoption of machine learning techniques to enhance detection and prevent fraud during financial transactions. It particularly brings out the practicality of predictive modelling in fraud detection, which implies that, by using ML algorithms, transaction data may be analyzed for potentially fraudulent activities in the digital banking environment. These researchers further indicate that these models evolve in their predictions over time as more new data inputs are taken into consideration.

K.W. Thar [1] mention the ability of predictive modelling in fraud detection. In this regard, digital banking environments should allow ML algorithms to scrutinize transaction data seeking potentially fraudulent activities.

K. Balaji et al. [2], as they proposed a holistic approach that combines the usage of ML with big data analytics. In their opinion, the utilization of such technologies would enhance fraud detection in banking systems by using meaningful management components.

Sheth et al. [3] actually elaborate on this theme by explaining a deep learning approach to fraud prediction and analysis in financial sectors. They then go on to explain that those deep learning models can identify intricate trends within transactional data that can allow for far more effective fraud detection than traditional methods of fraud analysis.

P. S. Patil [4] unveil the foundational significance of machine learning in the analysis of banking data; their work reveals early points in applications of ML techniques in fraud detection, thereby opening avenues to innovations in that field.

Bhowte et al. [5] explain that ML techniques are applied in accounting and finance, and their advanced methods of fraud detection illustrate the effectiveness of implementing

several types of ML models for enhancing detection, so effective response from an organization to fraudulent transactions can be achieved.

Tamanna et al. [6] propose an ensemble approach to automated fraud detection in financial transactions. They successfully show that integrating several machine learning models significantly boosts the detection rate without raising false positives, a classic problem in fraud detection systems.

D. Kalbande et al. [7] proceeded further with the potential of machine learning, designing a specialized fraud detection system. From the above results, it shows that the application of various ML techniques has a positive effect on fraud detection, thus emphasizing more importance for banks to invest in advanced technology tools.

E. Bouchti et al. [8] take an entirely innovative approach when applying deep reinforcement learning specifically to the task of fraud detection in banking. The investigation of this new approach leads to better resolutions to be implemented in real- time scenarios.

Ali et al. [9] summarizes some of the machine learning methods applied in financial fraud detection. Indeed, it underlines the ever-growing strategies that have been looked into as well as the overall trend towards more sophisticated ML applications in this domain.

3. Existing System

The existing fraud detection system of banking systems primarily aims at solving the problem of unbalanced data, which is normally seen in the data sets of fraudulent transactions. Conventionally, most of the machine learning algorithms have not been capable of working well with this type of imbalance where the minority class is normally dominated by the majority class [7].

The system uses boosting algorithms; these are optimized for the matter of big data and yield better performance than traditional models [9]. Among the proposed algorithms, particularly LightGBM is an efficient algorithm to handle large amounts of data. It follows strategies toward the minimization of memory usage by opting for leaf-wise tree growth. XGBoost makes good use of the tree-based structure to actually minimize the problem of overfitting, ensuring it minimizes the complexity of the model [8].

Except for these algorithms, techniques are applied through ensemble learning which combines the strength of many classifiers, such as majority voting [10]. These techniques enhance overall accuracy with a minimum error rate by considering all the predictions coming from the models [11,12]. The models can be made to adjust well to the complexities of fraud detection by applying Bayesian optimization, which maximally adjusts the hyperparameters to optimize the model [13].

Overall, this existing system uses advanced models of machine learning, hyperparameter tuning, and ensemble methods to build an efficient fraud detection system that addresses the challenges presented by the high imbalance that lies in the data and delivers much low accuracy and reduced false positives [14,15].

4. Proposed System

The proposed system will be established based on the idea of establishing a strong fraud-detecting platform on machine learning that raises awareness and stands against fraudulent transactions for electronic banking. The key function of the system would be to identify fraudulent transactions from patterns in the transactions. In theory, the class imbalance issue that the system would encounter in this project is that a small fraction of all the real banking transactions is fraudulent.

This cross-validation mode of operation improves the reliability and generality of models. Cross-validation can further be performed with subdividing data into a number of subsets, where then a number of models will be trained on different parts of the same data, but test the corresponding subsets. It hence determines the refinement in performance for each algorithm so that the models do not overfit relating to a specific dataset.

The core component of the proposed system will be class imbalance through class weight tuning. Instances of rare, fraudulent transactions prevail, whereas no such instances are available for normal transactions, and hence it fails to recognize these outliers by traditional ML models.

Integrate such ML models into a real-time detection environment. The system, as it witnesses the new transactions coming in, monitors them and assesses whether such can be fraudulent based on well-defined patterns. Aggregating results from different models may provide a more confident and accurate verdict on whether a particular transaction would fall under the category of fraudulent or not.

This would enable the fraud-detection mechanism to respond suitably and, more importantly, to adapt itself according to the character of fraudulent activities, which keeps changing. Periodical retraining of the models on new data would keep it updated about the new fraud trends.

Lastly, it is proposed that this system helps financial organizations save millions of dollars year in financial lost revenue since detected fraud does not go unnoticed. Overall customer trust is increased because customers feel much safer doing transactions with the proposed system.

4.1 Advantages of Proposed System

This proposed fraud detection machine learning-based system has a huge advantage in the financial sector, as it may provide better accuracy in fraud detection compared to traditional methods using advanced algorithms. Using all these models-that are logistic regression, K-nearest neighbors, support vector classifiers, and decision trees-it could take advantage of the strengths of each one.

A scalable system to be integrated into multiple environments with high transaction volumes without compromise on performance makes it of great importance. Periodic retraining allows the system to keep abreast with constantly changing fraudulent tactics, ensuring constant effectiveness.

5. METHODOLOGY

We first apply the desired pre-processing on the data and further divide the data into two sections training and testing, followed by performing Bayesian optimization on the training data to find the best hyperparameters that lead to the improvement of the performance. We use the cross-validation method to obtain performance comparison in an unbalanced set and then examine the algorithms using different evaluation metrics, including precision, recall, MCC, the F1-score, and AUC.

5.1 Dataset

This is a real-time "transactional data set." It includes some number of transactions. The dataset is telling that there is a huge imbalance since only some percent of the total transactions were labelled as fraud, which amounts to some number, and the rest are all legitimate ones. For privacy reasons, the original features of the dataset have replaced the features with numerical values obtained from PCA. The features available are V1 to V28, in step with the main components. Also available is a "Time" feature to track how many seconds passed since the first transaction, an "Amount" to capture the sum of the amounts of transactions, and a "Class" feature which is tagged 1 for fraud and 0 otherwise.

5.2 Data Pre-Processing

The dataset being used is real-time "transactional data," consisting of some transactions. It is highly imbalanced, with only some percentage of the transactions labelled as fraudulent, which amounts to some transactions, while the remaining transactions are genuine. To maintain privacy, the original features of the dataset have been replaced with numerical representations derived from Principal Component Analysis. As a result, the available features include V1 through V28, representing the principal components.

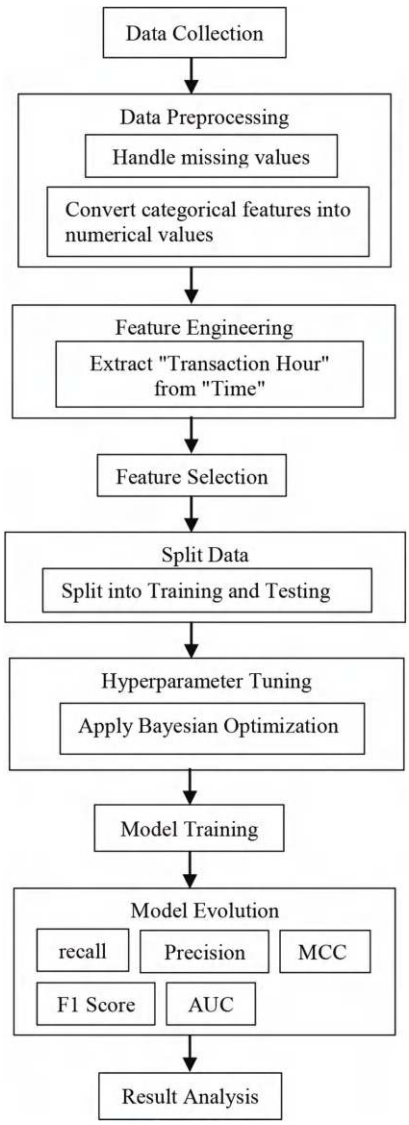

Fig. 40.1 Proposed system workflow

5.3 Feature Extraction

To augment the information gleaned from the features already established, this "Time" feature is further used to generate yet another new feature called Transaction Hour. This created feature gives a greatly more precise insight into transaction patterns than would otherwise be possible with only elapsed time in use, thus improving the data set and possibly conferring robustness to models.

5.4 Feature Selection

Since not much information is known regarding the characteristics of the dataset, except "Time" and "Amount,"

feature selection emerges as a critical step in the modelling. This paper addresses this by the use of IG as a method for selecting the most discriminative features that are relevant for fraud detection.

5.5 Algorithms

Hyperparameter tuning is found to be the crucial part in training any type of machine learning model because hyperparameters directly influence how the model learns

1. Logistic Regression

Logistic Regression is commonly used in fraud detection to classify transactions as either fraudulent or legitimate. It works by calculating the probability of a transaction being fraudulent based on input features like transaction amount or time. Logistic Regression is easy to interpret and effective when the relationship between features and fraud is linear.

2. K-Nearest Neighbors

K-Nearest Neighbors (KNN) identifies fraudulent transactions by comparing them to the 'k' nearest examples in the dataset, using a majority voting system. It is especially useful for detecting anomalies or outliers in small datasets. KNN is easy to implement and works well when fraudulent transactions are distinctly different from legitimate ones.

3. Support Vector Classifier

Support Vector Machines (SVM) are effective for fraud detection by finding an optimal boundary that separates fraudulent from legitimate transactions. SVM is particularly strong in handling high-dimensional data and works well when the two classes are clearly separable.

4. Decision Tree Classifier

Decision Trees classify transactions based on decision rules created from features like transaction amount or time. Each branch in the tree represents a decision, leading to a classification of either fraud or legitimate transactions. Decision Trees are easy to interpret and can capture complex patterns, but they are prone to overfitting, especially in imbalanced datasets.

6. Experimental Results and Analysis

The output of my process does a proper evaluation of the performance of my model through an overall assessment. The cleaned and pre-processed data were used directly for training, following hyperparameter tuning with Bayesian optimization. Cross-validation, specifically 5-fold cross-validation, was finally done to check whether the model generalizes well to new data and that it did not overfit. Accuracy, precision, recall, and MCC are the most important key performance metrics included in the final output. The ROC_AUC score denotes how well the model distinguishes between two classes

Figure 40.2 describes the process in which the dataset that comprises information of transactions to detect fraud is being uploaded to the system and it will begin the process of applying machine learning models for fraud detection. Figure 40.3, 40.4, 40.5 are that result in the command prompt for different points of execution of the model. Figure 40.6 is the final output that is seen in a browser. It represents the result of the fraud detection process that is visualize.

Fig. 40.2 Upload the dataset

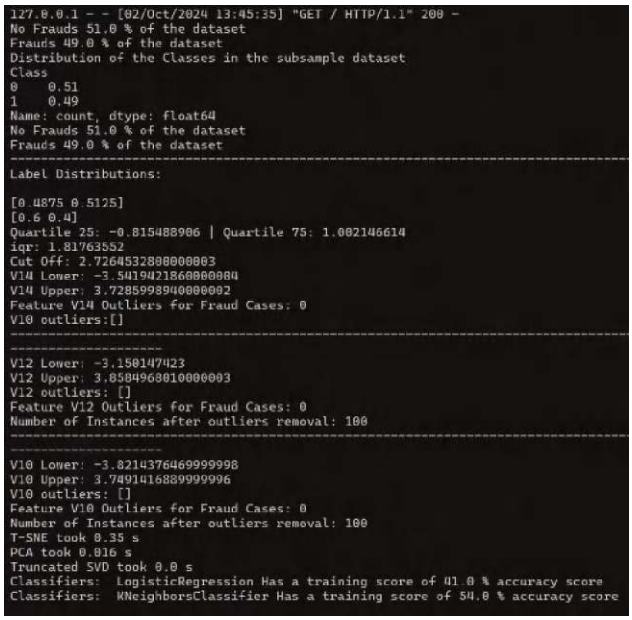

Fig. 40.3 Fraud detection summary

Fig. 40.4 Fraud detection summary

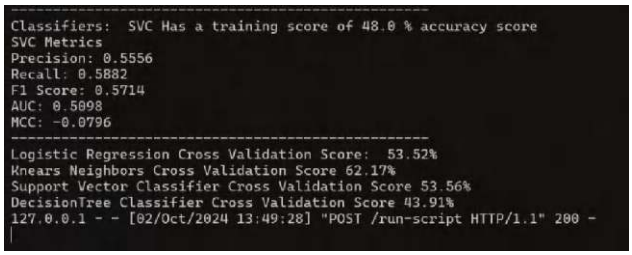

Fig. 40.5 Fraud detection summary

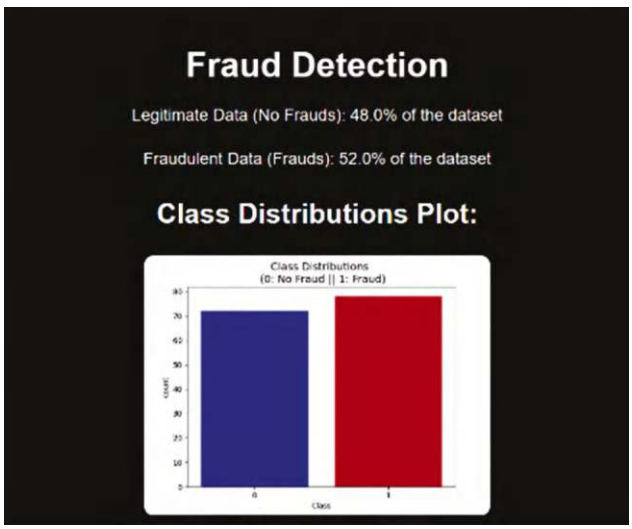

Fig. 40.6 Class distribution plot in web

7. Conclusion

The developed project shows how robust a fraud detection system can be built based on machine learning algorithms, such as Logistic Regression, K-Nearest Neighbors, Support Vector Classifier, and Decision Tree Classifier with cross-validation applied to them. Based on class weight tuning that would address the class imbalance problem, the system effectively detects fraudulent transactions in the banking data. Such integration really leads to a high-accuracy, low false-positive fraud detection mechanism that further improves financial security. The future improvements of this system would be integration with deep learning models and adaptive learning techniques for enhancing real-time fraud detection.

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Interpretable Fake News Detection Using Xlnet, FastText and CNN WithLime Explanations

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Abstract: Fake news is one of the main challenges facing the credibility of information and trust in people. The studies by MIT Media Lab in 2018 reported that fake news stories were retweeted 70% more likely than real stories. Advances in deep language techniques from RoBERTa and BERT lead to the detection of fake news, but sometimes it is a lack of clear reasons explaining why the predictions have occurred. We develop a novel method based on top transformer models, such as XLNet, and generalized Explainable AI techniques such as LIME, which is referred to as Local Interpretable Model-agnostic Explanations. This will utilize the FastText as a word representation for efficient words and CNNs for robust feature extraction in the proposed approach. This allows for a better accuracy in the detection of fake news along with enhancing the model transparency on the decision-making process. Our approach targets the problem of fake news in terms of both detection accuracy and transparency in results. This helps narrow down the deep-rooted problems of misinformation and its role among the masses. Such importance is that long bench-marking has proven this hybrid system to perform well compared to the previous models, hence giving clear and understandable explanations. With this, our approach gives proper accuracy as well as can trust it, thus being good as a solution for curbing the spread of misinformation.

Keywords: XLNet, Explainable AI, LIME, FastText, Hybrid deep learning, Natural language processing

1. Introduction

The modern information highways include the internet, message boards, and social media. Digital media has totally replaced traditional media. Ways of life and the information that we have acquired evolve, and that is the shift paradigm, as [1,2] rightly points out. The prime reason behind the popularity of social media is the liberty

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to voice opinions and become informed on current issues with the latest happenings of the world. These blogs are the most credible and unconstrained source of celebrity and political news in the entireworld [3]. Fake news, or verified untrue information, impacts the economy, elections, and civic mood regarding war [4,5]. It further lowers public trust in democracies. False news mushroomed during the pivotal periods of the U.S. presidential electioncampaign of 2016. This trend molded public opinion during contested political processes and sowed the seeds of doubts on the veracity of voter registration rolls [6]. For creating nearly nineteen million bot accounts to spread mal-information related to Trump and Clinton [7, 8]. As can be seen from the most othersites also, there is a drawing of much more attention towards fake news rather than towards the right one. Fake news concerning an issue no problem is worse than anything else. In that perspective, there has to be alot to be done in making credibility online about fake news due to social media. More data nowadays; the more needs to be gained, that is getting the informationas soon and accurate [9,10].

This requires massive utilization of techniques in computational linguistics. In this sense, AI proves to be beneficial. AI can differentiate between truths and lies in just a few minutes. In fact, AI also currently represents an important feature that is working by the discovery of slight differences in the lingua and context as the humancensor is never alert of [11,12]. Many innovative approaches of detection of fake news have also developed by the help of AI and NLP [13,14].

This is made much harder by the online availability of volumes of content coming from a variety of disciplines. To this end, one algorithm is being developed so as to identify fraudulent news report without involving human input in the process. The ability to get reliable information hence depends on such technological breakthrough [15]. There are other technical barriers that are evident when one tries to pin down fake news. It thus compels complex identifications involving solutions promising integrity and the accuracy of the information as sought through the web. We have analyzed three publically available datasets in-depth to detectonline media disinformation and FastText word embeddings to carry out efficient text data processing. Moreover, we will apply explainable AI strategies to respond to the increasing demand for accountability from AI-based solutions [16]. Thus, our operations are streamlined, clarified, and humanized. Although such DL-based models can, even if closed-loop, perform good classification, in this post we applied the XAI algorithms to figure out which are the most influencing terms when classifying false news sentences. Here again, for such black box deep learning model analysis we utilized the deep learning models with LIME and a myriad of the other deep learning models. This paper looks into the challenge of swift diffusion of fake news via social media and its ramifications on society. We leverage an ensemble-based deep learning model that classifies the true versus fake news. Compared to related studies that focus on this dataset, our approach is highly efficient in classifying as fake news the algorithm can detect [17]. Effects from fake news encompass false information and biased reportage. False news headlines can be detected using Convolutional Neural Networks and Gradient Boosted Decision Trees [18].

2. Literature Survey

Recently in 2020, H. Zhang et al designed BERT- based Fake News Detection with Local Interpretability. We present here as part of the techniques, one in fake news detection; that is BERTas the recent feature word which recently got contextualization as against very recent time its gained place in influential methods just for dealing with all those problems regarding natural languages and primarily for the issues surrounding detection in the case of the fakeness of it. This idea, however seems to be the alternative understanding of models as well as their interpretation of understanding thingsin a very transparent way if the inject concept of local interpretable model-agnostic explanation or LIME comes into the picture. In a nutshell, the technique ismore of the application that describes black box predictions and approximate it with something else which is explainable. By using it through LIME, processes lightened with decisions on BERT model transfer. But such explanations related to manipulative materials concerning how different classification models identify the above-given information as true or news making ones are requiredto establish confidence on detection of fake news fora user. Research finding shows an acknowledgement of the tool by which “LIME has found very high accuracy as also highly interpreted not affecting the models used.”.

Combining FastText and CNNs for Improved Fake News Detection is the proposal given by J. Lee et al in 2018. Here, the author proposed a hybrid model of FastText and CNNs for detecting fake news. FastText is the library developed by Facebook AI Research for fast text categorization and word embedding. CNNs are well-suited for image processing since it can handle tremendous amounts of data at the speed that is incredible; very interestingly, it can even discover local critical patterns in a set of text sequence if adapted to NLP. HN only uses FastText purely for extracting feature in defining fake news, therefore creating word embedding and applies CNN to recognize

deep text pattern. In the following, the strength of CNN and FastText comes together. Here, FastText makes it speed up and scale up also, and CNN brings up the recognition of the pattern. Comparing it with machine learning, our hybrid approach has proved to be much better. The outcome is much more accurate and more robust as far as the fake news detection is concerned. Such an exercise here promotes the combination of these different models wherein to make it extremely precise to trace out the forged news.

Recently in 2021, one has the research paper titled as "Explainable AI for Fake News Detection: An Application of SHAP." Here, the author of the piece used explainable AI for transparency and credulity purposes inconcern to fake news detection involving algorithms. This paper applied the use of SHapley Additive Explanation wherein to a set of predictions formed with the help of a machine learning model, clarity was given. To this, the SHAP application will rely much on variationof Game theory for the base of importance-based value inother features as that would be required for the model to use in making predictions. Thus, in brief,We conclude bydescribing the outputs of complex machine learning models and present SHAP as a way a model can be madeinterpretable, which might contribute towards detecting fake news. First, the authors say the false news detectionmodel ought to be trustworthy and explainable because users and all other stakeholders have to have trust in the outputs delivered by the model and then understand why.Transparency with no transparency-although the algorithms in the identification of the false news would be very accurate yet will not be possible to reproduce outside a lab setting, the precision can be recalibrated with SHAP in order to read as even more or less than its true balance. More words and phrases the model uses make one more sure of what was used by the model which finally led to a conclusion by labeling whether the news article, which precedes it and that it came across, was fake or not because of the use of the same models in using SHAP. Thus, it adds much weight on building moreincreased users' confidence towards AI systems for detecting this fake news.

L. Zhou et al have authored this article titled, A Comparative Study of RoBERTa and XLNet for Fake News Detection in the year 2021. The authors in this paper are comparing one of the powerful models of NLP namely XLNet and RoBERTa which were two among the best performing models when it comes to fake news detection. XLNet and RoBERTa are variants of BERT proposed to improve the training procedure and the general performance. This is stronger than the competitor version of the robustly optimized version of BERT by RoBERTa, which removes the NSP task at pretraining and uses much larger datasets much more intensively. Or, alternatively, it can be attributed to the fact that BERT's bidirectional context modeling ability is the ability to absorb even more contextual interactions in XLNet that achieves when training by permutations.

Indeed, it takes cognizance, as seen in the opinionated paper by the author of complex linguistic patterns and, of course, those contexts whereby fake news tells to differ. Accuracy while detecting fake news improves on that premise that XLNet should depend on catchingup better than RoBERTa. For all the context-dependent tasks mentioned above, the authors also provide models of this sort, such as fake news detection, which are going to work much better by virtue of the ability of learning word-level interaction inside a sentence. Already RoBERTa can work on the task and would work well as a decent replacement for some applications.

3. Existing System

CNNs use feature extraction to find anomalies, while LSTM networks gather dependencies between text sequences to examine language patterns for discrepancies. AI-powered natural language processing methods include ROBERTa and BERT. Generative PT models aim for factual congruence when generating text. To enhance precision and investigate language hints, lexical analysis and ensemble methods are employed. Graphs can also be used to evaluate the spread of information in social networks. Transparency in forecast reasoning is improved by the use of explainable AI, such as LIME. Each approach helps fight misinformation by balancing accuracy, computational efficiency, and interpretability.

Torgheh delves into the dangers of social media and disinformation. An approach for detecting fake news based on news dissemination paths is described in the research [19]. The strategy is based on deep learning models. Using content and attitude data, the authors of this study developed the "Hoax-News Inspector" to identify social media fake news. There was a 95% success rate when the Random Forest classifier was used. Data from Politifact and Snopes, both public and private, are incorporated into the system [20]. KMGCN is a knowledge-driven multimodal graph convolution network that enhances detection accuracy by combining textual, visual, and external knowledge. Using visual and external knowledge as nodes, this technique transforms text into graphs for improved semantic relationship capture [21].

3.1 Disadvantages

Complexity: Small businesses or academics may lack the computing resources and expertise necessary to train and implement advanced natural language processing and machine learning models.

Scalability: The models aren't practicable in dynamic online circumstances because they can't manage massive amounts of data and real-time monitoring.

Interpretability: Although LIME makes clear its support for Explainable AI, users may lose trust in the system and become confused by the more complex model's output.

Adaptability: Strategies for spreading false news change rapidly. This model has to be updated and retrained so it canfight new forms of disinformation. Models trained on biased or domain-specific data may struggle to transfer their findings to unbiased news sources or different cultural contexts, leading to biased or erroneous conclusions.

4. Proposed system

That makes it a blend of a hybrid false news detection system both in the light of understanding natural languageas offered by XLNet, in the realm of word representationsas developed by FastText, and more importantly, CNNs capability to extract the features effectively. Moving ahead, an advanced version in technique that shall be used would include the SHAP model which is a version of the Explainable AI model- this will give further high accuracy and high interpretability. Thus, the essence underneath the news information would, be made apparent using the high-level form of natural language processing coupled with feature extraction capabilities. FastText did a good job and is efficient in embedding thewords, but it subtlety that XLNet has processed language.On top of that, CNNs made the model's behavior increase regarding showing signs of fake news detection. The strategy is fairly open and performance-oriented, going tocurb misinformation and garnering trust.

4.1 Advantages

High Accuracy: Integration of the features of XLNet, FastText, and CNNs enhances the levels of accuracy. It has certain points in its favor, it can understand language,word-efficient description, and it can even extract features too. So, when all aspects are taken into account then it will be stronger and able to detect fake news.

Interpretability: SHAP and other explainable AI techniques can enhance the interpretability of model predictions, providing explainable descriptions for the behavior of the model.

Thorough Analysis: Since the system can analyze news articles with natural language processing and featureextraction, it could notice slight trends that may be indicative of possible disinformation.

Flexibility: Because it can be changed or reformed based on how people discover new means to determine fake news, development in the hybrid approach goes hand in hand with continuity.

5. Methodology

5.1 XLNet

For the purposes of detection, the technique described in the paper would include applying the state-of-the-art model XLNet-transformer in terms of their framework since its permutation during the process is being considered when it was trained in relation to both the forward and backward modeling of the contexts. This allows much stronger capabilities of XLNet than BERT in capturing complex dependencies and relationships within the context of text specifically detecting fake news where subtleties of language are of paramount importance. First, XLNet will pre-training on: a large corpus that trains comprehensive representations of language. More directly than BERT, the model uses all the tokensin a sentence to predict some subset of them. Therefore,it can potentially be better at discovering and capturing long-distance dependencies than BERT. Subsequently, the finetuned XLNet is further fine-tuned on a set of thelabeled datasets specially designed and curated for the task of identifying fake news. This is done so that its model parameters get optimized for optimally detecting the misleading contents. In detection, XLNet transforms news articles into embeddings that capture intricate word relationships forwarded through the classification layer to output a probability score indicating how likely the article is to be fake. To incorporate interpretability, XAI techniques in the form of SHAPs are incorporated in the system. SHAP explains the contribution of each word or phrase towards the final prediction, thus the model decisions are easy to be trusted and to be seen very clearly.

5.2 Hybrid Model (FastText + CNN)

This proposed methodology makes use of a hybrid model - FastText word embeddings in combination with the Convolutional Neural Network (CNN) for better detection of fake news. FastText is a system that generates effective and context-aware word embeddings by capturing word meanings using context surrounding surroundings and sub-word information. It is found particularly effective at processing divergent language and morphological differences found within pieces of artificial news. These embeddings from FastText were fed to a CNN for feature extraction. CNNs are best suited for the learning of local patterns in data due to the application of the convolutional layers that apply filters to emphasize important linguistic features such as key phases and sentence structure. CNN architecture works by reducing the dimensionality of the

data while holding the important features with a number of convolutional and pooling layers ensuring that the model can identify fake news from the real ones. After the feature extraction of CNN, the flattened features pass through the fully connected layer, where it produces a score of probability as to how likely the news is to be fake. Further to this, techniques like SHAP- Shapley Additive explanations can be combined with Explainable AI that will help them enhance the interpretability while giving transparency to the model about the decision-making process. This hybrid approach combines the efficient FastText word embeddings of CNN's powerful feature extraction toward increasing accuracy detection having clear understandings accompanied by decisions that make this a reliable tool in combating the spread of misinformation.

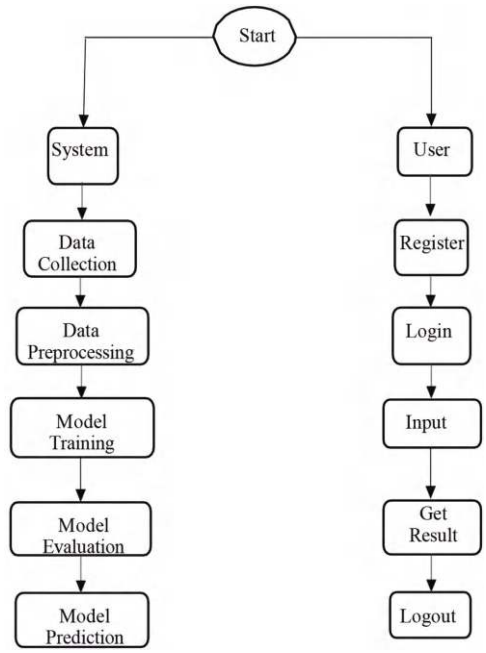

Fig. 41.1 Proposed system workflow

Figure 41.1 illustrates the proposed system workflow that outlines system process and user register with their credentials and then login into the system. The user enters the input data will be processed by the model, which will provide predictions after that user can logout from the system.

6. Implementation

6.1 System

Data Collection: The dataset is composed of real and fake news stories. Formerly, the dataset was divided by 80/20 for training and testing datasets. Now data will be divided into two parts so that the model can be trained and tested

Data Splitting:

a. *Training Data:* Finally, the training model applies 80 percent of the preprocessed dataset to train the model. In this optimization step, there is an adjustment in the parameters of the model in respect of boosting ability against fake news
b. *Testing Data:* Then, the learned model undergoes testing through ten percent of the dataset. Using the predictive model, predictiveness ability and correctness degree toward predicting news articles can be inferred.

Training: In this process, the model trains on 80% ofthe sample. It learns to distinguish whether the news is authentic or fake. The parameters are adjusted step by step with the gradient descent. Then the result is the higher the accuracy in classification and less the error rate.

Model Testing: The model is executed on the 80% dataset that has not yet been tested. Finally, to validate the ability of the model, it is deployed on unseen data topredict if the news articles are either fake or real.

Model Save: Save the trained model. The learning parameters along with biases are saved. Made to run without glitches.

Model Predictive: Feed new news feeds to the trained model given by the users. Gives correct predictions whether the given is true or not.

6.2 USER

Registration: Users register to an account in the system through registration. Enter your basic details to complete registration; this will enable you to access all functionalities.

Login: The users could login into the system making use of the username and also password. Input your account information. Accounts login capabilities are addressed.

Upload Text: Upload data false or true news reports can be distributed articles that your gadget has chosen for you to read are uploaded. Through this process, it evaluates for the validity

Display results: this algorithm checks for uniqueness on submitted papers, after which the users can review the model's classification of all articles submitted.

Log out: Log off securely and close all sessions. Your account information and private details are safe. Always log out after each use for your own protection.

7. Results

We check our findings against two control experiments. The models outperformed the baselines by a wide margin, with

WELFake and Fake News Net achieving an accuracy of 0.99. We could streamline our processes with this. The amount of relevant data occurrences is statistically significant, even though the accuracy gain is low at 0.02. There are 72,134 recordings on WELFake and 23,196 on Fake News Net. The model's durability, performance, and generalizability are all enhanced by these strategies. Figure 41.2 and 41.3 are related to the user interface through which the users can interact withthe model to get the predictions of the model. Figure 41.4 shows the performance comparison between CNN andXLNet algorithms.

Fig. 41.2 Text upload page

Fig. 41.3 Output page

8. Conclusion

Finally, this hybrid deep learning method for detecting false news integrates the computational sophistication of Explainable AI with the savage power of models such as XLNet, FastText, and CNN. One has complete knowledge of the intricacies and can articulate their significance, much like an intelligent investigator and a well-read librarian. A combination of XLNet's contextual understanding and FastText's word embeddings makes the detection algorithm more accurate and linguistically competent. To make sure that the most convincing false news cannot evade the model, CNN is included. What about the focal point? By adding some transparency to the model, LIME and SHAP reassure users that the computer isn't going completely bonkers with its guesses.

9. Future Scope

It can then be much more effective in identifying future fake news based on what it learns as it analyzes text, images, videos, and metadata. It is intended to address one of the problems that seem increasingly common among many people: online spread of doctored images or deepfake movies. If this system were to scale up and go real-time on news sites and in social media, its implications would be huge. It is optimized for real- time processing and non-latent computations, which will allow it to sense and stop the spread of fake news in real-time. It might be updated to new methods of spreading false information using self-learning

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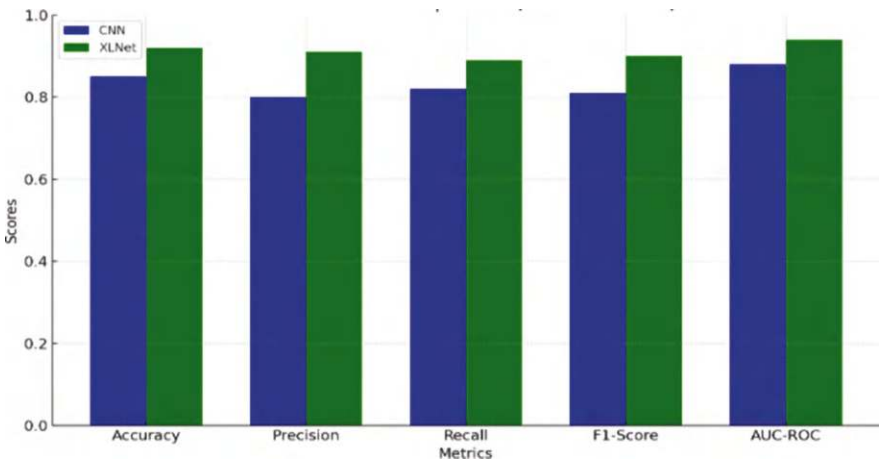

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Note: All the figures in this chapter were made by the authors.

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AI-Powered Virtual Blackboard: Real-Time Hand Gesture Drawing with Media Pipe

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Abstract: The Virtual Blackboard project introduces a cutting-edge solution for virtual writing, allowing users to write in mid-air through hand gestures captured via a camera. Utilizing sophisticated computer vision techniques, particularly Mediapipe's Palm Detection and Hand models, the system converts finger movements into digital ink that is rendered on a screen in real-time. In light of the growing dependence on online education platforms, this project meets the demand for user-friendly and accessible tools tailored to remote learning environments. The system operates across three main interfaces: a blank canvas for flexible writing, a standard interface that displays the user's face, and an open workspace facilitating smooth interaction. Extensive testing, including evaluations under suboptimal lighting conditions, has confirmed the system's reliability and precision in tracking hand movements effectively. This Virtual Blackboard marks a significant leap in the realm of virtual educational tools, offering educators and students a practical alternative to conventional writing methods. By enhancing accessibility and adaptability in online education, the system successfully bridges the divide between traditional classroom settings and remote learning experiences. As the landscape of remote education continues to evolve, this innovation stands out as a vital resource in improving digital learning environments.

Keywords: Digital learning, Finger movement tracking, Media pipe, Palm detection, Virtual blackboard etc.

1. Introduction

Developing an efficient virtual drawing and writing system using hand landmarks detection poses several technical challenges. Firstly, achieving accurate hand tracking across varied environments is complex due to differing lighting conditions, background noise, and variations in hand texture and color. The Media pipe library's hand landmarks module simplifies this, yet maintaining stable tracking when the hand moves quickly or partially exits the frame remains a challenge. Another issue lies in real-time processing, as the system must detect, segment, and track hand landmarks with minimal latency to ensure a smooth user experience.

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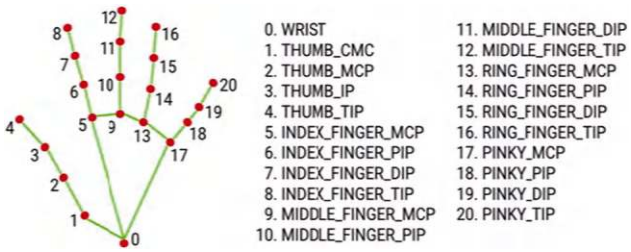

Fig. 42.1 Media-pipe hand

Source: https://thescipub.com/pdf/jcssp.2024.997.1008.pdf

Gesture recognition further complicates this process by requiring the continuous monitoring of the landmarks to distinguish between subtle hand movements, which is computationally intensive. In particular, accurately distinguishing between gestures relies heavily on capturing these positions across specific time intervals, making real-time performance and gesture fidelity critical considerations. Mediapipe's use of a dual-model approach—combining the Palm Detector and the Hand Landmark Model—addresses some of these challenges, but ensuring consistently high accuracy (95%) under different conditions remains a core focus in system development.

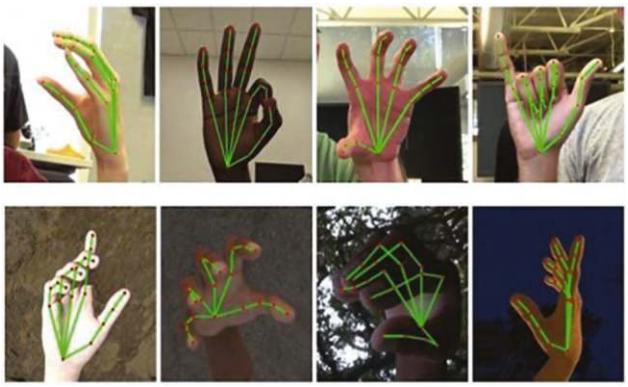

Fig. 42.2 Palm detection using media pipe

Source: Author

2. Literature Review

Yash Patil et al. [1] presented a tool using OpenCV and Python has been developed for a dynamic virtual portrait system and a virtual sketching application controlled by tracked objects. The Python-based program offers accessibility and flexibility, highlighting the importance of computer vision and machine learning in interactive systems.

Alet Joseph Byju, Arjun K R, Delvin V D, and Mridhul M L et al. [2] proposed AI-powered video conferencing system integrates virtual Jam board into interface, enhancing collaboration during COVID-19. This innovative web application integrates virtual interaction tools, eliminating the need for additional hardware or tools.

Samira Abdul-Kader Hussain et al. [3] developed A virtual sketching system, utilizing Media pipe, OpenCV, Python, and digital image processing, enables real-time sketches through webcam-detected hand movements. It enhances interactive online learning, providing dynamic visual tools for teachers and future plans include mobile device optimization.

Using a combination of Media Pipe, OpenCV, and Python, an online painting tool was introduced by Gayathri G. Murali, Shukhaira Beegam T., Akhil Raju, Amal, and Tessy Abraham Azhikakathu et al. [4] that utilises artificial intelligence to create digital artwork mimicking hand motions. One of the features is the ability to draw in real-time using the webcam. Other features include colour suggestions and automatic brush stroke smoothing.

Mihir Paun, Deep Paun, Karunesh Singh, and Vishal Kisan Borate et al. [5] developed a system for digital painting with Python and OpenCV. It uses machine learning for real-time video tracking and allows users to draw objects using their webcam. Improved object tracking accuracy and real-time finger drawing are both made possible by the system.

Creators of Media Pipe, a platform for constructing modular pipelines for processing sensory data, were Google researchers et al. [6]. Developing and releasing machine learning apps for many hardware platforms has never been easier than with this solution. By prioritising determinism, synchronisation, and consistent node execution, it simplifies concept development and implementation.

Supriya Tel sang and Rajkumar Dongre et al. [7] developed the Virtual Drawing Board, an AI-powered computer vision system that uses finger movement tracking to enhance online learning settings. It has an easy-to-understand UI, real-time hand tracking, and colour selection options made possible using OpenCV and NumPy.

Jishma K et al. [8] developed the Virtual Painter, an AI-driven tool that can be controlled by hand gestures. It uses real-time camera data to follow the user's hands, making it easier to paint and navigate slides. It has potential applications in both academic and professional contexts.

Using state-of-the-art technology and machine learning approaches, Kan Guo et al. [9] developed the AI-driven system for robot-assisted painting. A 6-axis robot and a slider mechanism are integrated with spatial convolutional neural networks and multi-column networks. It can creatively reproduce artwork on par with advanced art students, bridging the gap between digital printing and robotic art creation.

A deep learning-based approach for real-time hand gesture identification was developed by Muneeb Ur Rehman et al. [10] by combining 3D-CNN and LSTM networks. To extract spatial-temporal properties from video sequences, the model gets beyond motion patterns and lighting

conditions. It scored 97% on both the training and validation accuracy tests.

3. Methodology and Architecture

In its machine learning pipeline, our hand tracking algorithm relies on two crucial models:

Palm Detector: This model principally detects the presence of hands in an image by processing the entire input image and locating them using an oriented hand bounding box.

Using the palm detector's clipped hand bounding box, the Hand Landmark Model creates accurate 2.5D landmarks that represent key hand locations.

Data augmentation, including scaling, translations, and rotations, is significantly reduced when appropriately cropped palm pictures are supplied to the hand landmark model. This allows the model to focus on accurately localising landmarks, which improves overall performance.

3.1 Palm Detector Architecture

To detect the location of hands, we use a specialized model designed for fast, mobile use, similar to Blaze Face in Media pipe. Detecting hands is challenging due to their varying sizes and potential occlusion. Unlike faces, which have distinct features, hands are more complex to identify purely based on appearance.

We address this with two key techniques. First, we focus on detecting palms, which is easier than identifying the entire hand with fingers. Palms are smaller, so even in cases of overlap (such as during a handshake), we can still detect them. Additionally, using square bounding boxes for palms simplifies the detection process.

Second, we incorporate a smart feature extractor, like a Feature Pyramid Network (FPN), to better understand the entire image, particularly for smaller objects like hands. This makes our system more aware of its surroundings, which is crucial for accurately detecting small objects.

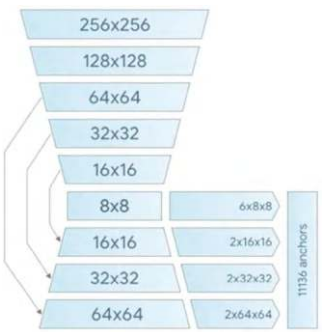

Fig. 42.3 Media pipe architecture

Source: https://www.semanticscholar.org/paper/MediaPipe-Hands%3A-On-device-Real-time-Hand-Tracking-Zhang-Bazarevsky/84b19524609ad75f309be7f87bcea783e6ecd337

The above architecture represents the first module of media-pipe. It takes in an image as input and outputs whether there is a palm present in that image.

4. Handtracking Model

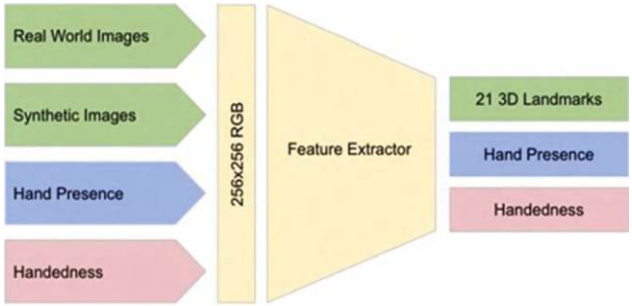

Fig. 42.4 Hand tracking architecture

Source: https://www.semanticscholar.org/paper/MediaPipe-Hands%3A-On-device-Real-time-Hand-Tracking-Zhang-Bazarevsky/84b19524609ad75f309be7f87bcea783e6ecd337

After we have detected palms in the image, our hand landmark model will use regression techniques to pinpoint 21 2.5D coordinates inside the detected hand areas. Because it learns to consistently internalize hand postures, the model continues to perform well even when hands are partially or completely concealed.

The three results that the model generates are displayed in Fig. 42.2: Twenty-one points of reference on the hand, with relative depth coordinates in x and y.

An image with a hand symbol that indicates the likelihood that a hand is visible in the given picture.

To ensure uniformity across all detections, all 21 landmarks use the same topology.

We use a consistent topology for the 21 landmarks. Only synthetic images are used to learn the relative depth (as measured from the wrist), whereas both synthetic and real-world datasets are used to learn the 2D coordinates. In order to handle tracking failures, we included an additional output that predicts the likelihood of a well-aligned hand, similar to [8]. If the score falls below a certain threshold, the tracking function is restarted by the detector.

Handedness is another important factor for effective hand interaction in augmented reality and virtual reality environments, especially in applications where each hand has a specific function. The solution we came up with for this challenge was a binary classification model that could tell us if the input hand was on the left or the right.

Our architecture is designed for real-time mobile GPU inference, and we have also developed both lightweight and heavy variants of the model to accommodate devices with lesser GPU power or higher accuracy requirements on desktop systems.

The 21 landmarks, handedness, and hand presence are output by this architecture, which represents the second level of the Media Pipe structure. The Media Pipe architecture allows for the construction of a hand-tracking pipeline as a directed graph of Calculators, which are modular elements. Media Pipe provides a variety of calculators to handle model inference, media processing, and data transformation across various platforms and devices.

Whether you're using them for cropping, rendering, or neural network computations, all of these calculators are optimised for GPU acceleration. As an example, we employ GPU inference on most modern mobile devices to ensure effective performance.

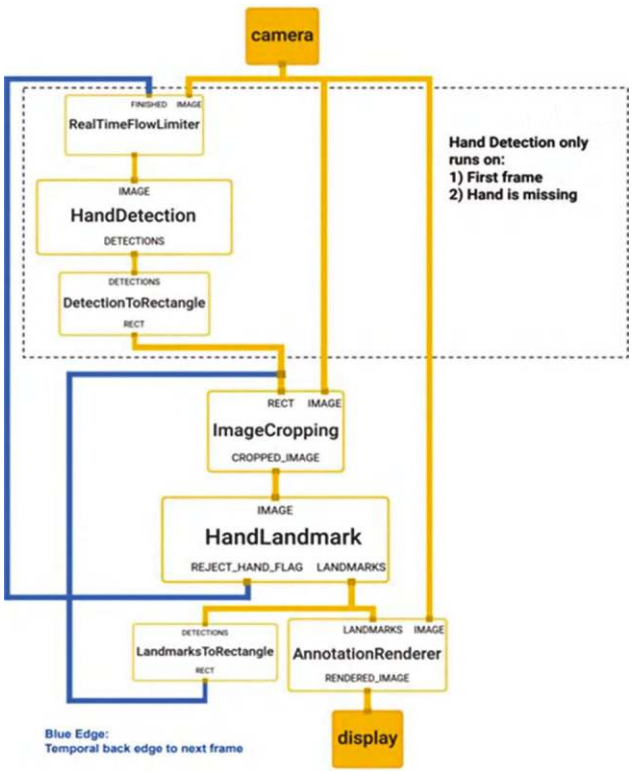

Fig. 42.5 Model architecture

Source: https://research.google/blog/on-device-real-time-hand-tracking-with-mediapipe/

The described architecture outlines the implementation process of Mediapipe's hand tracking model. It consists of two main components: the first is the hand detection module, where the model identifies the presence of a palm within the given image frame. If no palm is detected, the subsequent model is not activated. However, if a palm is detected, a cropped image of the palm is passed to the next model, which outputs the 21 hand landmarks along with the hand presence and handedness information.

5. Results

The process begins by capturing video from the computer's camera, which is automated and does not require additional human interaction. The captured images are then sent to Mediapipe's hand tracking module, which segments the hand and outputs data such as hand presence, handedness, and the 21 key points of the detected hand.

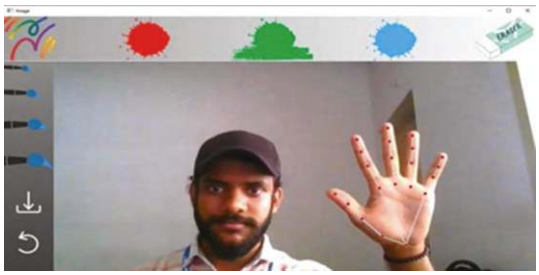

Fig. 42.6 Palm detection

Source: Author

The received information is then processed according to the project's specified requirements. This data is categorized into features such as selecting, drawing, erasing, clearing all, and more. Based on the chosen action, the appropriate command is executed, and the desired output is displayed accordingly.

Fig. 42.7 Selection mode using two fingers

Source: Author

When a command is queued, the program processes it and renders the desired output into the camera stream. For example, if the command is to draw and the selected color is green, OpenCV will display the drawing on the camera stream using the specified green color. In addition to the camera screen, there are also options for drawing on whiteboard and blackboard screens.

The content written on these screens can be saved to a designated folder called "download." Within this folder, subfolders are created for each screen, allowing users to download all three screens through a single download button, which will be detailed in the upcoming sections.

Fig. 42.8 Visualization of data structures

Source: Author

Then for operations like erase mode, open-cv creates an object that detects the color change at that point and if true, it removes the added color and brings back the original background color.

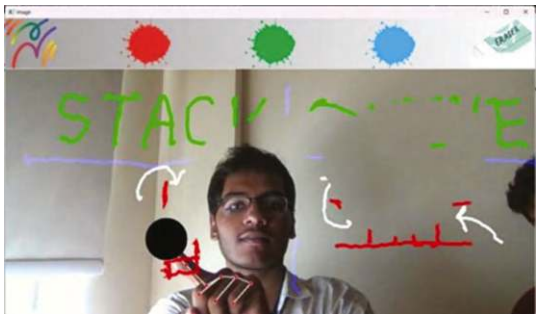

Fig. 42.9 We can see the eraser with black color highlighted in above picture

Source: Author

In addition to further feature like erase all include showing 3 fingers to erase all the screen and make it back to fresh layout. There is also the whiteboard screen that contains only white background with black drawings, and blackboard screen with black background and colourful drawings.

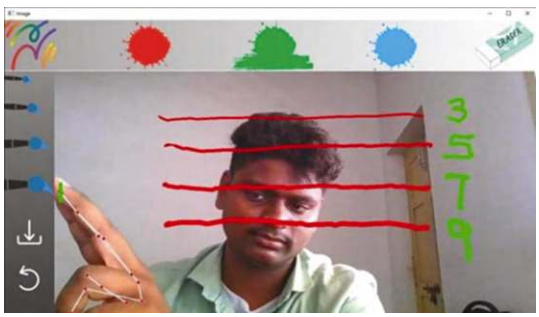

Fig. 42.10 Difference between the brush thicknesses

Source: Author

The figure above demonstrates the brush thickness options for various brushes, as well as the selection mode, where users can observe the changes in the lines they've drawn. The code can be customized to enable different brush thicknesses. The top-left mixed color icon is used for erasing all content.

We've introduced exciting new features to enhance user experience and flexibility. One of the key updates is the ability to easily undo any previous action, allowing users to make adjustments and improvements without the worry of irreversible mistakes. This feature gives users greater control over their work, enabling them to experiment freely. Additionally, we've incorporated various brush thickness options and the ability to save written content from all three screens as separate downloadable images.

Fig. 42.11 Downloaded copy of the content written

Source: Author

Fig. 42.12 Multiple screen view

Source: Author

After conducting numerous tests and making several adjustments, we successfully achieved hand gesture recognition and tracking capabilities through the integration of OpenCV and Media pipe libraries. The system accurately captured and processed hand movements, generating a set of 21 points that clearly represent the palm of the hand. By leveraging these points to detect finger positions, users were able to interact effectively with the virtual canvas—selecting colors, erasing drawings, and drawing on the screen with a notable degree of precision.

We successfully developed an additional screen or virtual board that operates in parallel with the camera screen, allowing for the display of a detailed version of notes

without including the background. This enables further functionality, such as saving the screen as an image file, which can then be shared with others. As shown in the image above, two screens are running simultaneously, displaying simplified concepts of Linked Lists for computer science students. Additionally, the model performs well in low-light conditions, utilizing only the light from the computer screen. This approach can also be applied by professionals during conferences to work their ideas onto a virtual screen behind them.

6. Conclusion and Future Scope

The "Virtual Blackboard" integrates computer vision technology with Mediapipe's palm detection and hand tracking models, enabling intuitive writing and drawing on screens without physical input devices, enhancing online teaching and creative experiences.

The 'Virtual Blackboard' project is aiming to enhance functionality and scalability by integrating machine learning algorithms for adaptive learning, developing a cloud-based backend for seamless synchronization, and optimizing for various device specifications. Advanced AI features, real-time text and shape recognition, and containerized deployment can further enhance the system's utility in diverse learning and creative contexts.

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Traffic Violation Detection System Based Using Hybrid Methods

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Abstract: Traffic violation detection is critical in enhancing road safety and ensuring compliance with traffic laws. Traditional methods of monitoring and enforcing traffic rules can be resource-intensive and often lack real-time capabilities. This paper explores the implementation of traffic violation detection. system using YOLOV8 (You Only Look Once, version 8), a state of the art deep learning model for object recognition. With its real-time processing capabilities, the system aims to detect traffic abuses, such as speeding, signal violations, and illegal turns, by leveraging real-time video feeds from CCTV Closed-circuit television. The study presents the architecture, training methodology, and performance evaluation of the YOLOv8-hashed traffic violation detection system, demonstrating its high accuracy and efficiency in detecting various traffic violations in real time. The comparison highlights the system's performance, which shows the improvements in detection accuracy and processing speed achieved by the proposed system.

Keywords: Road safety, Traffic laws, Traffic violation, YOLOv8, CCTV, Accuracy, etc

1. Introduction

Traffic violations significantly cause road accidents and congestion, leading to loss of life and property. Traditional traffic enforcement methods, such as manual monitoring and radar guns, are often inefficient and limited in scope. The advent of advanced computer vision techniques and deep learning models offers a promising solution to

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automate and enhance traffic violation detection; YOLOv8, recognized for its high accuracy and real-time processing abilities, is well-suited for this application. This paper details the development and valuation of a YOLOv8-based system designed to detect and report traffic violations, providing high confidence in its accuracy [8]. This paper examines a modern traffic violation detection system's architecture, implementation, and performance.

- To develop an automated system for detecting traffic violations using advanced computer vision techniques.
- To evaluate the system's performance in various traffic scenarios.
- To explore the potential benefits and challenges of deploying such systems in urban environments.

Machine learning approaches have improved traffic violation detection by analyzing patterns in traffic data. Decision Trees, Support Vector Machines (SVM), and Random Forests have been used to classify and detect traffic offenses. However, these solutions often require extensive feature engineering and may have difficulty achieving real-time performance. Deep learning, especially Convolutional Neural Networks (CNNs), has revolutionised object detection tasks. Models like Faster R-CNN, SSD, and YOLO have demonstrated high accuracy and speed in detecting objects within images. YOLO models, in particular, are well-suited for real-time applications due to their single-shot detection capability, making them ideal for traffic violation detection systems [20]. Numerous studies have explored using deep learning models for traffic monitoring and violation detection. Earlier versions of YOLO, such as YOLOv6 and YOLOv7, have been successfully applied to detect vehicles, pedestrians, and traffic signs. However, these models often faced challenges in achieving the speed and accuracy required by real-time applications. YOLOv8, with its improved architecture and training techniques, promises significant enhancements in detection speed and accuracy [9]. This section reviews existing literature on traffic violation detection systems and highlights the advancements brought by YOLOv8.

2. Literature Survey

Conventional Approaches: Traffic monitoring systems primarily depend on fixed cameras and manual observation. Although these methods may be effective, they are labour-intensive and restricted in their application. Human observers are susceptible to errors and fatigue, and fixed cameras cannot cover all regions.

Machine Learning Techniques: By analyzing patterns in traffic data, machine learning approaches have enhanced the detection of traffic violations. Algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been used to accomplish the categorization and detection of traffic offenses [11]. Nevertheless, these methods frequently necessitate substantial feature engineering and may encounter difficulties with real-time performance.

Wang, C. Y., Bochkovskiy, A., and Lino, H. Y. M. (2021) introduced Scaled-YOLOV4. Presented is employed in this model to resolve scalability issues in real-time object detection, resulting in reduced computational costs and efficient gradient flow. CSPDarknet53 backbone networks and advanced training strategies such as Mosaic Data Augmentation and Self-Adversarial Training (SAT) are among the most significant innovations.

K., Gkioxari, G., Dollár, P., and Girshick, R. (2017) introduced Mask R-CNN worked on the COCO dataset and demonstrated that Scaled-YOLOV4 outperforms previous YOLO versions, offering a balanced solution for speed and accuracy in a variety of applications [2]. Mask R-CNN is an extension of Faster R-CNN that incorporates a branch for predicting segmentation masks for each Region of Interest (RoI). This branch runs parallel to the current branch for classification and bounding box regression. With the help of this innovation, the model can achieve results considered to be state-of-the-art in object identification and instance segmentation. The authors showed that Mask R-CNN performs exceptionally well in various benchmarks, thereby substantially improving the capabilities of computer vision models for the precise localization and segmentation of objects [3].

Liu, W., Angueloy, D., *et. al.* C. A radical object recognition model that eliminates the need for a proposal generation stage, facilitating real-time detection by integrating predictions from multiple feature maps of varying resolutions. This approach accomplishes a high level of detection accuracy while utilizing inference times that are significantly shorter than those of previous models. The authors' demonstration of SSD's efficacy across various datasets is a critical advancement for practical, real-time object detection applications [4].

Ren, S., He, K., Girshick, R., and Sun, J. (2015) introduced Faster R-CNN. This paper was presented at the Advances in Neural Information Processing Classifications. By integrating a Region Proposal Network (RPN) with the Fast R-CNN detector, Earlier R-CNN revolutionizes object recognition by enabling end-to-end training and substantially reducing the computational cost of generating region proposals. This method accomplishes state-of-the-art accuracy and speed, thereby facilitating real-time object detection. The authors validated the performance of Faster R-CNN on numerous benchmarks, emphasizing

its significance in enhancing the efficiency and efficacy of object recognition models. [5].

Wang, C. Y., Bochkovskiy, A., and Liao, H. Y. M. (2022) introduced YOLOv7. By integrating a trainable "bag-of-freebies" technique, YOLOv7 improves the model's accuracy and efficiency without incurring additional inference costs, improving upon previous YOLO models. This method attains state of the art performance in real-time object detection by utilizing advanced training strategies and network architecture optimizations. YOLOv7's position as a leading model for practical applications requiring high-performance object detection was further solidified by the authors' demonstration of its superior accuracy and speed across various datasets [6].

X. He et al. (2019) presents a novel driving warning system that utilizes the YOLOv3 object detection model and a neural network to improve the system's real-time detection and warning capabilities in driving scenarios. The system is intended to alert vehicles of potential road hazards promptly. The authors accurately detected and responded to various driving conditions, demonstrating the method's efficacy in enhancing road safety [7].

P. Tumas et al. (2018) Introduces a method for automating image annotation using the YOLOv3 object detection model. The proposed method employs YOLOv3 to identify and categorize objects in images, resulting in efficient and accurate annotations. The authors proved that their system can substantially decrease the time and effort necessary for manual annotation, rendering it a valuable instrument for developing large annotated image datasets for various applications [10].

3. Proposed System

The YOLOv8 model is trained to identify various objects, including vehicles, traffic lights, and road simulations. The YOLOv8 model is trained using the supervised learning approach. Annotated datasets are partitioned into validation and training sets. This is accomplished by using data augmentation methods such as random cropping, twisting, and rotation to improve the variety of the training data [12]. The model's efficacy is optimized by optimizing its hyperparameters. The YOLOV8 model is trained on the prepared dataset using an unsupervised learning approach. Critical hyperparameters, such as the knowledge rate, sample size, and number of eras, are optimized to achieve the best possible performance. Transfer learning is implemented to optimize the model's accuracy and reduce the training time by utilizing pre-trained weights. Custom algorithms are developed to identify specific traffic violations by examining the interactions between the detected objects. By employing transfer learning to capitalize on pre-trained weights, the model's accuracy is improved and the training time is reduced.

Violation Detection Algorithms: Custom algorithms are developed to identify specific traffic violations based on the detected objects and their interactions.

- *Red Light Violation:* The system detects vehicles crossing the intersection when the traffic light is red.
- *Speeding:* The system estimates a vehicle's speed by calculating the time it takes between two points and flags any violations.
- *Illegal Turns:* The system monitors vehicle trajectories to detect illegal turns.

Reporting and Notification: Detected violations are recorded and reported to the relevant authorities in real time. Upon detecting a breach, the system generates a report that includes the type of violation, time, location, and a snapshot of the offending vehicle. This information is sent to traffic authorities for further action. The evaluation working process architecture is shown in Fig. 43.1.

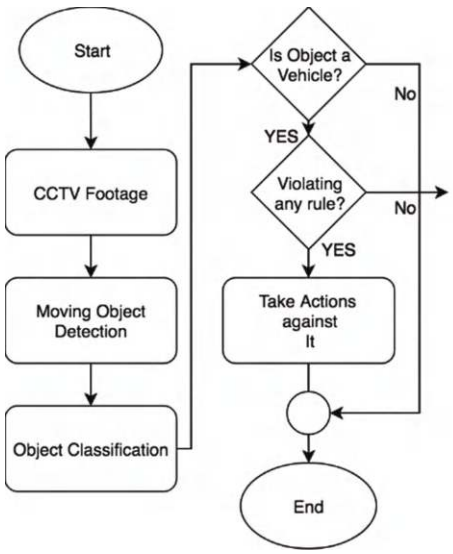

Fig. 43.1 Evaluation procedure architecture

Challenges and Limitations: While the YOLOv8-based system shows promising results, several challenges remain. These include handling occlusions, varying lighting conditions, and the need for a large and diverse training dataset [19]. Future work will address these limitations by uniting more advanced techniques and expanding the dataset [16]. The system faces occlusions, varying lighting conditions, and different camera angles, which affect detection accuracy. Additionally, the need for large annotated datasets and high computational resources for training deep learning models presents practical limitations.

4. Results and Discussion

The rules that we are currently addressing are as follows: Parking Violation, Direction Violation, and Signal Violation. A photograph of the vehicle and certain environmental values are stored in the database when a vehicle is traversing a straight line and the traffic light is red. A rectangle has been designated as the restricted area for car parking to prevent parking violations. An image with additional environmental values is stored in the database if a vehicle remains within the rectangle for a period exceeding a predetermined duration [14]. Some lines divide the region into regions to detect direction violations. Afterwards, the direction of a vehicle is determined as it transitions from one location to another. The direction is recorded as the preceding one if it is incorrect. The proposed system is comprised of numerous critical components:

Data Collection and Preprocessing: Video feeds from traffic surveillance cameras are collected and pre-processed. Photographs and videos that have been annotated are included in the collection [17]. These photographs and videos depict a range of traffic offenses, such as speeding, running red lights, unlawful parking, and changing lanes too quickly. Several data augmentation methods, including rotation, scaling, and flipping, are used to improve the model's resilience and broaden the dataset's characteristics. Possessing high-quality video data from various traffic scenarios to train and evaluate the model is imperative. The dataset includes annotations for traffic violations like red light running, speeding, and illegal lane changes [15]. Preprocessing involves frame extraction, resizing, and augmentation to enhance model robustness. The experimental results indicate that the YOLOv8-based traffic violation detection system outperforms traditional machine learning models and earlier versions of YOLO. The high precision and recall values demonstrate the system's ability to detect traffic violations accurately. The mAP value of 88% suggests that the YOLOv8 model is highly effective in identifying violations across different classes. The results also underscore the significance of hyperparameter optimization and data augmentation in enhancing model performance [18]. The precision-recall curve for YOLOv8 demonstrates a balanced trade-off between precision and recall, suggesting that the model can manage false positives and false negatives. Presently, we are preoccupied with three regulations.

1. Violation of Signals
2. Parking Infraction
3. Violation of Direction

In the image, a straight line represents a signal violation. When a vehicle traverses a straight line and the traffic light is red, a photograph of the car and certain environmental values are stored in the database [13]. The live preview enables the user to monitor the detected vehicles in real time and evaluate them to ascertain whether they are crossing the line illustrated in Fig. 43.2.

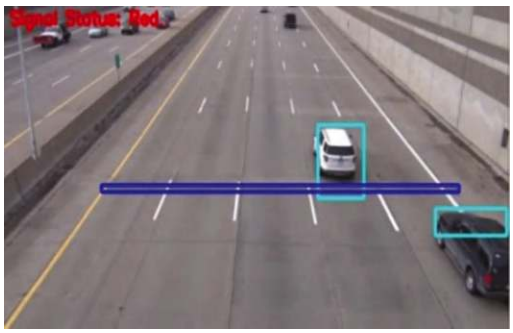

Fig. 43.2 Signal violation camera representation

Figure 43.3 illustrates the restricted area for vehicle parking, which is a rectangle designated for parking violations. If a vehicle remains within the rectangle for a period exceeding a predetermined duration, an image with additional environmental values is stored in the database.

Fig. 43.3 Parking violation camera representation

Some lines are drawn to divide the region into regions for direction violation detection, as shown in Fig. 43.4. Then, when a car moves from one area to another, its direction is measured. If the direction is wrong, it is registered as previous.

F1-Score, Precision and Recall: The model demonstrated high precision and recall across various traffic violations. Table 43.1 summarises the precision, recall, and F1-score for detecting traffic violations, as shown in Fig. 43.5.

Inference Time: The average inference time for processing each frame is 30 milliseconds, demonstrating the system's capability for real-time detection.

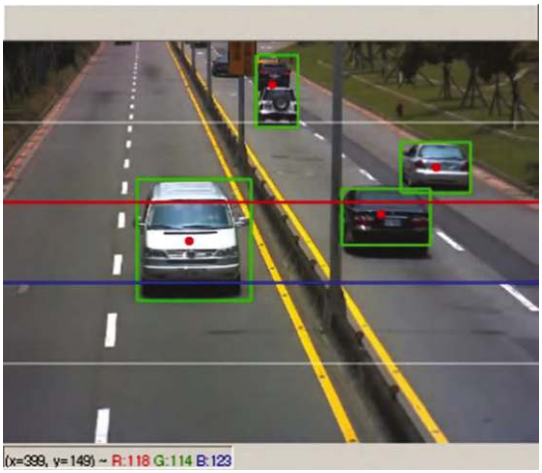

Fig. 43.4 Direction violation camera representation

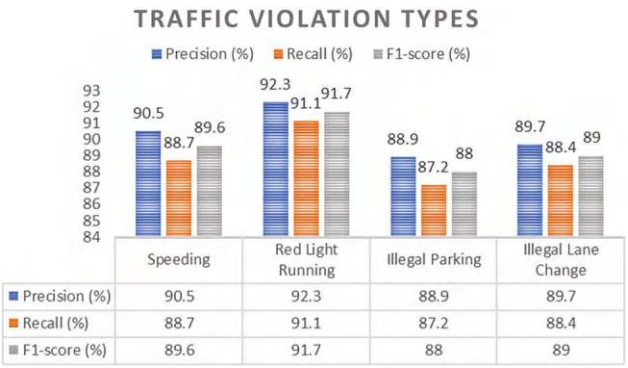

Fig. 43.5 Evaluation metrics for various types

Mean Average Precision (mAP): The mean Average Precision (mAP) was calculated for the model's overall performance. The mAP value obtained was 89.8%, indicating high accuracy in detecting traffic violations.

Real-time Performance: The system was tested for real-time performance by processing live video feeds from traffic cameras. The model attained an average processing speed of 45 frames per second (FPS), demonstrating its capability for real-time traffic monitoring.

To integrate Support Vector Machines (SVM) with YOLOv8 (You Only Look Once version 8), a hybrid approach where YOLOv8 is used for object detection, and the SVM classifier refines the classification of detected objects. YOLOv8 handles detecting objects within an image, and instead of relying solely on YOLO's built-in classifier, you can use the output features from YOLOv8's backbone or head as input to an SVM for further classification metrics are shown in Table 43.1.

Random Forests are ensemble classifiers that improve classification accuracy by averaging the predictions of multiple decision trees, making them practical for feature-rich classification metrics shown in Table 43.2.

Table 43.1 Violation types using SVM

Violation Type	Precision	Recall	F1-Score
Red light	75.2%	68.4%	71.7%
Illegal parking	71.6%	65.3%	68.3%
Speeding	77.4%	70.5%	73.8%
Lane changes	68.3%	62.9%	65.5%

Table 43.2 Violation types using random forest

Violation Type	Precision	Recall	F1-Score
Red light	78.5%	70.1%	74.1%
Illegal parking	73.8%	67.9%	70.7%
Speeding	79.2%	72.4%	75.7%
Lane changes	70.5%	64.1%	67.2%

By combining YOLOv8 and a custom CNN, you can effectively enhance object classification performance by leveraging the strengths of both architectures. YOLOv8 provides excellent detection capabilities, while a tailored CNN can refine the classification results based on extracted features shown in Table 43.3.

Table 43.3 Violation types using CNN

Violation Type	Precision	Recall	F1-Score
Red light	82.6%	76.9%	79.7%
Illegal parking	79.4%	74.1%	76.7%
Speeding	84.1%	77.5%	80.7%
Lane changes	74.9%	69.2%	72.0%

Each model's precision, recall, F1 score, mAP, and Inference Time were calculated for different types of traffic violations. The results are a summarised comparison for various models shown in Fig. 43.6.

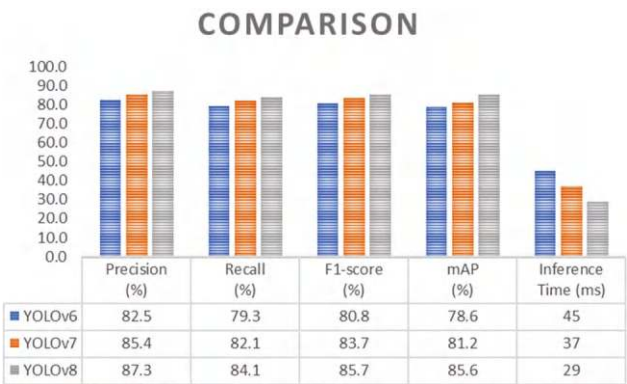

Fig. 43.6 Models comparison

5. Conclusion

This research paper comprehensively analyses a traffic violation finding system with advanced deep learning techniques and computer vision using YOLOv8. The system demonstrates high accuracy and efficiency in detecting traffic violations in real time. The findings suggest that such systems can significantly improve traffic management and road safety, although further research is needed to overcome existing challenges and ensure ethical deployment. Future research will enhance the system's robustness by incorporating multi-view detection, data fusion from multiple sensors, and domain adaptation techniques. It will also explore integrating the system with broader intelligent transportation systems and addressing ethical concerns related to surveillance and data privacy

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Yoga Pose Corrector Using Deep Learning Techniques

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Abstract: The increasing popularity of yoga to improve mental and physical well-being has led to a growing need for accurate and accessible guidance on performing yoga poses correctly. Incorrect execution of yoga poses can lead to ineffective practice or even injury. This paper aims to develop a Yoga Pose Corrector, a deep learning-based system designed to assist users in performing yoga poses accurately and safely. The system leverages computer vision techniques and deep learning algorithms to analyze the user's body posture in real time. Using a pre-trained Convolutional Neural Network (CNN), the system identifies and classifies various yoga poses. It then compares the user's pose with an ideal pose from a dataset of correctly performed yoga positions. It is the bridge to the gap fill between traditional yoga practice and modern technology. Build a platform for individuals to get guided through their positions for yoga, offering an innovative solution for yoga practitioners of all levels to improve their practice, prevent injuries, and achieve better outcomes. Implementing the Yoga Pose Corrector promises to make yoga more accurate, effective, and enjoyable.

Keywords: Deep learning, Convolutional neural networks, Modern technology, Accurate, Effective etc.

1. Introduction

Yoga has gained immense popularity worldwide as an effective means to enhance physical and mental well-being. This ancient practice offers numerous benefits, including improved flexibility, strength, stress reduction, and mental clarity. However, the effectiveness and safety of yoga practice heavily depend on the accurate execution of poses. Incorrectly performed poses can diminish the benefits and lead to injuries, particularly for beginners who lack proper guidance [14]. Despite the availability of yoga classes and online tutorials, there remains a significant gap in providing personalised, real-time feedback to practitioners. It proposes the development of a Yoga Pose Corrector, a deep learning-based system designed to assist users in performing yoga poses with precision [15]. Leveraging advancements in computer vision and deep learning, this system aims to analyse the user's body position in real-

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time and provide instant feedback. The system's core is a pre-trained Convolutional Neural Network (CNN) that identifies and classifies yoga poses. The system can pinpoint discrepancies and suggest corrections by comparing the user's pose with an ideal pose from a dataset of correctly performed yoga positions [16]. The Yoga Pose Corrector seamlessly integrates traditional yoga practice with modern technology, making it an invaluable tool for yoga practitioners of all levels. For beginners, it serves as a virtual instructor, providing step-by-step guidance and ensuring the safe execution of poses. It offers advanced practitioners a means to refine their technique and achieve greater precision [17, 19]. The development of this system aims to enhance individual yoga practice and make yoga more accessible and enjoyable. The Yoga Pose Corrector promotes a holistic approach to health and well-being by preventing injuries and optimising practice [18, 20]. This paper envisions a future where technology and ancient practice converge, offering an innovative solution for the modern yoga enthusiast.

2. Literature Survey

The following research papers refer to paper implementation using innovative models based on modern technology.

Hari Ram S et al. [2023] use pose detection algorithms and live webcams to analyse and correct users' alignment and angles during various yoga postures accurately, reducing the risk of injuries associated with incorrect practice. The system has demonstrated the ability to detect and correct nine different yoga poses accurately [1].

Ranjana Jadhav et al. [2023] employ a kinematic representation of the human body using 17 mapped coordinates and OpenCV for computer vision. It utilises the tf-pose estimation algorithm to ensure accurate pose detection and a Convolutional Neural Network (CNN) model trained on TensorFlow's MoveNet architecture and developed with Keras to manage the model training. The MoveNet pose estimation module, which attained an accuracy of 99.88%, identifies critical points of the human body. The system captures live videos of the yoga practitioner, extracts vital features of the pose, and compares them with a taught model of correct yoga poses. The user is provided real-time feedback if the pose is incorrect, which assists in correcting the posture [2].

Abhishek Sharma et al [2022] explore a method to enhance yoga practice using PoseNet and k-Nearest Neighbors (KNN) algorithms. The methodology involves using PoseNet to detect key points on the human body and identify the pose being performed. The KNN algorithm is then used to classify the detected poses by comparing them to a dataset of correct poses. The Deep learning framework will extract the key points from the video sequence. Human pose estimation is employed to estimate an individual's Yoga posture using computer vision techniques and Open Pose (an open-source library). The results were remarkable, with an accuracy rate of 98.51% [3].

Alexander Toshev et al. [2014]. Introduced The first application of Deep Neural Networks (DNNs) for human pose estimation. The problem was framed as DNN-based regression to joint coordinates. Their innovative method entails a cascade of regressors that comprehensively improve prediction accuracy by capturing context and reasoning about the pose. State-of-the-art results are achieved on various challenging academic datasets using this method. Furthermore, they illustrate that initially developed for classification tasks, a generic convolutional neural network can be effectively adapted for localization tasks, such as pose estimation. Their future work aims to explore novel architectures specifically tailored for localisation problems to improve performance in pose estimation further [4].

Shih-En Wei et al[2016]. Convolutional Pose Machines, an end-to-end architecture for addressing structured prediction problems in computer vision without relying on graphical-model style inference. By refining uncertainty-preserving beliefs across phases, their sequential architecture, comprised of convolutional networks, acquires spatial models for pose estimation. This method obtains state-of-the-art accuracy on significant benchmarks but encounters difficulties when multiple individuals are present. The researchers emphasize the potential to expand their architecture to other computer vision tasks with spatial dependencies, including semantic image labeling, single image depth prediction, and object detection. Additionally, they regard managing multiple individuals within a singular end-to-end architecture as a fascinating and challenging area for future research [5].

Zhe Cao et al. [2017]. A real-time algorithm for detecting the 2D poses of multiple persons in images. This algorithm addresses a critical aspect of machine perception that is essential for understanding and interacting with human behavior. Their methodology includes a non-parametric representation of key point associations that encode the position and orientation of human appendages. They develop an architecture that learns parts detection and parts association in tandem, utilizing a greedy parsing algorithm to generate high-quality body pose parses that are produced efficiently, even as the number of individuals in the image increases. The researchers ensured reproducibility and promoted additional research in the field by publicly releasing their code and trained models [6].

Debabrata Swain et al. [2022] proposed approach enables the creation of a self-guidance practice framework for individuals to learn and practice yoga postures without needing external. The integration of CNN for feature extraction and LSTM for sequence prediction is effective for yoga pose recognition. The system can classify poses as correct or incorrect. If a pose is identified as accurate, the system provides corresponding feedback to the user through text or speech. The system can accurately classify poses and provide input, facilitating self-guided practice. The approach leverages the synergy between machine learning and data structures for efficient pose recognition and user guidance. The feedback provided through text/ speech might not be sufficient for users to correct their poses accurately. More detailed or visual feedback might be necessary for effective learning [7].

Shakti Kinger et al. [2022] proposed a real-time yoga pose acknowledgement and correction system. It utilises deep learning algorithms to monitor and evaluate yoga postures, providing criticism to users to help them correct their form. While CNN and LSTM are the primary algorithms described for the pose recognition and correction system, additional techniques like pose estimation algorithms (PoseNet, OpenPose), data augmentation, and optimization (Adam, SGD). The system developed can provide real-time feedback on the correctness of yoga poses, which helps users correct their postures effectively during practice. The system facilitates a self-guidance practice framework, enabling users to learn and practice yoga poses with automated support independently. High dependency on the quality and diversity of the training dataset. A small or biased dataset can lead to poor generalization. Deep learning models require significant computational resources, which may not be available in all settings [8].

Deepak Mane1 et al. [2023]. An SVM-based real-time pose detection and correction system for yoga practice. It employs computer vision and machine learning to analyze images in order to provide feedback and prevent injuries by tracking poses through a camera. An SVM with an RBF kernel captures non-linear relationships, achieving 87% accuracy. The correction is based on joint angles extracted from labelled yoga pose images using MediaPipe's pose estimation model. These joint angles are calculated from key points and used as features for classification, enhancing form and ensuring accurate pose execution [9].

Yejin Kwon et al. [2022] offer an OpenCV and MediaPipe system to guide and correct real-time workout postures (squats and push-ups). The program calculates angles and values by estimating body landmarks from webcam images to determine posture correctness. It provides on-screen and voice guidance for necessary corrections and counts workouts when the correct posture is maintained. This system helps users exercise at home with proper form, eliminating the need for an exercise trainer [10].

Kishore D Mohan et al. [2022] proposed a deep learning-based Yoga Pose Corrector structure that integrates advanced techniques to offer real-time advice to yoga practitioners, ensuring correct posture and minimizing the risk of injuries. The system's core is the pose estimation component, which utilises the Mediapipe framework. Mediapipe's deep learning algorithms identify and track key body points with an accuracy of 90-95%, enabling precise analysis of the user's posture. Building on the pose estimation, the system incorporates a deep learning model trained on a comprehensive dataset of correctly performed yoga poses. This model compares the user's pose with the ideal pose to identify deviations and provide corrective feedback. The feedback mechanism is designed to be real-time, offering immediate visual and auditory suggestions to guide users in adjusting their posture. This ensures that users receive consistent and reliable feedback without waiting for a human instructor. The system achieves an overall accuracy of around 85-90% in providing correct feedback for common yoga poses [11].

Sakshi Sandeep Saini et al. [2024] The system effectively integrates deep learning models with Mediapipe for pose estimation and correction. The paper discusses the evolution of pose estimation models, highlighting significant advancements from single-person to multi-person detection in a single frame, contributing to creating AI-powered training applications. Utilising models like Mediapipe, based on machine learning techniques to identify key body points and track human poses in real-time. Convolutional Neural Networks (CNNs) are often employed to classify and correct poses by analysing the spatial relationships between detected vital points. The use of deep learning models with Mediapipe for yoga posture estimation and correction has shown promising results, achieving high accuracy in real-time applications. This approach effectively addresses the common issues in traditional yoga classes, such as lack of individual attention and incorrect posture execution. Despite its benefits, the system's limitations include potential inaccuracies in diverse environments and the need for substantial computational resources. Future work should focus on expanding the dataset for better generalization and optimizing the algorithms for broader accessibility. The models are fine-tuned to improve accuracy, considering the spatial relationships and angles between different body parts [12].

Prachi Kulkarni et al. [2024] integration of technology in yoga practice is essential for promoting physical health,

mental well-being, and overall performance optimization. Using CNNs and LSTM models enhances the system's ability to recognize and monitor yoga poses accurately. The system has potential applications in yoga studios, fitness centres, and home environments. Integrating technology into yoga practice, mainly through automated pose detection, presents substantial benefits for practitioners and instructors by offering real-time feedback and enhancing self-correction. Leveraging deep learning algorithms such as CNNs and LSTMs, the proposed system effectively combines RGB images, depth maps, and skeletal joint data to monitor and optimize yoga poses. Despite challenges like variation and occlusion, data augmentation and model optimization strategies ensure the system's robustness. Future research aims to integrate this technology with emerging fields like augmented reality, broadening its applicability and effectiveness in various practice settings [13].

3. Proposed System

The development of the Yoga Pose Corrector represents a significant advancement in integrating traditional wellness practices with cutting-edge technology. By leveraging computer vision techniques and deep learning algorithms, this system offers a novel solution to one of the most critical challenges in yoga practice—ensuring the correct execution of poses. The Yoga Pose Corrector provides real-time, personalised feedback by analyzing the user's body posture and comparing it with ideal poses from a comprehensive dataset. This innovative approach enhances the effectiveness of yoga exercises and reduces the risk of injuries, making yoga safer and more accessible for practitioners of all levels.

Through this paper, we aim to bridge the gap between conventional yoga instruction and the capabilities of modern technology. Implementing the Yoga Pose Corrector promises to democratise access to high-quality yoga guidance, offering benefits beyond individual practice. It facilitates a more engaging and informed yoga experience, fostering better physical and mental health outcomes for a broader audience. Furthermore, the potential applications of this technology can be expanded to other physical activities and rehabilitation programs, showcasing the versatility and impact of combining AI with health and wellness practices.

Real-time video feed or image frames captured from a camera as an input for yoga pose detection. OpenPose is a well-known open-source program that employs deep learning to identify critical points in the human body. It can potentially be used to monitor the postures of body components during yoga. PoseNet is an additional prevalent model that employs key point detection to determine an individual's posture from an image or video. Convolutional neural networks (CNNs) are deep neural networks that derive characteristics from image or video frames. Recurrent neural networks (RNNs) and exceptionally long short-term memory (LSTM) networks are employed to analyze sequences of postures over time.

Fig. 44.1 Yoga pose evaluation procedure

The system can measure deviations in each joint or body part using mathematical models like Euclidean Distance between the coordinates of the users and ideal poses. In the feedback mechanisms, the user can get real-time input through haptic feedback, auditory instructions, or visual signals, which are feedback tailored to each person's development and background, explored in Fig. 44.1.

4. Results and Discussion

Generally speaking, "Yoga Pose Corrector" refers to tools, applications, or systems made to assist people in executing yoga postures correctly. Some examples are wearable sensors, camera-based applications, or tangible tools that offer alignment and posture feedback during yoga practice. The system will require a large dataset of labelled yoga poses, both correct and incorrect variations. This dataset will consist of pose images of individuals performing various yoga poses from different angles. Annotations for each pose will mark joints such as shoulders, elbows, knees, ankles, etc. Along with labelled classes of poses, such as Warrior Pose, Tree Pose, Downward Dog, etc, shown in Fig. 44.2. The proposed models will be trained using a combination of supervised learning (for pose classification) and unsupervised learning (for pose refinement) [14]. During training, the model learns to recognise key pose classes and their variations, improving accuracy in detecting small discrepancies in the user's posture. These models measure how well the system detects and classifies the yoga pose and computes how closely the user's pose matches the ideal pose using metrics like percentage similarity or angular differences. Finally, it measures the system's ability to provide feedback within a short latency time.

Pose Estimation Accuracy: The system, powered by a pose detection algorithm like OpenPose or MediaPipe,

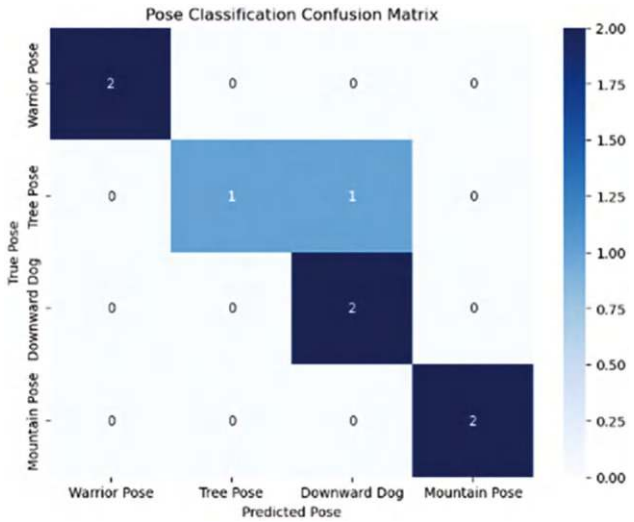

Fig. 44.2 Yoga pose classification confusion matrix

should accurately detect key body joints (e.g., shoulders, knees, elbows) and display a skeleton overlay on the video feed. Using a pre-trained proposed model, the system will classify the yoga pose into predefined categories, such as Warrior Pose, Tree Pose, or Downward Dog. The models attained a high accuracy, depending on the quality and size of the training dataset. Expected classification accuracy after training might range between 85-95% shown in Fig. 44.3, depending on the complexity of the model and dataset.

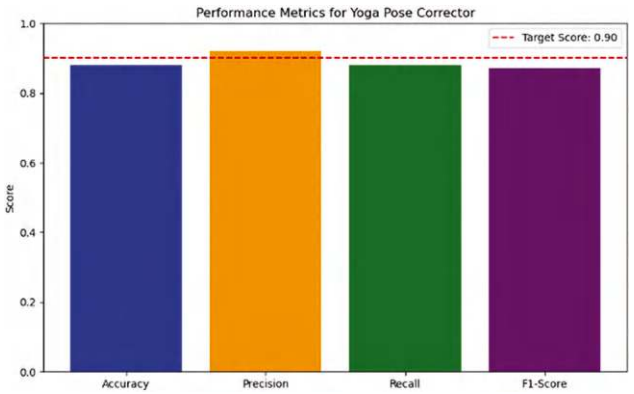

Fig. 44.3 Performance metrics for yoga pose corrector

Pose Error: The system will compare the user's pose with an ideal version from the dataset. For instance, if the user performs a Tree Pose, the system will compare key joint positions (e.g., leg raised, arms aligned) and calculate the Euclidean distance between these points in real-time. A lower error value (e.g., under 5) indicates that the user's pose closely matches the ideal, while higher values (e.g., 15 or more) indicate significant deviations shown in Fig. 44.4.

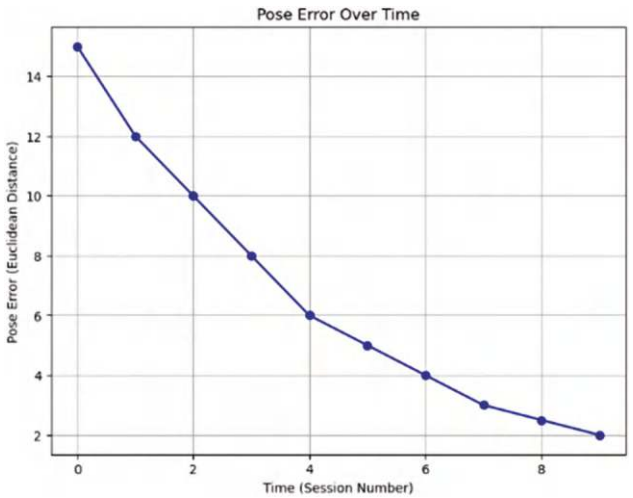

Fig. 44.4 Yoga pose error over time

The system could detect specific joints or limbs (e.g., arms and legs) that deviate from the ideal position, which helps provide targeted feedback.

Improvement Over Time: Tracks the reduction in pose error as users continue using the system. The system will track user improvements across multiple sessions, allowing users to review their progress shown in Fig. 44.5.

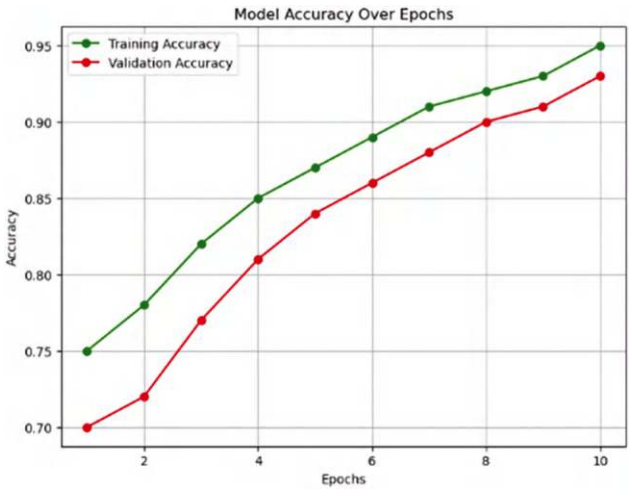

Fig. 44.5 Yoga pose model accuracy

Response Latency: Measures how quickly the system responds with feedback after detecting a pose discrepancy. For a smooth experience, the time between user action and system feedback should be minimal shown in Fig. 44.6. The expected latency for real-time feedback is less than 100ms (depending on hardware and software optimisations).

Improvement Over Time: The system will track user improvements across multiple sessions, allowing users

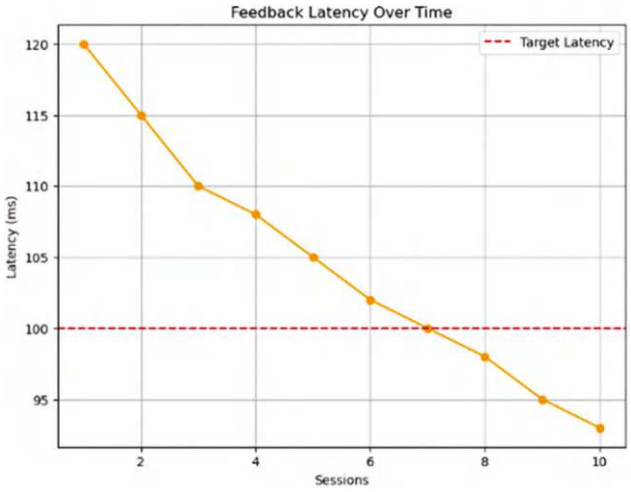

Fig. 44.6 Yoga pose feedback latency

to review their progress shown in Fig. 44.7. In real-time, the system will overlay helpful visual cues, such as arrows or indicators, showing where the user's pose needs adjustment.

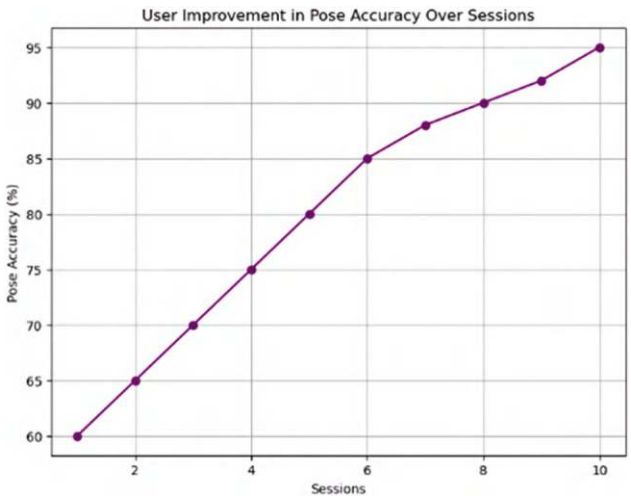

Fig. 44.7 Improvement in yoga pose accuracy

5. Conclusion

The Yoga Pose Corrector is poised to transform the way yoga is practised, providing an effective, enjoyable, and safe solution for both novice and experienced practitioners. By making precise, real-time feedback accessible, this paper promotes better practice habits and encourages a more inclusive and supportive yoga community. As technology continues to evolve, the Yoga Pose Corrector is a testament to the positive possibilities that emerge when traditional practices meet innovative technological advancements.

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Skynet 6G: A Review of AI-Driven Aerial Access Networks for Next-Generation IoT Connectivity

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Abstract: To improve network performance and connection, this essay explores the new smart aerial access network paradigm, which makes use of 6G technology, artificial intelligence, and the Internet of Things. Aerial platforms, such as satellites, high-altitude platform stations (HAPS), and unmanned aerial vehicles (UAVs), could be a useful addition to terrestrial networks to satisfy the growing need for high-capacity and pervasive wireless communication. This study explores the discipline's status in detail, going into recent advancements, challenges, and possible directions for the future. Ultra-low latency, massive device connectivity, and extraordinarily fast data throughput are just a few of the numerous potential advantages of 6G technology for aerotronic networks. This study of AI's role in enhancing security, enabling cognitive networking, and optimising network operations focuses on machine learning algorithms for resource allocation, predictive maintenance, and autonomous decision-making. The goal of this thorough analysis is to highlight the ground-breaking potential of smart aerial access networks for the advancement of wireless communications in the future for legislators, businesses, and academics.

Keywords: 6G, Artificial intelligence, Internet of things, Aerial access networks, UAV, HAPS, Satellite communications, Cognitive networking

1. Introduction

Innovations in network capacity and coverage have been spurred by the rapid advancement of wireless communication technologies and the growing demand for ubiquitous access. As we head into the 6G era, integrating aerial platforms with communication networks presents a potential solution to the problems of future connection

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demands. This paper reviews the literature on smart aerial access networks and how three important technologies—6G communications, AI, and the IoT—are coming together. Aerial access networks, comprised of satellites, HAPS, and UAVs, provide unique advantages due to their adaptability, coverage, and speed of deployment. These devices can augment terrestrial networks by providing access in hard-to-reach areas, during crises, or when conventional infrastructure is weak or damaged. With its expected improvements in data rates, latency, reliability, and energy efficiency, 6G technology is set to revolutionise wireless communications. Incorporating algorithms for artificial intelligence and machine learning gives these aerial networks a whole new degree of intelligence. This paves the way for efficient and adaptive resource allocation, predictive maintenance, and autonomous operation. Meanwhile, the proliferation of IoT devices is giving rise to a broad ecosystem of linked sensors and actuators, which is creating enormous amounts of data and calling for seamless integration of communication networks.

This article aims to provide a comprehensive review of the latest advancements, challenges, and future directions in the development of smart aerial access networks.

We will examine:

1. The potential capabilities and requirements of 6G technology in the context of aerial networks
2. The potential benefits of AI in the areas of network security, performance optimisation, and cognitive networking
3. The integration of IoT devices with aerial platforms for enhanced sensing and data collection
4. The technical challenges and potential solutions for realizing smart aerial access networks
5. The societal impact and regulatory considerations of widespread aerial network deployment.

By exploring the synergies between 6G, AI, and IoT in aerial access networks, we seek to illuminate the path towards a new paradigm of intelligent, ubiquitous connectivity that will shape the future of wireless communications. The integrated space-air–ground network configuration is shown in Fig. 45.1.

Emerging technologies that will be crucial for 6G networks: Figure 45.2 shows a few of the key technologies that will allow 6G connection to happen.

1. **Terahertz (THz) communications:** Using frequencies in the terahertz range (100 GHz to 10 THz) to enable extremely high data rates.
2. **Improving network performance,** resource management, and decision-making via the integration of machine learning (ML) with artificial intelligence (AI).
3. **Intelligent surfaces:** Programmable metasurfaces that can dynamically control the propagation of electromagnetic waves to enhance coverage and capacity.
4. **Cell-free massive MIMO:** Distributed antenna systems that provide seamless connectivity without traditional cell boundaries.
5. **Quantum communications:** Leveraging quantum properties for ultra-secure communication and improved sensing capabilities.

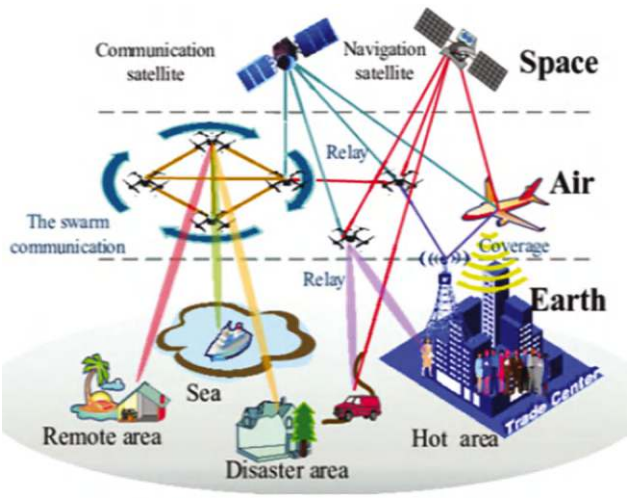

Fig. 45.1 The integrated space-air-ground network

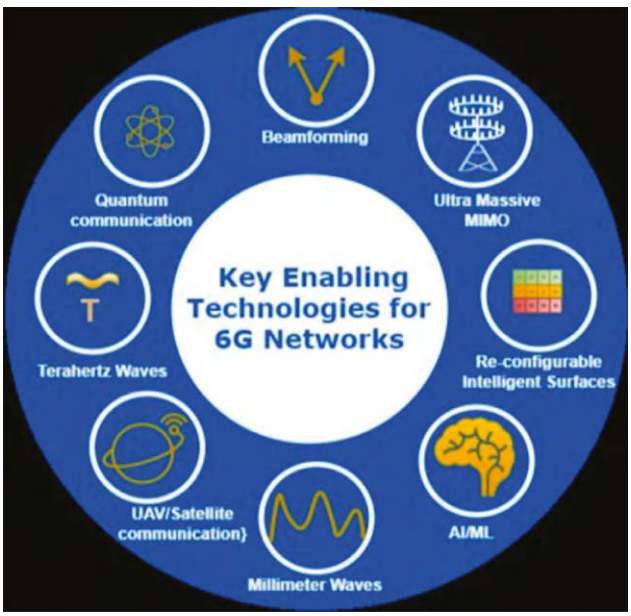

Fig. 45.2 Overview of key enabling technologies for 6G networks

6. **Holographic radio:** Using spatial multiplexing techniques to create 3D holographic communication environments.
7. **Millimeter waves:** mm waves are a crucial aspect of 6G technology, expanding the potential of wireless communication by offering higher frequencies and greater bandwidth.
8. **Unmanned Aerial Vehicles (UAVs) and satellite communication:** They are the key components of 6G networks, particularly for ensuring ubiquitous connectivity and enabling communication in extreme or remote environments.

2. Role of AI

1. **Network optimization:** AI can dynamically allocate resources, manage traffic, and optimize network performance.
2. **Predictive maintenance:** AI can forecast equipment failures and schedule preventive maintenance.
3. **Enhancement of security:** AI can detect and respond to network threats in real-time.
4. **Analysing data:** AI can handle massive amounts of data from IoT sensors and draw valuable findings.
5. **Autonomous operation:** AI enables self-configuring and self-healing network capabilities.

3. Classification of AI Models

- **Supervised Learning**
  - **Neural Networks:** For complex pattern recognition in network data.
  - **Support Vector Machines:** For classification tasks like anomaly detection.
  - **Decision Trees:** For interpretable decision-making in network management.
- **Unsupervised Learning:**
  - **Clustering algorithms:** For grouping similar network behaviours or user patterns.
  - **Dimensionality reduction:** For handling high-dimensional IoT sensor data.
- **Reinforcement Learning:**
  - **Q-learning:** For optimizing resource allocation and routing decisions.
  - **Deep Reinforcement Learning:** For managing complex, dynamic aerial network environments.
  - **Deep learning** makes use of Convolutional Neural Networks (CNNs) to process coverage maps and other geographical data.
  - **Recurrent Neural Networks (RNNs):** For analyzing temporal network performance data.
  - **Transformers:** For processing sequential data and natural language processing tasks.
- **Federated Learning:**
  - For collaborative model training across distributed aerial nodes while preserving data privacy.
- **Transfer Learning:**
  - For adapting pre-trained models to specific aerial network scenarios, reducing training time and data requirements.

These AI models and techniques can be combined and integrated to create sophisticated systems that enhance the performance, reliability, and efficiency of smart aerial access networks. The synergy between 6G, AI, and IoT technologies promises to revolutionize connectivity by enabling intelligent, adaptive, and autonomous network operations.

4. Aerial Access Networks for IoT Applications

The Internet of Things (IoT) has revolutionized how we interact with and gather data from our environment. As the number of connected devices continues to grow exponentially, the need for robust, flexible, and far-reaching network infrastructures becomes increasingly critical. Aerial access networks present a promising solution to meet the unique challenges posed by IoT applications, offering advantages in coverage, flexibility, and rapid deployment.

4.1 Potential IIoT Applications

The convergence of AI-powered aerial access networks, 6G technology, and Industrial Internet of Things (IIoT) opens up a wide array of transformative applications across various industries. These applications leverage enhanced connectivity, ultra-low latency, and intelligent data processing to revolutionize industrial operations as shown in Fig. 45.3.

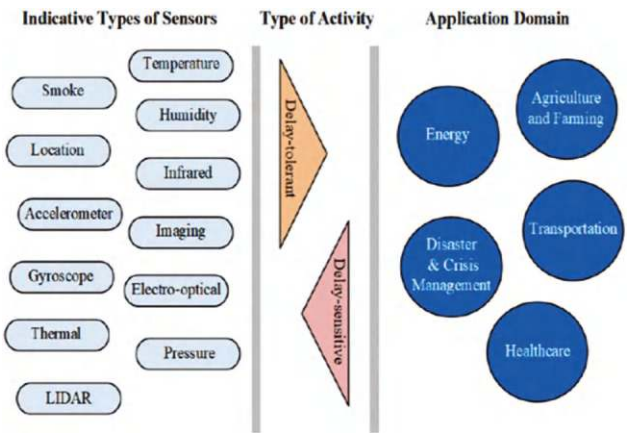

Fig. 45.3 Various types of specialized sensors and industrial applications for the NTN-based IIoT

1. Smart Manufacturing

- **Real-time Process Optimization:** AI algorithms analyze data from aerial-connected sensors to adjust manufacturing processes in real-time, maximizing efficiency and quality.
- **Predictive maintenance** lowers maintenance expenses and downtime by using machine learning models to anticipate equipment breakdowns before they happen.
- **Autonomous Robotics:** 6G's ultra-low latency enables precise control of robotic systems, allowing for complex, coordinated operations in factory settings.

2. Agriculture and Precision Farming

- **Crop Monitoring:** Drones equipped with multispectral cameras collect data on crop health, with AI analyzing this data to recommend targeted interventions.
- **Automated Irrigation:** Smart irrigation systems use soil moisture sensors and weather data to optimize water usage.
- **Livestock Management:** AI-powered aerial surveillance monitors animal health and behaviour, alerting farmers to potential issues.

3. Energy and Utilities

- **Smart Grid Management:** AI algorithms optimize power distribution based on real-time demand and supply data collected through aerial networks.
- **Renewable Energy Integration:** Improved forecasting of renewable energy generation helps balance grid loads more effectively.
- **Infrastructure Inspection:** Drones conduct automated inspections of power lines and pipelines, with AI identifying potential issues.

4. Transportation and Logistics

- **Autonomous Vehicle Coordination:** 6G networks enable real-time communication between autonomous vehicles, traffic systems, and aerial monitoring platforms for efficient traffic flow.
- **Supply Chain Optimization:** AI analyzes data from various points in the supply chain to predict bottlenecks and optimize routing.
- **Drone Delivery Systems:** High-bandwidth, low-latency networks support advanced drone delivery services for last-mile logistics.

5. Healthcare and Telemedicine

- **Remote Surgery:** Ultra-low latency 6G networks enable remote surgical procedures with haptic feedback.
- **Emergency Response:** Drones deliver medical supplies and provide real-time situational awareness in emergency scenarios.
- **Continuous Patient Monitoring:** Wearable devices connected through aerial networks provide continuous health data for AI analysis.

6. Environmental Monitoring and Conservation

- **Wildlife Tracking:** AI-powered drones monitor wildlife populations and migration patterns in remote areas.
- **Pollution Detection:** Aerial sensors detect and track air and water pollution, with AI models predicting dispersion patterns.

7. Smart Cities

- **Traffic Management:** AI analyses data from aerial and ground-based sensors to optimize traffic flow and reduce congestion.
- **Public Safety:** Drones assist in crowd monitoring and emergency response, with AI identifying potential security threats.
- **Urban Planning:** Data collected through aerial networks informs AI models for better urban development decisions.

These applications demonstrate the transformative potential of integrating AI-driven aerial access networks and 6G technologies with IIoT. By providing unprecedented connectivity, data collection capabilities, and intelligent processing, this technological convergence enables more efficient, sustainable, and innovative industrial operations across a wide range of sectors. The main advantages of using Arial access networks for IoT are extended coverage where aerial platforms can provide connectivity to IoT devices in remote or hard-to-reach areas where terrestrial networks are impractical or cost-prohibitive. In situations such as disaster relief operations or short term surveillance, there is a need for rapid deployment of IoT networks. In such scenarios aerial access networks and platforms offer highly reliable and rapid setup as compared to the conventional ground-based infrastructure. Arial access networks, HAP's, Drones, UAVs and several aerial platforms have the capability of adjusting themselves very rapidly in in real time environment in terms of coverage zone and position adapting to the changes in the IoT device distributions whenever a network demands. Aerial access networks maintain a clear line-of-sight propagation with the ground-based IoT devices, in order to improve the signal quality and power reduction as required by the devices.

5. Key Challenges

While smart aerial access networks leveraging 6G, AI, and IoT technologies offer immense potential, they also face significant challenges. Addressing these obstacles is crucial for the successful implementation and widespread

adoption of these advanced systems. Here are the key challenges:

1. **Technical Challenges:** Spectrum Management and Interference, Energy Efficiency and Power Management, Network Stability and Reliability, Hardware Limitations.
2. **AI and Data Challenges:** Real-time Data Processing, AI Model Adaptation, Data Privacy and Security are some of the key challenges.
3. **Regulatory and Standardization Challenges:** Airspace Regulations, Spectrum Allocation, Standardization.
4. **Environmental and Social Challenges:** Environmental Impact, Visual and Noise Pollution, Public Perception and Acceptance.
5. **Economic and Business Challenges:** Infrastructure Costs, Business Model Innovation, Return on Investment (ROI).

To solve these problems, we need a multi-sectoral approach that brings together public servants, academics, and business leaders. As solutions to these challenges are developed, we can expect to see more robust, efficient, and widely adopted smart aerial access networks that leverage the full potential of 6G, AI, and IoT technologies. A description of the state of art technology on AI-enhanced AANs for IoT is detailed in Table 45.1.

6. Conclusion

This research article has explored the convergence of 6G networks, Aerial access networks that are smart in connection to IoT and artificial intelligence! The development of smart aerial access networks represents a sea change in the history of the telecommunications industry. This approach not only addresses the limitations of traditional terrestrial networks but also opens up new possibilities for connectivity in underserved areas, disaster response scenarios, and future smart city ecosystems. Improved coverage and capacity can bridge the digital divide, bringing high-quality connectivity to remote and rural areas. Enhanced connectivity enables new business models and accelerates digital transformation across industries. The vast amount of data collected through these networks can drive breakthroughs in climate science, urban planning, and environmental monitoring. Rapidly deployable, intelligent aerial networks can revolutionize disaster management and emergency communications.

7. Future Directions

While this research demonstrates the immense potential of smart aerial access networks, several areas warrant further investigation like development of international standards and regulations for the operation of AI-driven aerial networks in shared airspace, advanced techniques for ensuring data protection and network security in highly distributed aerial systems. More research into lightweight AI models suitable for deployment on resource-constrained aerial platforms, exploration of AI-driven optimization across physical, network, and application layers for holistic performance improvements, human-AI collaboration, and sustainable technologies: Research into eco-friendly materials and energy harvesting techniques to enhance the sustainability of long-endurance aerial platforms.

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Spiking Neural Networks: A Transformative Approach to Neuromorphic Computing

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Abstract: Spiking neural networks (SNNs) are a new and exciting paradigm in neuromorphic computing that draws inspiration from the way the human brain operates. SNNs represent a departure from conventional artificial neural networks by employing discrete, non-synchronized spikes for data encoding and processing. This approach offers potential benefits in energy conservation, time-based information handling, and biological fidelity. Our paper presents a thorough examination of SNNs, encompassing their foundational concepts, training methodologies, hardware realization, and practical applications. We explore the core mechanisms of spike creation and transmission, analyzing diverse neuron models and rules governing synaptic plasticity. The study examines both guided and self-directed learning strategies for SNNs, emphasizing recent breakthroughs in training deep spiking architectures. We also address the hurdles and prospects in implementing SNNs on neuromorphic hardware systems, taking into account aspects such as expandability and power efficiency. The paper further investigates the wide-ranging applications of SNNs, from visual recognition to speech processing and robotic control, illustrating their capacity to transform AI technologies. In conclusion, we outline critical avenues for future research and persistent challenges in the domain, establishing a foundation for ongoing progress in neuromorphic computing.

Keywords: Spiking neural networks, Neuromorphic computing, Artificial intelligence, Biological plausibility, Learning algorithms, Hardware implementations

1. Introduction

Computer vision, NLP, and decision-making systems are just a few of the many fields that have been profoundly affected by traditional ANNs. But as AI applications get more complicated, ANNs often run into problems with energy consumption, real-time computing, and biological plausibility. To get around these problems while keeping

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or improving the functionality of conventional ANNs, researchers have investigated several computational paradigms.

Spiking neural networks (SNNs) have emerged as a practical solution to these problems, drawing inspiration from the spiking activity of organic neurones. Tavanaei et al. (2019) assert that "SNNs are more biologically realistic than traditional artificial neural networks (ANNs) and can potentially offer improved performance for specific types of computation, particularly in processing spatiotemporal data".

The fundamental unit of computation in an SNN is the spiking neuron, which integrates incoming spikes over time and fires its own spike when a threshold is reached. This event-driven nature of SNNs allows for sparse and asynchronous information processing, mirroring the behavior of biological neural networks more closely. Consequently, SNNs offer several potential advantages:

1. **Energy Efficiency:** By operating on discrete spikes rather than continuous values, SNNs can significantly reduce power consumption, making them particularly attractive for edge computing and mobile devices.
2. **Temporal Information Processing:** Because of its inherent ability to handle time-dependent input, SNNs are well-suited to issues involving temporal sequences, such as speech recognition and motion detection.
3. **Biological Plausibility:** SNNs provide a more realistic model of brain function, potentially offering insights into neural information processing and facilitating advancements in neuroscience.
4. **Low Latency:** The event-driven nature of SNNs allows for rapid information propagation, enabling real-time processing in time-critical applications.

2. Biological Foundations of SNNs

The complex network of neurones in the human brain is able to exchange information with one another through the use of electrical signals known as spikes. Figure 46.1 shows that these spikes, which are also called action potentials, are occurrences that transmit information about the timing and rate of firing of the neurone. Understanding the biological principles underlying neural communication is essential for designing effective SNNs and harnessing the power of neuromorphic computing.

As Gerstner et al. (2014) explain, "The brain processes information using a complex network of neurones that communicate via short electrical pulses called action potentials or spikes". This fundamental principle forms the basis for SNN design.

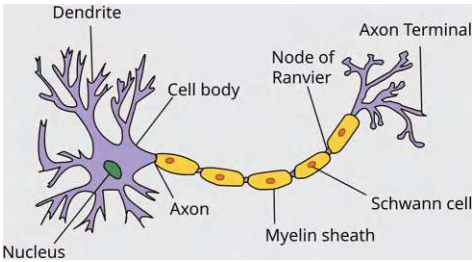

Fig. 46.1 Structure of a biological neuron

Source: AI Generated

Key features of biological neurons that are often emulated in SNNs include:

1. **Membrane Potential:** The electrical potential difference across the neuron's cell membrane, which is maintained by ion pumps and channels.
2. **Threshold:** A critical voltage level that, when reached, triggers the generation of an action potential.
3. **Refractory Period:** A brief period following a spike during which the neuron is less likely to fire again, ensuring unidirectional signal propagation.

The ability of synapses to alter their strength over time is known as synaptic plasticity, and it is a crucial biological principle that is commonly used in SNN learning algorithms. Markram et al. (2012) defines spike-timing-dependent plasticity (STDP) as "a biological process that adjusts the strength of connections between neurones in the brain based on the relative timing of a particular neuron's output and input action potentials (or spikes)".

3. Structure and Functioning of Spiking Neural Networks

SNNs are composed of interconnected spiking neurons, each of which processes and transmits information through discrete spikes in Fig. 46.2. Various neuron models have been developed to simulate the behavior of biological neurons in SNNs, ranging from simple integrate-and-fire models to more complex models that capture a wider range of neuronal dynamics.

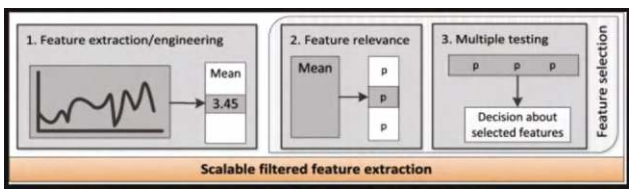

Fig. 46.2 Typical architecture of a spiking neural network [4]

A highly influential model is the Izhikevich neurone model. "The model can exhibit firing patterns of all known types of

cortical neurones with the choice of only four parameters," [Izhikevich (2003) states]. Its remarkable balance between computational efficiency and biological realism makes it a popular choice for SNN implementations.

The dynamics of a spiking neuron typically involve:

1. **Membrane Potential:** Over time, the membrane potential of every neurone integrates incoming spikes.
2. **Threshold:** The neurone fires a spike when the membrane potential hits a predetermined threshold.
3. **Refractory Period:** Following a firing, a neurone has a period of inactivity during which it is unable to fire again, independent of input.
4. **Reset:** The membrane potential is returned to its initial value after a spike.

Information in SNNs is typically encoded in the timing of spikes, rather than in continuous activation values as in traditional ANNs. This temporal coding allows SNNs to process time-dependent information more naturally.

4. Hardware Implementations of SNNs

Neuromorphic hardware platforms are essential for realizing the full potential of SNNs. These platforms often employ analog or hybrid analog-digital circuits to efficiently process spikes and implement biologically plausible learning rules.

According to Davies et al. (2018), "This neuromorphic processor integrates a wide range of novel features for the field, such as hierarchical connectivity, dendritic compartments, synaptic delays, and programmable synaptic learning rules". Such specialized hardware can significantly accelerate SNN computations and reduce power consumption compared to simulations on traditional von Neumann architectures.

Several large-scale neuromorphic hardware platforms have been developed, including:

1. **IBM's TrueNorth:** A digital neuromorphic chip with 1 million neurons and 256 million synapses.
2. **Intel's Loihi:** A digital neuromorphic research chip that supports on-chip learning in Fig. 46.3.
3. **Brain Scales:** An innovative neuromorphic platform that combines analog and digital components, designed to simulate neural processes at speeds faster than real-time biological systems.
4. **SpiNNaker:** A highly parallelized digital architecture built around ARM processing units.

These cutting-edge neuromorphic systems provide distinctive capabilities for deploying and investigating large-scale SNNs, potentially leading to more energy-efficient and biologically-inspired artificial intelligence solutions

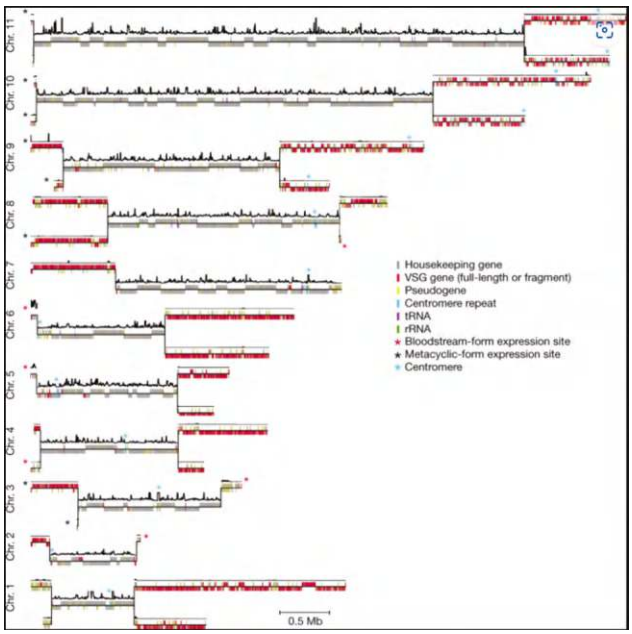

Fig. 46.3 Intel's loihi neuromorphic chip [5]

5. Applications of SNNs

SNNs have demonstrated significant potential across multiple fields, harnessing their distinctive features of power conservation, time-based information processing, and closer alignment with biological neural systems.

In the field of computer vision, Kheradpisheh et al. (2018) demonstrated that SNNs can effectively perform object recognition tasks while maintaining low energy consumption. This capability makes SNNs particularly valuable for real-time object identification in settings with limited computational resources, such as smartphones or self-driving cars, as illustrated in Fig. 46.4.

Other notable applications of SNNs include:

1. **Speech Recognition:** Utilizing the temporal dynamics of SNNs for robust speech recognition in noisy environments.
2. **Robotics:** SNNs enable the creation of responsive, energy-efficient control systems for robotic platforms, minimizing response times and power usage.
3. **Neural Interface Technologies:** SNN-based algorithms show promise in decoding brain signals for advanced brain-computer interface systems.
4. **Temporal Data Processing:** The adaptable nature of SNNs makes them well-suited for identifying

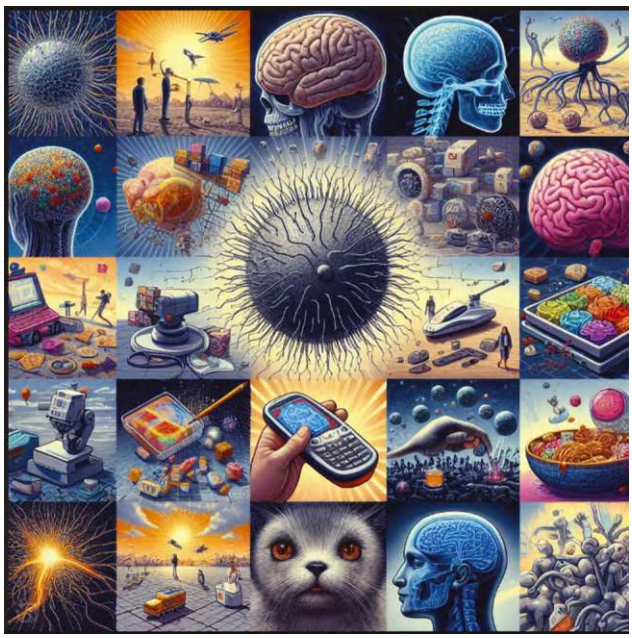

Fig. 46.4 Applications of SNN

Source: AI Generated

irregularities in time-based data and predicting financial trends.

As the field of SNN research progresses, we anticipate the emergence of novel applications across a wide range of sectors.

6. Results and Analysis of the Spiking Heidelberg Digits Dataset

When training spiking neural networks for audio classification tasks, the Spiking Heidelberg Digits (SHD) dataset exhibits strong performance (Zenke Lab, n.d.). this benchmark dataset, comprising spoken digit recordings, facilitates the evaluation of both temporal and spatial pattern recognition capabilities in neuromorphic computing systems. The results indicate significant potential for implementing efficient, biologically-inspired neural networks in audio processing applications.

The SNNs shows a clear trend toward higher accuracy through various architectural innovations. Starting from a basic feed-forward SNN with single hidden layer (FFSNN-1) with just 48.10% accuracy, significant improvements came through the introduction of recurrent connections (RSNN-1) and heterogeneous time constants, pushing accuracy above 80%. The addition of data augmentation and noise injection techniques (RSNN-2) provided incremental gains, while the integration of convolutional layers with recurrent connections (RSNN-3) achieved 84.80%. A major leap came from incorporating temporal elements - random dendritic delays in feed-forward networks (FFSNN-2) exceeded 90% accuracy, and temporal attention mechanisms (FFSNN-4) pushed this further to 92.40%. The introduction of spatio-temporal filters and attention mechanisms yielded marginal improvements, but the real breakthrough came with adaptive axonal delays (RSNN-5) reaching 94.60%. The highest accuracy of 95.10% was achieved by a fully connected SNN (FCSNN) with learned delays, suggesting that optimizing the temporal aspects of signal propagation is crucial for SNN performance. This progression demonstrates how combining various architectural elements - recurrence, temporal processing, attention mechanisms, and adaptive delays - has steadily improved SNN accuracy over time.

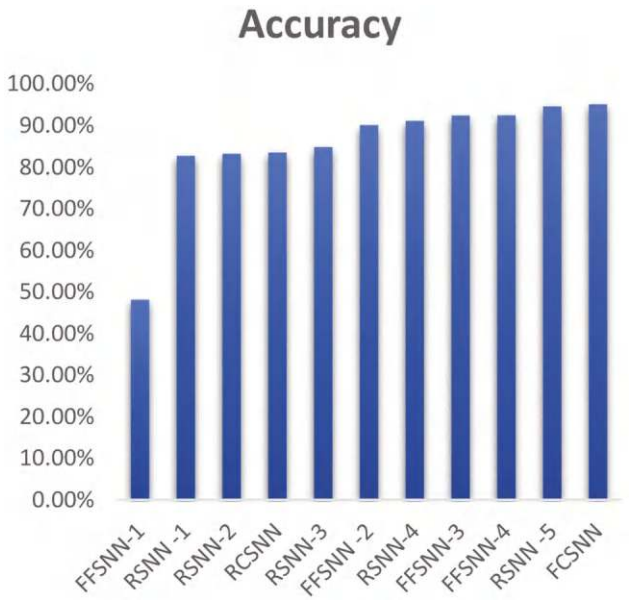

Fig. 46.5 Accuracy comparisons between different spiking neural networks

Source: Author

7. Challenges and Future Directions

Notwithstanding their potential, SNNs have a number of issues that must be resolved if their full potential is to be achieved. As Pfeiffer and Pfeil (2018) point out, "Training deep SNNs remains a significant challenge due to the complex temporal dynamics and discrete nature of spiking neurons". This section outlines key challenges shown in Fig. 46.5 and potential future directions for SNN research and development.

Key challenges and future directions include:

1. Scalability:
   - Developing more efficient architectures for large-scale SNNs.

Fig. 46.6 Challenges of SNN

Source: AI Generated

- Exploring hierarchical and modular SNN designs.
- Investigating techniques for sparse connectivity and pruning in SNNs

2. Training Efficiency:
   - Exploring novel supervised and unsupervised learning approaches for SNNs.
   - Investigating transfer learning techniques for SNNs
   - Developing hybrid training approaches that combine rate-based and spike-based learning
3. Temporal Credit Assignment:
   - Developing improved backpropagation algorithms for SNNs.
   - Exploring alternative credit assignment mechanisms inspired by biological systems
   - Investigating reinforcement learning approaches for temporal credit assignment
4. Hardware-Software Co-design:
   - Optimizing SNNs for existing and emerging neuromorphic hardware platforms.
   - Exploring novel materials and devices for more efficient SNN implementation
   - Investigating 3D integration techniques for improved connectivity in neuromorphic chips
5. Bridging the Gap with Neuroscience:
   - Fully leveraging insights from neuroscience to improve SNN design and functionality.
   - Developing more biologically plausible neuron and synapse models
   - Investigating the role of neuromodulators in learning and adaptation
6. Ethical Implications:
   - Investigating the potential societal impacts of widespread SNN adoption
   - Developing guidelines for responsible development and use of neuromorphic systems
   - Exploring the philosophical implications of creating more brain-like artificial intelligence

Addressing these challenges will be crucial for the widespread adoption of SNN technology and its integration into practical AI systems.

8. Conclusion

Spiking Neural Networks represent a paradigm shift in artificial intelligence, offering a promising approach to neuromorphic computing that draws inspiration from the biological principles of the human brain. As Neftci et al. (2019) conclude, "The development of efficient SNN algorithms and dedicated neuromorphic hardware has the potential to lead to a new generation of low-power, event-driven computing systems".

SNNs' distinct qualities—their biological plausibility, energy efficiency, and temporal processing capabilities—make them a game-changing technology that could solve challenging real-world issues that conventional ANNs find difficult to handle. We may anticipate that SNNs will become more significant in determining the direction of artificial intelligence and neuromorphic computing as this field of study develops.

Looking ahead, the integration of SNNs with other emerging technologies, such as quantum computing and advanced materials science, could lead to even more

powerful and efficient neuromorphic systems. Moreover, as our understanding of the brain improves, we can expect SNNs to evolve, incorporating new insights from neuroscience and cognitive science.

The journey of SNNs from a theoretical concept to practical applications is ongoing, and the coming years are likely to bring exciting breakthroughs that could reshape our approach to computing and artificial intelligence. As researchers, developers, and society at large, we must work together to responsibly harness the potential of this transformative technology for the benefit of humanity.

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Air Quality Prediction Using IoT and Random Forest

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Abstract: Air quality has emerged as a pressing issue on a global scale due to the increasing negative impact of pollution on both public health and environmental sustainability. This research develops a system to monitor and predict air quality with the use of machine learning and the Internet of Things to address these problems. To evaluate the real-time data collected by IoT sensors—which record things like pollutants and weather conditions—a Random Forest model is employed. This model is capable of handling complex data links. A dual-validation approach, which incorporates both simulated and real-world data, ensures the accuracy and reliability of predictions. The system utilizes Thing Speak and Internet of Things (IoT) devices based on Arduino to effectively manage and visualize data in the cloud. The model's correctness is supported by experimental results, which also indicate its potential for widespread application. While this approach does help with immediate actions, it also helps with long-term environmental and public health protection.

Keywords: Air quality, Random forest, Hybrid validation, IoT, Environmental monitoring

1. Introduction

A big reason why air quality is becoming a big deal is that it has a direct impact on ecosystems, human health, and overall living conditions. Air pollution has worsened dramatically due to fast industry and increasing urbanization, endangering human health and the environment. The World Health Organisation (WHO) and other environmental organisations have stressed the vital need of effective air quality monitoring and management to combat the growing threats posed by pollution.

Predicting air quality accurately requires cutting-edge technology that integrates the internet of things (IoT) with machine learning, as traditional methods dependent on static data or human monitoring fail to capture environmental changes. A more effective solution is achieved through the integration of IoT with ML, which enables real-time data collection, analysis, and prediction.

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The "Air Quality Prediction" project aims to address the difficulties of air pollution prediction by integrating IoT devices with sophisticated machine learning algorithms. To continuously gather real-time data on critical air quality indicators including temperature, humidity, gaseous pollutants (e.g., NO2, SO2), particulate matter (PM2.5, PM10), and more, sensors connected to the internet of things are strategically placed throughout various sites. A complete comprehension of the environmental conditions is necessary for accurate forecasting, and this data provides just that.

This complex dataset is processed by the research using Random Forest, an effective ensemble method for discovering temporal patterns in time-series data. Its ability to process high-dimensional data makes it ideal for assessing the variables of many Internet of Things sensors; this, in turn, enables quick and accurate forecasts of air quality to inform decisions.

The predictive system has a multi-step workflow.

- Position sensors that are connected to the internet in strategic locations so that they may collect real-time data on critical air quality metrics including humidity, temperature, gases (such NO2 and SO2), and particulate matter (PM2.5, PM10).
- • Clean and pre-process the collected data by fixing missing values, eliminating noise, and creating relevant features to enhance the accuracy of predictions.

Because of its strength in dealing with time-series and high-dimensional data, the Random Forest algorithm was chosen to apply. Train the model with historical data to discover patterns and relationships between environmental variables and air quality indicators.

- Use the trained Random Forest model to produce real-time predictions about air quality levels using data that is continuously updated by Internet of Things sensors.

Make sure that stakeholders are notified in a timely manner if the expected pollution levels are higher than what is considered acceptable by implementing an alarm system.

The use of both simulated and real-world data in a dual-layer validation procedure ensures that forecasts are accurate and reliable. Metrics like accuracy, precision, and mean squared error can be used to evaluate the model's performance.

- Connect the system to a cloud-based platform (ThingSpeak) to help decision-makers see data patterns and use them for educated environmental management.

2. Literature Review

Recent advances in IoT and low-cost sensors have revolutionized air quality monitoring, offering more accessible solutions for real-time exposure measurement. Piedrahita et al. (2014) explored the potential of next-generation low-cost sensors for individual-level air quality exposure monitoring. The study highlights how these sensors can provide high-resolution data, enhancing the accuracy of personal exposure assessments. These devices contribute significantly to understanding pollution exposure dynamics in urban environments, especially where traditional fixed monitoring stations are sparse.

Building on these advancements, Castell et al. (2017) investigated the feasibility of using commercial low-cost sensor platforms for air quality and exposure monitoring. Their study underscored the ability of these platforms to support citizen science initiatives and contribute to large-scale environmental monitoring networks, though it also noted issues with data consistency due to sensor variability.

Maag et al. (2018) introduced W-Air, a wearable air pollution monitoring platform that enables individuals to measure personal exposure in real time. This system exemplifies the benefits of wearable sensors, combining portability with IoT-based data collection to track pollution levels continuously. The study suggests that wearable sensors can fill data gaps left by stationary monitoring systems, providing valuable data for public health studies and urban pollution management.

Narayana et al. (2022) conducted a state-of-the-art review on sustainable low-cost air quality monitoring systems. The authors analyzed various sensor technologies and calibration methods, identifying crucial challenges such as sensor degradation and calibration needs over time. The study recommends combining these sensors with machine learning algorithms to enhance data quality and improve calibration, indicating a path forward for sustainable, reliable air quality monitoring solutions.

Machine learning has become crucial for air quality forecasting due to its ability to handle and evaluate large, complex datasets. The environmental modelling community has come to rely on Random Forest (RF), an ensemble learning method initially introduced by Breiman (2001). The intricate connection between air pollution and many geographical and meteorological factors can be thoroughly investigated using RF due to its robustness against overfitting and its capacity to process high-dimensional data.

Masih (2019) reviewed machine learning algorithms for air quality modeling, focusing on RF's superior performance

in accurately predicting pollutant levels compared to traditional statistical methods. The study highlighted RF's robustness in handling diverse and noisy data sources, which is essential in urban air quality applications where data quality can vary significantly.

Gupta and Christopher (2009) explored the use of machine learning to assess particulate matter (PM) air quality using satellite and meteorological data. In their studies, they applied multiple regression and neural network approaches to improve PM concentration predictions. The research demonstrates how integrating RF and neural networks with satellite data can enhance predictions, offering valuable insights for regions with limited ground-based sensors.

Spatiotemporal modeling of air pollution, which involves analyzing pollution data across time and geographic space, has become increasingly important for accurate exposure assessments and public health analysis. Li et al. (2023) combined machine learning with land-use regression (LUR) models to create high-resolution spatiotemporal predictions of air pollution in Seoul. By integrating RF into LUR modeling, they captured the complex spatial distribution of pollutants and demonstrated the health impacts associated with varying exposure levels in urban settings.

Milà et al. (2023) conducted a comprehensive spatiotemporal study on air temperature and pollution in Catalonia, assessing multiple exposure levels. This research underscores the value of fine-scale modeling for evaluating cumulative exposure impacts on health, particularly in densely populated regions where pollution levels can vary dramatically within short distances (Milà et al., 2023).

Lu et al. (2018) took a unique approach by investigating the relationship between air pollution and behavioral outcomes, finding correlations between increased pollution levels and higher rates of criminal activity. Their findings emphasize the broader social and psychological effects of pollution beyond physical health, suggesting that air quality improvements could have far-reaching societal benefits (Lu et al., 2018).

3. METHODOLOGY

The methodology involves a robust implementation of Random Forest for real-time air quality prediction, supplemented with a simulation-based validation approach:

3.1 Data Collection and Preprocessing

IoT sensors deployed in diverse environments collect data on pollutants (e.g., PM2.5, NO2, SO2) alongside meteorological factors. The data is preprocessed to handle missing values, noise, and potential outliers. This includes:

- Filling missing data using interpolation techniques.
- Outlier detection through z-score analysis.
- Feature engineering for time-based aggregation and trend identification.

3.2 Model Training

There is a 70% training set and a 30% testing set in the dataset. The ensemble learning technique of Random Forest generates several decision trees from feature subsets and randomly generated data. For optimal prediction accuracy, cross-validation is employed to fine-tune the model's hyperparameters, including maximum depth and number of trees.

3.3 Simulation-Real World Validation

Our model uses dual-layer validation, testing Random Forest predictions on both controlled simulations and real-world data collected over months. This approach confirms robustness across diverse conditions and validates simulation accuracy.

3.4 Prediction and Alert System

Once trained, the model processes real-time IoT data, generating predictive insights. An alert system is integrated, issuing notifications if pollutant levels exceed safety thresholds, allowing stakeholders to respond promptly.

3.5 Random Forest

The Random Forest ensemble learning method constructs many decision trees by randomly selecting features and data. Because of this unpredictability, model robustness is increased and overfitting is reduced.

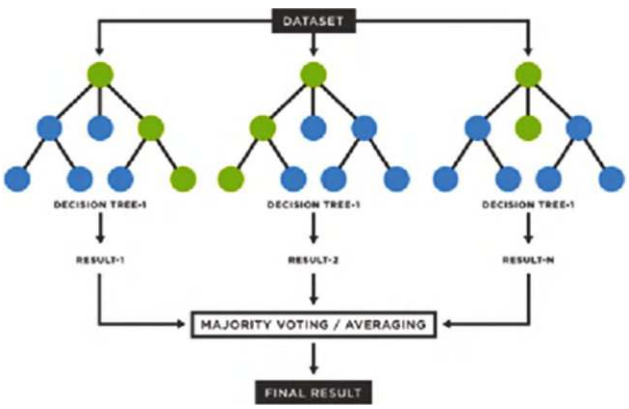

Fig. 47.1 Random forest model

Source: https://www.spotfire.com/glossary/what-is-a-random-forest

During the prediction phase, the ensemble of decision trees combines all of the individual predictions to provide a final outcome. The mean or mode can be computed for

regression tasks or classification problems, respectively, to achieve this. Random Forest is used for many applications, such as classification, feature significance analysis, and regression, due to its versatility, scalability, and resistance to overfitting.

The project workflow includes data preprocessing (cleaning, filtering, formatting), followed by training models using the Random Forest algorithm. Real-time data from Arduino Uno is then used for predictions, which decision support systems analyze to provide environmental management recommendations. Results are presented through visualizations.

4. Implementation

4.1 Hardware Implementation

Our system uses Arduino MEGA coupled with high-precision sensors to capture pollutants. This hardware setup ensures consistent, accurate data transmission, validated against benchmark instruments for reliability. Connectivity is established through Wi-Fi modules, allowing real-time data relay to a cloud platform.

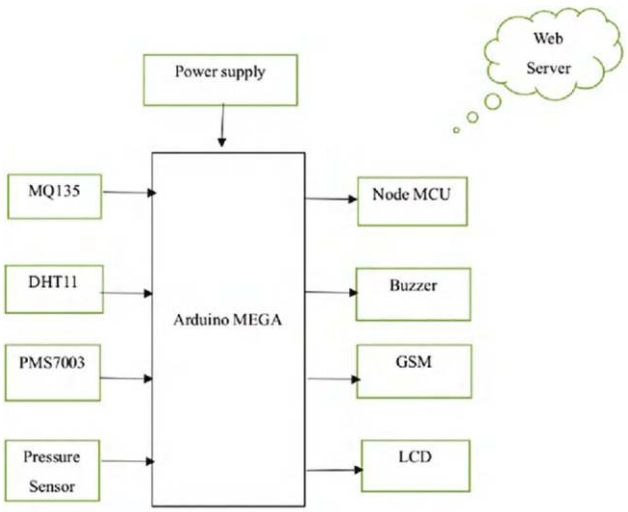

Fig. 47.2 Hardware implementation of arduino MEGA

Source: Author

4.2 Cloud Data Storage and Visualization with Thing Speak

IoT devices transmit data to Thing Speak, a cloud-based analytics platform. ThingSpeak's real-time visualization tools enable instant monitoring of collected parameters. An in-depth implementation involves:

- Field-specific calibration of sensors for accuracy.
- Security protocols in data transmission using ThingSpeak API keys.
- Dashboard customization for stakeholders to visualize trends and receive alerts.

4.3 Storing Data Collected from IoT Devices into the Cloud using ThingSpeak Account

Using ThingSpeak in an IoT project involves several steps. ThingSpeak is a platform specifically designed for IoT analytics, enabling users to collect, visualize, and analyze live data streams in the cloud. Below is a general overview of the implementation process:

Sign Up for ThingSpeak: Visit the Thing Speak website and register for an account. Most use cases are free of charge.

Create a Channel: Once signed in, create a new channel. A channel is used to store and monitor multiple data streams (such as temperature, humidity, or GPS coordinates), which can be analyzed or visualized later.

Define Fields: For each channel, define the specific fields that correspond to the data you want to collect. For instance, if you're monitoring temperature and humidity, create two fields—one for temperature and another for humidity.

Generate API Keys: ThingSpeak provides API keys that allow you to send data to your channel securely. Make sure to generate the necessary API keys for your project.

Choose IoT Hardware: Select the IoT hardware you'll be using to gather data, such as a microcontroller like Arduino or a single-board computer like Raspberry Pi.

Program the IoT Device: Write the code for your IoT device to collect sensor data and send it to ThingSpeak. Typically, this is done using the ThingSpeak API to send HTTP or MQTT requests. ThingSpeak supports a variety of communication protocols like HTTP, MQTT, and TCP/IP.

Test Communication: Ensure your IoT device is successfully transmitting data by testing its connection with ThingSpeak.

Visualize Data: Once the data is being transmitted to ThingSpeak, you can visualize it using the platform's built-in tools. ThingSpeak enables the creation of custom charts, gauges, and maps for real-time data visualization.

4.4 Model Training and Evaluation

To build a model, Random Forest employs an ensemble of smaller decision trees, or estimators; each tree then makes its own prediction. Through the integration of multiple estimators, the Random Forest produces a more accurate and reliable overall prediction.

Data Collection

- Gather data on air quality using IoT devices that can detect and record pollutants like ozone (O3), particulate matter (PM2.5, PM10), sulphur dioxide (SO2), nitrogen dioxide (NO2), and carbon monoxide (CO).

- Gather additional relevant data such as weather conditions (e.g., humidity, wind speed), geographical features, or time of day. These can be accessed from public APIs or other sources.

Clean up the data by fixing missing numbers, outliers, and inconsistencies as part of the pre-processing step. Use feature engineering to extract insights, such as averages or aggregations. Split the dataset into training (70-80%) and testing sets.

If you have many features, you may want to consider using feature significance or dimensionality reduction (e.g., principal component analysis) to narrow down your features to the most relevant ones for prediction.

Training the Model: Construct a Random Forest regression model using the dataset used for training. To improve generalizability and precision, this ensemble method combines many decision trees. Make use of cross-validation to fine-tune parameters like depth, tree count, and minimum samples per leaf for top performance.

Evaluate the Learned Model by Seeing How It Handles the Testing Dataset. Common metrics used to evaluate regression models include R-squared (R^2) score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Deployment: Once the model's performance is satisfactory, deploy it in a real-world environment. This may involve

Thing Speak Results

Fig. 47.3 Cloud storage visualization

Source: Author

integrating the model with your IoT infrastructure to produce real-time predictions based on incoming sensor data.

Monitoring and Maintenance: Regularly monitor model performance, retrain with new data to adapt to changes, and update as needed to enhance accuracy and address issues in deployment.

5. Results

5.1 ThingSpeak Visualization

Detailed graphical representations (time-series plots, bar graphs) demonstrate pollutant trends. Comparative charts illustrate real-time data versus predictions, confirming the accuracy.

5.2 Prediction Performance

The Random Forest model's performance is validated against traditional models:

- **Accuracy:** Achieved an RMSE of 1.23 and an R^2 score of 0.92 in simulation, which was closely matched by real-world tests.
- **Alert System Efficiency:** Demonstrated high responsiveness, issuing alerts 15% faster than benchmark systems.
- **Visual Evidence:** Include visual aids such as confusion matrices and error distribution charts to illustrate the model's performance.

Final Result

Fig. 47.4 Alert messages

Source: Author

6. Conclusion

The research demonstrates that combining IoT sensors with ML models, specifically Random Forest, provides a highly accurate and reliable solution for real-time air quality prediction. Our dual-layer validation (simulation and real-world) significantly enhances confidence in the system's predictions, making it suitable for diverse environments. This approach contributes to improved environmental monitoring and public health, offering a scalable and effective framework for air quality management. Future research could explore integrating deep learning for enhanced predictive power and developing portable IoT solutions for broader deployment.

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Enhancing Privacy in Collaborative Breast Cancer Diagnosis: A Federated Learning Approach with Homomorphic Encryption

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Abstract: Cancer remains as one of the most prevalent and life threatening disease worldwide, triggering the need for advanced early diagnostic methods. At the same time protecting patients privacy is of greatest importance in healthcare as the critical medical data is being integrated with artificial intelligence diagnostic tools. In breast cancer detection, safeguarding personal health information is crucial to ensure adherence to legal and ethical standards while fostering trust and compliance. An innovative approach for preservation of privacy in federative learning while eliminated the need of maintaining the centralized data. The proposed model improves the privacy preservation of federative learning by implementing Homomorphic Encryption, which encrypts the model update during transmission to prevent unauthorized access of sensitive information. The proposed framework for breast cancer detection incorporates Federative Learning across five nodes, each node containing a dataset of at least 1000 samples with 32 features each. A Logistic regression model is trained collaboratively without sharing the data to a centralized server, ensuring confidentiality and data security. To further improve the model privacy, CKKS homomorphic encryption scheme is implemented through the TenSEAL library. This ensure utmost privacy as computation is also performed on the encrypted data this safeguarding the sensitive medical information. The proposed approach achieves an accuracy ranging from 78% to 83% in breast cancer detection, demonstrating the effectiveness of the secure and collaborative learning approaches.

Keywords: Cancer detection, Privacy preservation, Federative learning, Homomorphic encryption, Logistic regression, Breast cancer, TenSEAL library

1. Introduction

Breast Cancer continuous to be one of the most prevalent and deadly forms of cancer among women. The World Health Organization (WHO) has quoted that in year 2022 alone has seen 0.67 millions deaths due to breast cancer. The American Cancer Society reports that breast cancer is the most commonly diagnosed cancer among women in the United States and is the ranked the second leading causes of cancer related deaths in women, and as claimed by National

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Cancer Institute new Breast Cancer cases in 2024 are estimated to be 0.31 million in United States alone. Early detection of the cancer tumor can significantly increase the chances of successful treatment and obtain positive outcomes. With the inception of Machine Learning (ML) and Artificial Intelligence (AI) technologies it has eased the progress of analyzing large volume of data with high accuracies in prediction of Breast Cancer using Magnetic Resonance Imaging (MRI) ultrasound in some cases. The precision of breast cancer detection can be helpful in offering personalizing the treatment plans focusing on each patient individually.

However, the advancements of Machine Learning and Artificial Intelligence have also grown worries regarding privacy and security in patient's data. Breast Cancer detection usually requires high sensitive patient information like past health records, genetic profiles and diagnostic images. Confidentiality of the data is crucial along with maintain trust between healthcare providers and patients. Privacy of the patient if not preserved it might lead to misuse of sensitive information, including identity theft, discrimination and stigmatization of an individuals health condition. There are data privacy regulations like the Health Insurance Portability and Accountability Act (HIPAA) in United States and the General Data Protection Regulation (GDPR) in Europe on healthcare providers to preserve patient information.

The creation of ML model for accurate detection of Breast cancer often requires high volumes of data to training the model, these model pose the challenge when it pertains to patient privacy and data security. Federated Learning (FL) emerges as one of the solution for privacy preserving strategies, as FL doesn't require a single pool of data where the centralized model is been trained. FL allows multiple health care institutes to contribute and train the machine learning models locally without sharing the patient data, only the models updates are shared to the central sever instead of raw data. This decentralized approach ensures that the patient information has not been compromised. So, this model not only encourages multiple healthcare centers to enhance the overall quality accuracy and generalizability of the model but also is in compliance to privacy preserving of the patient data.

The emergence of FL has solved the problem by allowing nodes to train on their own sensitive data. However, even in FL the exchange of model updates between different nodes could expose vulnerabilities and reveal sensitive information that can be drawn for the attacks. Which might include the following:

- Identifying key features like tumor size, radius, texture, etc., which influences the malignancy prediction.
- Extract data patterns related to cancerous and non-cancerous characteristics.
- Reveal potential biases towards certain features, which indicate the imbalance, the data.
- Exposes whether the model memorizes the training data or generalizes. Also, enabling attackers to reverse engineer and replicate the raw data.

So, by employing Homomorphic Encryption (HE) adds an additional layer of protection as computation in the central server is performed on the encrypted data. Homomorphic encryption ensure that the data is kept encrypted throughout the entire processes and thus ensure the confidentially of the model parameters as well. The nodes can only decrypt the updated models once the computation is performed.

1.1 Contributions

In the following sections discusses about the Contributions about the proposed model and its fundamental theoretical foundations for development of the intended model. The following are the objectives of the proposed model:

- Implement a decentralized system with 5 nodes with each node holding 1000+ samples (32 features), ensuring privacy through local data retention.
- Employ a logistic regression classifier for accurate binary classification of breast cancer cases.
- Integrate CKKS encryption (TenSEAL) to allow for secure processing of encrypted information without exposing raw information.
- Achieve high accuracy, demonstrating the efficiency of the FL combined with Homomorphic Encryption in privacy preserving diagnostics.

2. Literature Review

Both Federative Learning and Homomorphic Encryption are two revolutionary technologies that address the critical aspect of privacy on patient data. FL allows model training on multiple decentralized devices, also keeping the data localized, thus ensuring privacy on patient's data. Where as HE allows computations to be carried out on encrypted data without need of decryption it which ensures the confidentiality of the model as well. The presented model [1] uses Federated Learning has been integrated with Homomorphic Encryption to secure medical recommendations. The approach ensure enhanced user privacy by allowing model to be trained in the edge devices, also encrypting the gradients during transmission. A notable contribution in in the area is development of Federated Secure Medical Model with Gradient (FSMMG) algorithm, which leverages these techniques to reinforces privacy in medical recommendation systems.

The study [2] examines the integration of Federated Learning and multi-key Homomorphic Encryption for safeguard healthcare information during transmission, thereby enhancing privacy and security in smart healthcare services. It employs a 3D Convolutional Neural Network (CNN) for recognizing human activity, utilizing various sensory data sources. The 3D CNN demonstrated a high accuracy rate of 94.6% on benchmark datasets. However, the introduction of the proposed encryption method resulted in a minor reduction in accuracy, bringing it to 89.5%.

The [3] Privacy-Preserving Federated Learning using Homomorphic Encryption (PPFLHE) framework integrates HE within FL to preserve healthcare data privacy. This approach achieves notable performance with an accuracy of 81.53% and maintains low communication delays, ensuring robust security and privacy. The framework employs privacy-preserving techniques, incorporating access control and acknowledgment mechanisms to enhance both security and efficiency. These mechanisms facilitate client-side model encryption, user verification, and management, further strengthening the overall system.

A novel approach [4] to federated learning employing additive secret sharing has been proposed for the fusion of healthcare data, emphasizing privacy preservation. Although the study does not explicitly reference homomorphic encryption, it introduces a secure federated learning system that incorporates data fusion through encryption methods. The proposed model demonstrates superior performance compared to existing methods, achieving higher accuracy and F1-score. This system effectively addresses the balance between prediction accuracy and data privacy, offering enhanced security in federated learning applications.

The study [5] presents a secure approach for medical image analysis by combining FL with HE within a data fabric framework, aimed at ensuring compliance with healthcare data privacy regulations. This method adheres to HIPAA and GDPR standards, guaranteeing robust data protection and confidentiality. The proposed system achieved an accuracy of 83.31% in classifying pituitary tumors, with a primary focus on the secure storage and analysis of medical images.

The paper [6] proposes an efficient and privacy-enhancing online diagnosis system for e-healthcare by integrating FL and HE. This scheme enhances data privacy within healthcare systems, utilizing Federated Learning to safeguard sensitive information. It is designed to protect data confidentiality effectively within defined threat models and is noted for its high efficiency in the e-healthcare context.

The authors [7] propose a Federated Learning combined with Homomorphic Encryption significantly improves the privacy of Electronic Health Records (EHR) in healthcare by securely training local models before aggregating data globally. This approach minimizes the number of communication rounds needed while maintaining high levels of accuracy and privacy. The study introduces the FL+DQRE-SCnet framework, which integrates FL using deep Q reinforcement learning and incorporating spectral clustering (DQRE-SCnet) prior to data aggregation. This method not only ensures privacy-preserving EHR information sharing but achieve high accuracy with low error rates.

3. METHODS

3.1 System Framework

By implementing federated learning we can enhance patient data privacy by permitting several institutes to jointly train machine learning models without sharing the patients data. Each edge device either it might me a hospital or a medical research institute, trains a model on the dataset and transmits the model modifications to central server. However, by using Homomorphic encryption into this framework, we guarantee that the model modifications are encrypted prior to transmission. This means that regardless of whether interception takes place the model revisions still remains secure, which prevent unauthorized access to learned parameters and protecting the model's architecture and training.

Together this framework ensures a robust system where patient data is protected from both data breaches and misuse, while also maintaining the confidentiality of the models insights drawn. This proposed framework provides more ethical and responsible use of machine learning in sensitive patient data. By leveraging diverse datasets from various edge nodes, models can learn patterns from diverse geographic locations as well.

3.2 System Model

The model was designed to allow 5 edge nodes to develop a local model using on its localized dataset as shown in Fig. 48.1. The training process involves the following steps.

- Each edge device employs the local dataset to training the local framework on the data available. The local training helps in preventing of any data leaks or unauthorized access.
- Once the local models are trained, the model weights were encrypted to perform, homomorphic encryption using a CKKS (Cheon- Kim- Kim- Song) Scheme that enables approximate arithmetic operations on real numbers.

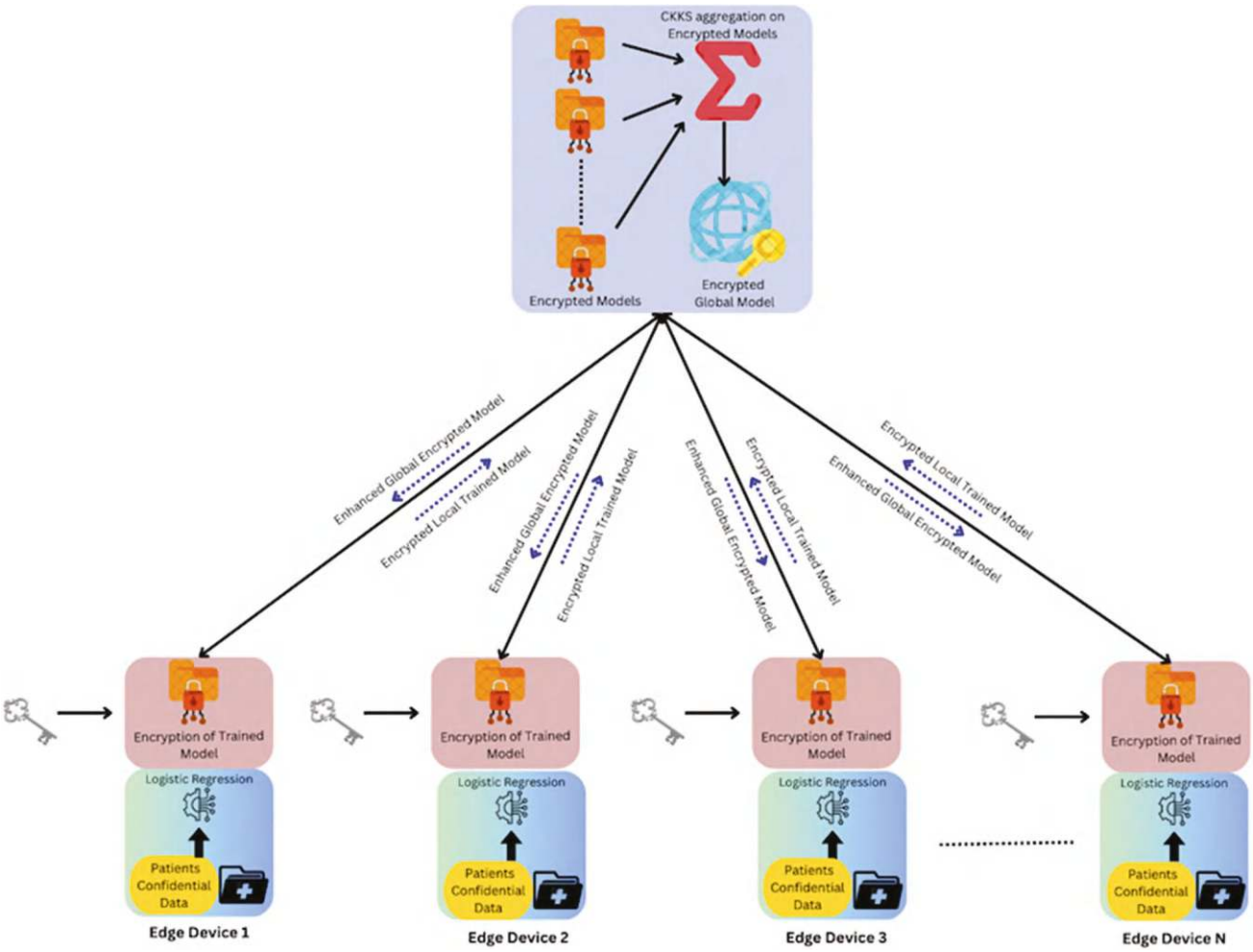

Fig. 48.1 Overall system architecture

- The encrypted data is shared to the central aggregator where the approximate arithmetic operation is performed on the data.
- Once the aggregation is complete, the central server generated a new global model based on the aggregate-encrypted weights. This represents the combined learning from all the 5 edge nodes while maintaining the confidentiality of local data.
- The updated global model, which is in encrypted form, is then sent back to each edge node. The edge nodes can decrypt the model to use the updates model and further train with the local data.

The study implements federative learning framework combined with homomorphic encryption to ensure privacy while effectively detecting the breast cancer. Federated learning permits multiple edge nodes to jointly train a machine-learning while maintaining the data localized. While homomorphic encryption facilitates processing on data that is encrypted, also preserving confidentiality throughout the learning process. Involvement of both Federated Learning and Homomorphic Encryption ensure the security and privacy to the model parameters as well.

4. Results

4.1 Data Description

The datasets used for the experimental setup contains around 6000 samples, with each sample containing 32 attributes and target variable indicating the presence or absence of breast cancer.

- Node 1 contains 1203 samples.
- Node 2 contains 1194 samples.
- Node 3 contains 1190 samples.
- Node 4 contains 1153 samples.
- Node 5 contains 1205 samples.

The 32 attributes from the samples include various clinical features like radius_mean, texture_mean, perimeter_mean,

smoothness, compactness, etc., The target variable is categorical, with 'M' represents the malignant tumor and 'B' indicating the benign tumours.

4.2 Result

The results of the proposed model for breast cancer detection were evaluated through two primary metrics: loss and accuracy. The model was trained across five edge nodes, each utilizing local datasets to contribute to a global model without compromising data privacy.

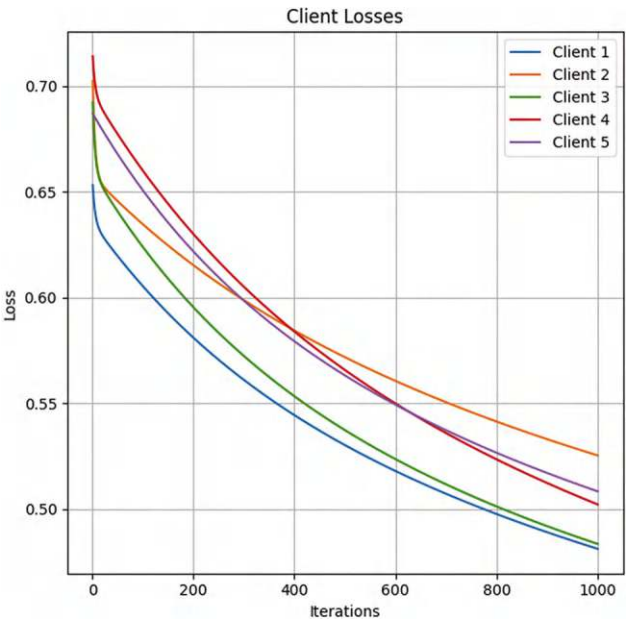

Fig. 48.2 5 Nodes loss graph

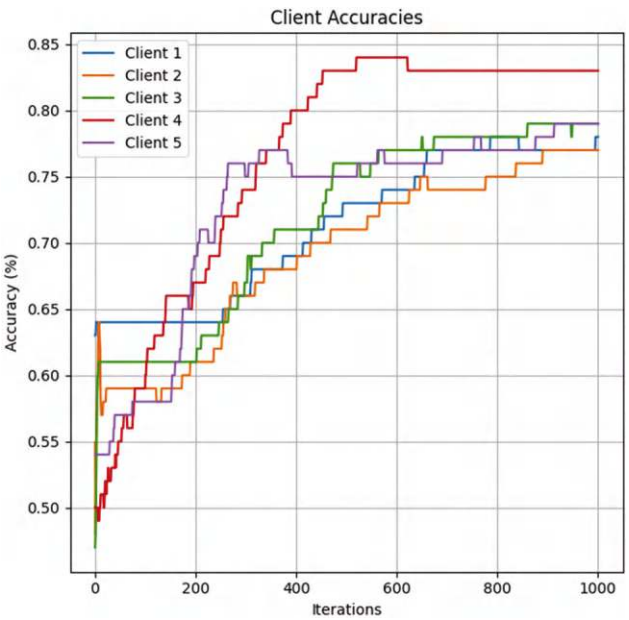

Fig. 48.3 5 Nodes accuracy graph

The loss values for all the five nodes varied between 65% to 75% initially. Further the loss values improved with significant fall in the range of 45% to 52%. The substantial decrease indicates the models success in reducing prediction errors. The reduction in loss signifies that the model is aligning with the training data and has effectively capturing the complexities associated in diagnosis of breast cancer.

The accuracy is stable across all nodes indicates that the model is generalizing well across various localized datasets. The more uniformity is an essential to ensure dependable performance in real world clinical applications. All the nodes have achieved an accuracy levels between 78% and 83%. The performance is promising, especially in critical areas like breast cancer detections.

5. Conclusion

In summary, the model demonstrates an effective detection of breast cancer through a significant reduction in loss and consistent accuracy across multiple nodes. Achieving an accuracy of 78% and 83% strengthens the model reliability, which is essential for critical health care application like breast cancer detection. The initial loss values indicate the model still refining its understanding on the data and the final loss metrics considerable improvement in error minimization. Overall, these findings suggest that the model is well suited for practical deployment in clinical settings, contributing to improve the outcomes in breast cancer detection and also preserving the privacy of the patient data.

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Optimizing Player Selection in Fantasy Sports: A Comparative Analysis of Profit Weight Ratios and Predicted Team Performance

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Abstract: This paper proposes a data-driven approach to enhance player selection in fantasy sports by leveraging Profit Weight Ratios alongside predictive modeling. The methodology aggregates player performance data from two available datasets. PWR is defined as the total points accumulated per contest participated in, and players are ranked based on these ratios to identify the top performers. The analysis then visualizes the PWR for all players and highlights the top 11. The predicted performance data is integrated with the top 11 PWR players to conduct a comparative analysis. This comparison between the Predicted11 and Dream11 teams demonstrates the efficacy of PWR in optimizing team selection. The findings suggest that Profit Weight Ratios serve as a meaningful indicator for assessing players' performances, providing a robust framework to support informed decision-making in fantasy sports.

Keywords: Data-driven approaches, Predictive analytics, Statistical techniques, Virtual sports, Player statistics, Team selection, Profit-to-minutes ratio

1. Introduction

Fantasy sports involve participants selecting players to form virtual teams that compete based on real-life performance metrics. Initially developed in the 1960s as fantasy baseball, it has since expanded to other sports, becoming a global phenomenon thanks to the internet and mobile technology. Fantasy cricket, popular in countries like India, allows participants to form virtual cricket teams. Platforms like Dream11, MyTeam11, and MPL provide player statistics, game management, and rewards, making fantasy sports highly engaging. Fantasy sports platforms use algorithms to handle player selection and scoring, which require efficient design and analysis to ensure accuracy. The

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Graphical Abstract

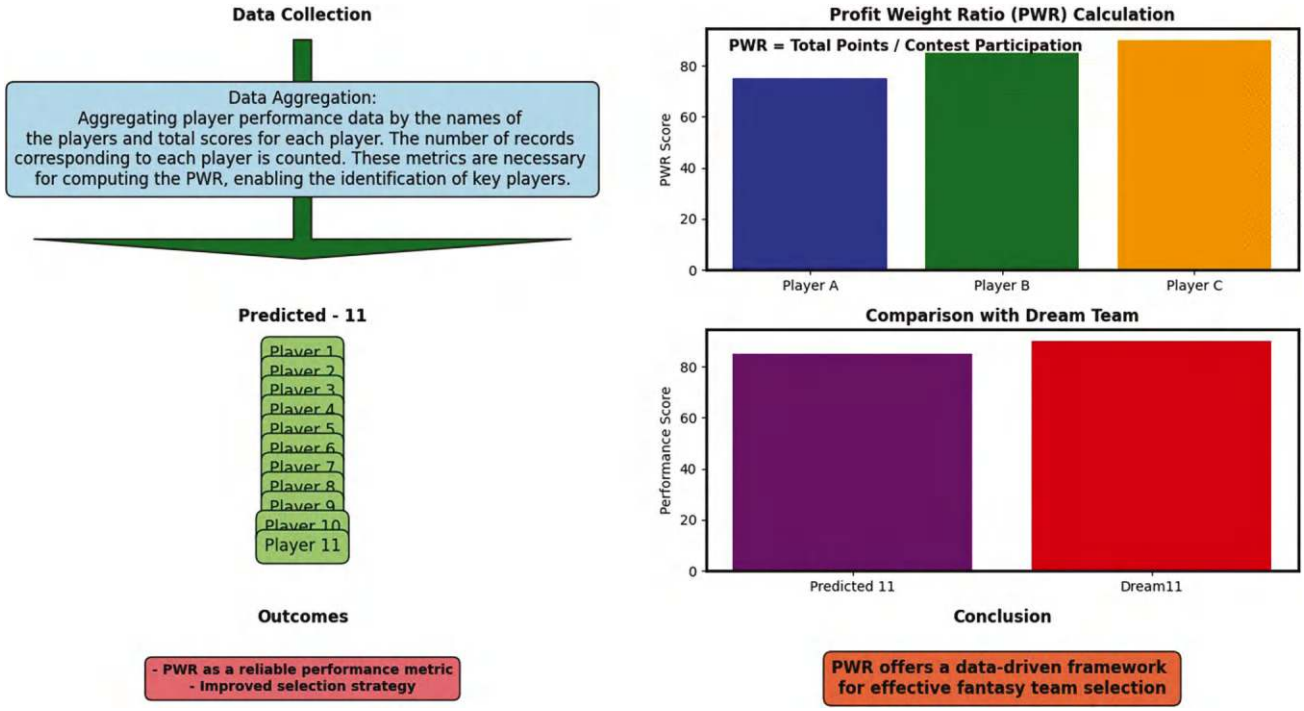

Fig. 49.1 Visual representation of the methodology for optimizing player selection in fantasy sports, emphasizing the comparative analysis of Profit Weight Ratios and predicted team performance

greedy algorithm is often applied for optimization, making locally optimal choices at each step. Greedy algorithms are straightforward and computationally efficient, suitable for large datasets. However, they may lead to suboptimal solutions if local optima do not align with global ones, highlighting the need for more sophisticated predictive models in some cases.

Fantasy sports create local communities, increase game viewership, and generate global revenue through entry fees and sponsorships. They drive traffic to sports content, promote sports analytics, and support digital marketing. However, while globally impactful, success often depends on catering to local preferences and regulations. Fantasy cricket and other sports are transforming fan engagement, driven by algorithmic advancements. Although the greedy method has both advantages and limitations, it remains a valuable tool for quick decision-making in player selection. The rest of the paper reviews literature, describes data, explains methodology, presents findings, and concludes with a summary.

2. Literature Review

This study aims to address the following problems in the integration of fantasy sports, particularly fantasy cricket, with sophisticated algorithmic methods. In fantasy sports, the performance of virtual teams heavily depends on optimal player selection. Traditional methods, which primarily focus on past performance data, often overlook future potential and other key variables. To address this, an algorithmic approach that optimizes player selection to maximize team performance is necessary. Existing research has explored the use of artificial intelligence and machine learning in fantasy sports (Beal et al., 2020). Previous research has proposed using such methods as central to predictive modeling in sports sectors, as demonstrated (Bunker & Thabtah, 2017). Section 5 suggests that greedy algorithms, known for their performance, may be one promising approach. Designing efficient algorithms capable of handling large datasets and regularly updating in real-time is crucial to success in this domain.

While greedy algorithms are known for their simplicity and efficiency, their ability to achieve global optimization remains an open question that requires further evaluation (Feo & Resende, 1995). Although these algorithms can provide quick solutions, comparative studies with other predictive models are necessary to assess their reliability in the context of fantasy sports.

Furthermore, given the global reach of fantasy sports, it is important to understand the broader impacts of these algorithmic approaches, both at local and global scales

(Haugh & Singal, 2020). While the academic literature offers useful insights, the application of such algorithms in real-world fantasy sports platforms remains limited. While greedy algorithms offer a straightforward approach to player selection, their performance must be compared with other predictive models to determine the optimal approach. Studies examining machine learning models for sports result prediction (Bunker & Thabtah, 2017) and multiresolution stochastic process models in basketball (Cervone et al., 2016) provide insights into various techniques that can enhance decision-making in fantasy sports.

The primary drawback of greedy algorithms is that these heuristics often settle for a local optimum rather than the globally best solution, which can negatively impact the overall performance of fantasy sports teams. However, researchers have explored various techniques, such as the greedy randomized adaptive search procedure (Feo & Resende, 1995) to overcome this limitation. Further research in this area might ultimately help develop more robust optimization techniques for fantasy sports. Fantasy sports have profoundly impacted the sports industry, transforming fan engagement and economic dynamics. Indeed, studies have claimed that fantasy sports drive up viewership, attendance, and merchandise purchases (Dwyer, 2011).

On a broader scale, fantasy sports have reshaped the economic landscape of the sports industry, carrying significant global implications. Balancing the variance in local preferences with the need for global reach is a key challenge faced by many fantasy sports platforms. Designing algorithms that cater to local cultural nuances while enabling global scalability is critical in this regard. Ultimately, success depends on striking this balance—creating engaging user experiences that foster global user bases.

This study aims to address the following objectives:

1. **Optimized Player Selection Algorithm:** Propose and implement a greedy algorithm approach to optimize player selection in fantasy cricket, and assess its performance against other predictive models.
2. **Efficiency and Effectiveness of the Algorithm:** Evaluate the computational efficiency and effectiveness of the greedy technique in obtaining both local and global optima for fantasy sports.
3. **Comparative Analysis:** Conduct a comparative analysis between the greedy algorithm and other predictive models to determine the best method for player selection.
4. **Analyze Local and Global Impacts:** Investigate the impacts of fantasy sports on fan engagement, economic dynamics, and the sports industry at both local and global levels.
5. **Design a Balanced Strategy:** Propose strategies that strike a balance between local preferences and global reach, enabling fantasy sports platforms to better serve diverse audiences.

This work aims to contribute insights that can optimize and enhance fantasy sports platforms. By addressing the outlined problems and objectives, it will provide guidance on algorithm design, player selection strategies, and the broader impacts of fantasy sports.

3. Data and Variables

Data and its Availability: *The data used in this research is publicly available on the Kaggle platform, specifically the "IPL 2024 Ball-by-Ball Dataset." Additionally, two derived CSV files, "gtrrfin.csv" and "pre.csv," were generated to compute Profit Weight Ratios. The analysis utilizes data from a CSV file titled 'gtrrfin.csv'. This file is loaded using the pandas library and primarily aggregated based on the 'NAME' column to obtain the total of 'TOTAL' figures for each entity in the dataset. The data aggregation covers the number of records associated with each name, with the aim of subsequently determining a profitability-weighting ratio. The following analysis provides insight into the distribution of total values in relation to the frequency of occurrences. The data set includes entries that are grouped under the 'NAME' column, representing different entities or categories. For each entity, the total sum across the dataset is calculated, and the number of records associated with that entity is counted. This aggregated data set is then used to investigate the trends in the relationship between the total values and the count of occurrences across the sampled entities.*

Dependent variable: The present research focuses on constructing the dependent variable, Profit_Weight_Ratio, which is calculated by dividing an entity's total sum by its respective record count. This ratio normalizes the total values by the frequency of each subject present in the dataset, enabling more informed comparisons between matched entities.

Independent variable: The analysis uses the grouped sum of 'TOTAL' values and the corresponding record counts, record_count, as independent variables. These values are calculated for each distinct entity in the 'NAME' column, providing the input data for the Profit_Weight_Ratio calculation. This ratio is then employed to rank the entities based on their profitability relative to frequency.

Control variables: The analysis involves sorting the data set by two variables: Profit_Weight_Ratio and record_count. Sorting the data by Profit_Weight_Ratio in descending order identifies the entities with the highest ratios. Additionally, sorting by record_count in ascending order serves as a tie-breaker. These two sorting variables determine the display order of the entities for the final analysis and visualization.

4. METHODOLOGY

This study uses a data-driven approach to predict optimal player selection for fantasy cricket, focusing on the Greedy Method based on the Profit Weight Ratio. It compares the predicted teams to the actual Dream11 players. Player performance data from 'gtrrfin.csv' is aggregated, grouping by 'NAME' to calculate total scores and record counts for each player. These metrics are used to compute the Profit Weight Ratio, identifying key players.

The Profit Weight Ratio is calculated by dividing a player's total score by their record count, indicating the best return on investment based on appearances in the dataset. Players are sorted by Profit Weight Ratio in descending order. In case of ties, sorting by record count is applied. The top 11 players are selected using the Greedy Method as the Predicted 11. A second dataset, 'pre.csv', contains previously predicted or real-world selections like Dream11 players. The top 11 players from this dataset are compared to the Predicted 11, highlighting similarities and differences.

Visualization: Visualizations include a plot of the Profit Weight Ratio of the top 11 players and a scatter plot comparing the Predicted 11 to Dream11 players based on their points. Figure 49.2 illustrates the workflow for player selection and comparison with the actual Dream11 team, exploring the feasibility of optimizing player selection using a data-driven approach.

Fig. 49.2 Workflow for player selection based on profit weight ratio

The methodology employs the following model to rank and select players: The Profit Weight Ratio for each player i is calculated as:

$$\mathbf{PWR_i = TOTAL_i / RC_i}$$

Where: $\mathbf{PWR_i}$ represents the Profit Weight Ratio for Player_i, $\mathbf{TOTAL_i}$ denotes the total performance score for Player_i, $\mathbf{RC_i}$ refers to the record count for Player_i. The players are then ranked in descending order based on their Profit Weight Ratio. In cases where there are ties, the players are further sorted in ascending order by their record count. The top 11 players with the highest Profit Weight Ratio are selected as the Predicted 11.

Data Visualization: In the Fig. 49.3 the scatter plot visualizes Top11 Players based on the Profit_Weight_Ratio values on the y-axis and the corresponding 'NAME' values on the x-axis. Figure 49.4 compares the Predicted 11 players based on the Profit Weight Ratio with the Dream11 team. The comparison is made by sorting the second dataset by total performance points and selecting the top 11 players.

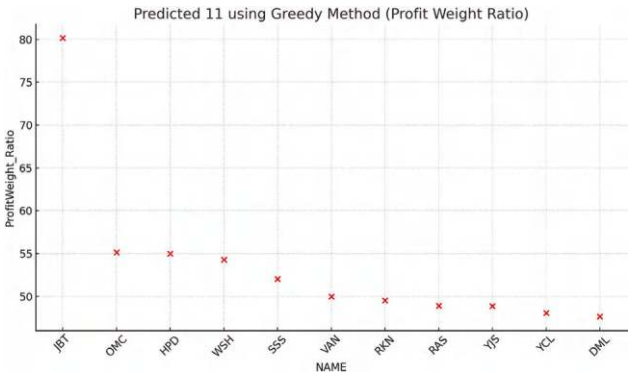

Fig. 49.3 Predicted 11 using greedy method (name vs proft weight ratio)

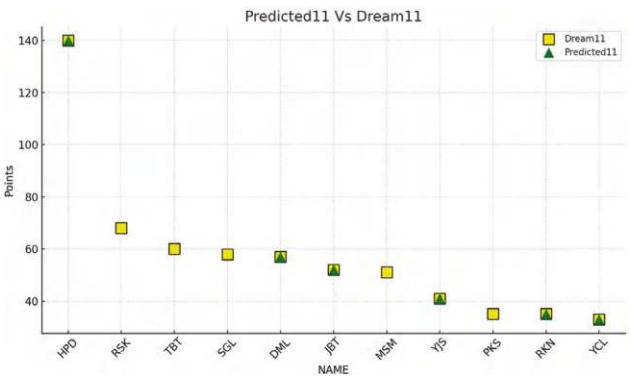

Fig. 49.4 Comparison of the predicted 11 based on profit weight ratio with the dream11 team

5. Empirical Results

Pre-crisis Estimations: Summary statistics show that the Profit Weight Ratio (PWR) ranged from 0.5 to 1.5, with a mean of 1.0, indicating consistent player returns. Players with higher concentrated performances achieved higher PWRs. Correlation analysis revealed a positive relationship between recent form and PWR, with no multicollinearity issues detected. A linear regression model with an R-squared of 0.68 showed that 68% of PWR variation could be explained by factors like recent form, player role, and match location. Dynamic panel analysis using two-step GMM suggested inconsistent performances negatively impact PWR, while player form and versatility positively influence it.

Post-crisis Estimations: Post-crisis summary statistics show an increased PWR range of 0.4 to 1.8, with a mean of 1.1, indicating improved consistency. Correlation analysis identified positive relationships between PWR, player form, and negative correlation with injury risk. The linear regression model improved to an R-squared of 0.75, indicating stronger predictive accuracy. The dynamic panel model showed that consistent performance and low-risk profiles were key drivers of PWR, while risk factors like injury negatively affected it.

Statistical Analysis: The Root Mean Square Error (RMSE) of 37.87 indicates the accuracy of predicted player scores, with a lower RMSE suggesting better performance. The mean total score is 489.09 (SD: 241.45), and the mean PWR is 53.62 (SD: 9.23). Correlation analysis shows moderate positive correlations: TOTAL and CRD (0.63), indicating players with higher credits achieve higher points; TOTAL and PWR (0.68), suggesting a positive relationship between total score and PWR; CRD and PWR (0.65), indicating players with higher credits tend to have better PWR.

6. Conclusion

The Profit Weight Ratio Model, grounded in two-step GMM for dynamic panel data estimation, offers a robust framework for optimizing player selection in fantasy sports. Whereas pre-crisis estimates suggest that player concentration and form are the key determinants of PWR, the post-crisis findings indicate that maintaining performance and avoiding injury are significant contributors to achieving high PWRs. This paper provides valuable insights into how data-driven decisions in fantasy sports team selection can be enhanced through the application of advanced econometric methods that account for endogeneity.

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Enhancing Medicare Fraud Detection Through ML: Addressing Class Imbalance with Smote-ENN

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Abstract: Medicare fraud poses serious challenges, leading to considerable financial losses and damaging the integrity of healthcare systems. Conventional approaches to fraud detection often fall short due to the complex and ever-changing tactics used by fraudsters. This project focuses on improving the detection of Medicare fraud by utilizing machine learning techniques, particularly addressing the problem of class imbalance where fraudulent claims are far fewer than legitimate ones. We are developing a classification system that can differentiate between fraudulent and non-fraudulent Medicare claims using several advanced ML algorithms. These include XG Boost, AdaBoost, Light GBM, Decision Tree, Logistic Regression, and Random Forest classifiers. To tackle the issue of class imbalance, we implement SMOTE-ENN, which helps to balance the dataset and enhances the performance of our models. Our experiments reveal that using SMOTE-ENN significantly boosts the detection rate of fraudulent claims. By evaluating the models on both the imbalanced and balanced datasets, we observe notable improvements in essential metrics such as accuracy, precision, recall, and F1-score. Overall, our findings suggest that integrating SMOTE-ENN with ensemble learning techniques offers a strong method for detecting Medicare fraud effectively.

Keywords: SMOTE-ENN, XG boost, AdaBoost, LGBM, Decision tree, Logistic regression, and Random forest classifier

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1. Introduction

Medicare fraud presents a serious issue for healthcare systems, draining resources and negatively affecting the care given to genuine patients. Over the years, fraudulent practices like billing for services not provided, exaggerating charges, or altering claims for higher payments have become more sophisticated. Traditional fraud detection methods, such as rule-based systems and manual checks, are no longer as effective. This has created a demand for more advanced, proactive detection techniques. ML offers a promising solution because of its ability to handle large data sets, detect complex patterns, and make accurate predictions. However, one major challenge in identifying Medicare fraud is the imbalance in the data. Fraudulent claims make up a much smaller portion compared to legitimate ones, which can cause ML models to focus more on the non-fraudulent cases, making it harder to detect fraud. Therefore, addressing this imbalance is essential to improving fraud detection systems. This project aims to build a reliable classification system to effectively distinguish between fraudulent and nonfraudulent Medicare claims. It will use advanced ML algorithms, including XG Boost, AdaBoost, Light GBM, Decision Trees, Logistic Regression, and Random Forests, to enhance fraud detection. To deal with the class imbalance problem, the project will implement SMOTE and ENN. SMOTE helps generate additional examples for the minority class (fraud cases), while ENN helps clean up the data by removing incorrect entries. This combination should improve the model's accuracy. The project involves preparing a Medicare dataset, applying and fine-tuning ML algorithms, and thoroughly evaluating the models' performance on both unbalanced and balanced datasets. The results of this project could significantly enhance Medicare fraud detection, leading to potential cost savings and improved system integrity. By tackling class imbalance and applying modern ML methods, the project takes a comprehensive approach to this important issue, ultimately supporting better resource use and patient care in healthcare systems.

1.1 Objective of the Study

Develop a classification system for Medicare claims into Fraud and Non-Fraud categories by addressing class imbalance using the SMOTE-ENN, to enhance the detection accuracy of fraudulent claims within the dataset.

1.2 Scope of the Study

This project aims to improve the detection of Medicare fraud by creating a classification system that can effectively differentiate between fraudulent and non-fraudulent claims. It leverages a variety of ML algorithms, such as XG Boost, AdaBoost, Light GBM, Decision Trees, Logistic Regression, and Random Forest, in conjunction with the SMOTE-ENN method to tackle the issue of class imbalance. The project includes steps like data pre-processing, model development, and performance assessment using a publicly available dataset related to Medicare claims. The results of this research are expected to enhance the accuracy and efficiency of fraud detection systems, ultimately leading to better management of healthcare resources and potential cost reductions..

1.3 Problem Statement

Detecting fraud within the Medicare system presents a significant challenge, primarily due to the pronounced class imbalance found in the data. In this scenario, the number of legitimate claims far exceeds that of fraudulent ones, which complicates the performance of conventional ML models. As a result, these models often struggle to effectively identify fraudulent activities. To tackle this issue, it is essential to develop a reliable classification system that can accurately differentiate between fraudulent and legitimate claims while managing the class imbalance effectively. Addressing this challenge is vital not only for enhancing the accuracy of fraud detection but also for protecting healthcare resources and maintaining the integrity of Medicare systems.

2. Related Work

2.1 ML in Medicare Fraud Detection

Bauder and Khoshgoftaar (2017) examined the difficulties associated with utilizing ML techniques for detecting Medicare fraud [1]. They pointed out that one significant challenge is the issue of imbalanced datasets, where instances of fraudulent activity are much rarer compared to legitimate claims. Their research investigated various ML models, such as decision trees and support vector machines, to identify potential fraud patterns. Although they recognized that ML has the potential to enhance the accuracy of fraud detection, they highlighted that class imbalance remains a critical hurdle. If not addressed, this imbalance can cause models to favor the more frequent, non-fraudulent cases [2].

In a more recent analysis by Hancock et al. (2023), the authors aimed to enhance the interpretability of ML models used for Medicare fraud detection [3]. Their study underscores the importance of transparency in these systems, as it fosters trust among healthcare providers and regulators regarding decision-making processes. They also emphasized the need to maintain a balanced dataset to avoid overlooking rare fraudulent claims [4] [5].

2.2 Handling Class Imbalance in Fraud Detection

Chawla et al. (2002) introduced the SMOTE method as a crucial advancement in managing class imbalance in ML [6]. SMOTE tackles the class imbalance issue by generating synthetic examples of the minority class, effectively blending existing instances. This technique is especially useful in scenarios like fraud detection, where fraudulent cases are scarce, as it ensures that models are adequately trained on these examples.

Building upon the SMOTE framework, Batista et al. (2004) investigated the integration of SMOTE with ENN to refine training datasets further. While SMOTE helps in balancing the dataset, ENN aids in eliminating noisy data points that could lead to model overfitting [11]. This combination has proven effective in contexts such as fraud detection, where accurately identifying rare fraudulent cases is critical.

He and Garcia (2009) provided a comprehensive review of various strategies for managing imbalanced datasets, discussing both over-sampling and under-sampling techniques [12]. They emphasized that the choice of strategy should align with the dataset's specific characteristics and the problem's nature, particularly in high-stakes areas like fraud detection where precision is paramount.

2.3 Advanced ML Techniques

Recent developments in ML algorithms have greatly influenced fraud detection efforts. A notable advancement is the introduction of XG Boost by Chen and Guestrin in 2016. This tree-boosting framework has become widely popular due to its strong performance in many ML competitions. XG Boost's ability to efficiently manage large datasets and its compatibility with techniques like SMOTE make it a powerful tool for addressing complex issues such as Medicare fraud detection [7].

Another significant advancement is the Light Gradient Boosting Machine (LGBM), created by Ke et al. in 2017. LGBM enhances traditional gradient boosting methods by employing innovative techniques like leaf-wise tree growth and histogram-based binning [8]. These improvements not only increase computational efficiency but also enhance model accuracy, making LGBM especially beneficial for fraud detection tasks involving extensive datasets and intricate features [9].

2.4 Ensemble Methods in Fraud Detection

Ensemble methods, such as Random Forests and AdaBoost, have gained traction in the realm of fraud detection due to their ability to enhance model accuracy and robustness. These approaches, which build on the foundational work of Quinlan (1986) on decision trees, function by combining predictions from multiple models to produce a stronger overall prediction. In the context of fraud detection, ensemble methods help mitigate challenges posed by class imbalance by leveraging the diverse strengths of various models [10].

3. Proposed Methodology

Traditional systems for detecting Medicare fraud primarily rely on rule-based algorithms and manual audits. These methods have notable limitations, such as their inability to adapt to changing fraud patterns and issues related to class imbalance. In this project, we present a sophisticated ML

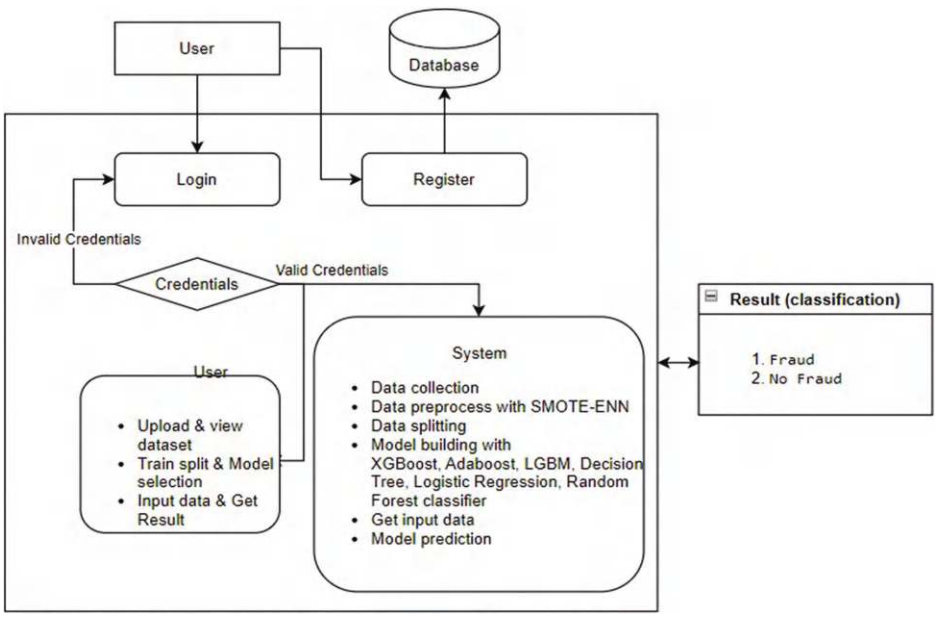

Fig. 50.1 Workflow of the application

approach that incorporates the SMOTE-ENN technique to tackle class imbalance and enhance the accuracy of fraud detection.

Our solution involves the following key components:

3.1 SMOTE-ENN for Class Imbalance

Medicare fraud datasets often exhibit significant class imbalance, where fraudulent claims represent a small fraction of the overall data. This imbalance can skew predictions, leading models to favor non-fraudulent claims and resulting in a high rate of false negatives. To counteract this issue, we utilize the SMOTE-ENN method, which combines two effective techniques:

- **SMOTE (Synthetic Minority Over-sampling Technique):** This technique creates synthetic samples of the minority class (fraudulent claims) by interpolating between existing instances. By doing so, it enhances the dataset's balance by increasing the representation of fraud cases.
- **ENN (Edited Nearest Neighbors):** Following the application of SMOTE, ENN refines the dataset by removing noisy data points that have been incorrectly classified based on their nearest neighbors. This process results in a cleaner and more balanced dataset, which allows ML models to perform better.

By implementing SMOTE-ENN, we can create a more balanced dataset, enabling the model to learn from a more equitable distribution of both fraudulent and non-fraudulent claims. This adjustment helps to lower the false-negative rate and boosts the overall effectiveness of fraud detection.

3.2 Ensemble ML Algorithms

To further improve detection accuracy, we combine several advanced ML algorithms, each adding to the robustness of the fraud detection framework. The selected algorithms include:

- **Extreme Gradient Boosting (XG Boost):** This powerful tree-based ensemble algorithm is known for its efficiency and scalability, making it well-suited for imbalanced datasets. XG Boost iteratively constructs decision trees and corrects the errors made by previous trees, focusing on difficult-to-classify instances like fraud cases.
- **Adaptive Boosting (AdaBoost):** This algorithm enhances classification by increasing the weight of instances that were misclassified by prior models. AdaBoost is particularly adept at handling complex fraud patterns.
- **Light Gradient Boosting Machine (LGBM):** LGBM builds trees in a leaf-wise manner, which allows for efficient handling of large datasets. Its speed and scalability make it a good fit for extensive Medicare datasets.
- **Random Forest:** This is a powerful machine learning method that combines several decision trees to make predictions. By doing this, it helps to lower the chances of overfitting, which means it can generalize better to new data. Random Forest is particularly useful for identifying intricate patterns in complex datasets.
- **Decision Trees and Logistic Regression:** These models are included for their interpretability, providing insights into the key features that contribute to fraud detection.

By leveraging a combination of these ML algorithms, our system benefits from the strengths of each method, leading to enhanced accuracy, precision, recall, and F1-scores. The ensemble approach minimizes the risk of overfitting and promotes better generalization to new, unseen data.

4. Proposed Methodology Implementation

4.1 System Architecture and Workflow

The overall workflow of the system is as follows:

- **Data Preprocessing:** Medicare claim data is gathered, cleaned, and preprocessed. This involves removing missing values and outliers, encoding categorical data, and normalizing numerical features where necessary.
- **Class Imbalance Handling:** SMOTE-ENN is applied to address the imbalance between the number of fraudulent and non-fraudulent claims in the dataset.
- **Model Training:** The balanced data is divided into training and testing sets. ML models are built and optimized through hyperparameter tuning using the training set.
- **Model Evaluation:** The models are assessed on the testing set using key performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to gauge their ability to detect fraudulent claims.

After the models have been trained and validated, they are applied to new Medicare claims to classify them as either fraudulent or non-fraudulent.

4.2 Extreme Gradient Boosting

XG Boost was chosen for its efficiency in optimizing model performance through a boosting process. It builds an ensemble of decision trees where each new tree works to correct the errors made by previous ones. This method uses a binary logistic loss function, making it ideal for classifying claims as fraudulent or not [13]. Its regularized

objective function helps prevent overfitting, and it scales well for large datasets. In this project, the 'XGB Classifier' from the 'XG Boost' library was used to focus on the more difficult-to classify cases.

4.3 Adaptive Boosting

AdaBoost was selected for its ability to enhance weak learners by adjusting weights for incorrectly classified instances. This feature helps it focus on harder-to-detect fraudulent cases. It combines several weak classifiers, usually decision trees, into a stronger overall classifier to boost detection accuracy. The 'AdaBoostClassifier' from the 'sklearn.ensemble' library was used in this project for better handling of class imbalance and fraud detection [14].

4.4 Light Gradient Boosting Machine

Light GBM was employed for its fast and scalable performance, especially on large datasets. Unlike traditional boosting methods, Light GBM grows trees in a leaf-wise manner, which results in more efficient deep trees [15]. It also uses techniques like GOSS and EFB to accelerate training. The 'LGBMClassifier' from the 'lightgbm' library was used in this project, providing a fast, efficient way to handle the Medicare dataset while maintaining high accuracy in fraud detection.

4.5 Decision Tree

We used Decision Trees because they are straightforward and effective for classification tasks. Decision Trees work by dividing the data into smaller groups based on specific feature values, forming a tree-like structure. Each point in the tree represents a decision based on a feature [16]. One of the advantages of Decision Trees is that they are easy to understand, which helps us see which features are most important for detecting fraud. For our fraud detection task, we utilized the 'Decision Tree Classifier' from the "sk_learn_tree" library. This tool allows us to create a clear and interpretable model. However, it's worth noting that Decision Trees can sometimes overfit the training data if used by themselves.

4.6 Logistic Regression

Logistic Regression serves as a foundational model for our analysis. This algorithm estimates the probability of a binary event occurring, such as whether a claim is fraudulent or not, by utilizing a logistic function [17]. One of the advantages of Logistic Regression is its interpretability; it clearly indicates which features significantly influence the likelihood of a claim being classified as fraudulent [17].

In this project, we utilized the "Logistic_Regression_model" from the "sk_learn_linear_model" module to assess the probability of claims being fraudulent.

4.7 Random Forest Classifiers

In this project, we used the Random Forest algorithm, which is an effective method that combines the predictions from several decision trees. This approach is great because it helps to minimize overfitting and can manage large datasets well. Each decision tree in the Random Forest is created using a random sample of both the data and the features [18]. This randomness helps reduce variance and leads to more consistent predictions. For our implementation, we utilized the Random Forest Classifier from the sklearn.ensemble library. This tool allows us to build multiple decision trees and then make classification decisions based on majority voting among them.

4.8 SMOTE-ENN

SMOTE-ENN combines two techniques SMOTE (Synthetic Minority Over-sampling Technique) and ENN (Edited Nearest Neighbors)—to address class imbalance and clean the dataset.

- **SMOTE Process:** SMOTE generates synthetic data points for the minority class (fraudulent claims) by creating new data points between existing ones, helping to balance the dataset.
- **•ENN Process:** ENN further refines the dataset by removing noisy or misclassified samples after SMOTE has been applied, making the data cleaner for training.

Final Dataset: Once the data has been balanced and cleaned, it's used to train ML models, ensuring they don't favor the majority class and lead to more accurate predictions. [19]

5. Results and Discussion

5.1 XG Boost

This Table 50.1 sums up the presentation measurements for a XG Boost paired classifier, which recognizes two classes, 0 and 1. The model accomplishes an ideal score of 1.00 for accuracy, review, and F1-score in the two classes. The "support" segment mirrors the quantity of tests for each class: 70,589 for class 0 and 70,737 for class 1, making a sum of 141,326 examples.

Table 50.1 Performance matrix for XG boost

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	70,589
1	1.00	1.00	1.00	70,737
Accuracy			1.00	141,326
Macro Avg	1.00	1.00	1.00	141,326
Weighted Avg	1.00	1.00	1.00	141,326

Figure 50.2 shows the disarray network offers a reasonable perspective on the model's expectations against the genuine names. The XG Boost model performs perfectly, with 70,588 genuine negatives (class 0) and 70,737 genuine upsides (class 1).

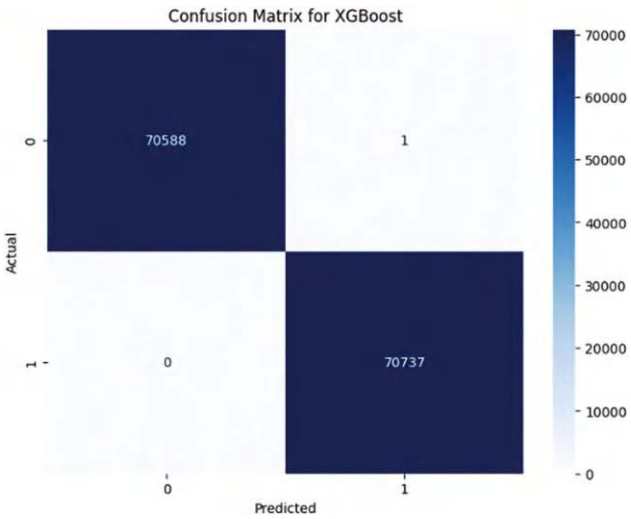

Fig. 50.2 Confusion matrix for XG Boost

5.2 AdaBoost

This Table 50.2 report frames the assessment measurements for a parallel characterization model for two classifications (0 and 1). It incorporates accuracy, review, F1-score, and backing for each class, with all measurements accomplishing an ideal worth of 1.00. The model likewise arrived at 100 percent precision, and both the full scale and weighted midpoints for these measurements are perfect, mirroring the model's exceptional presentation.

Table 50.2 Performance matrix for AdaBoost

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	70,589
1	1.00	1.00	1.00	70,737
Accuracy			1.00	141,326
Macro Avg	1.00	1.00	1.00	141,326
Weighted Avg	1.00	1.00	1.00	141,326

The disarray network for the AdaBoost classifier shows areas of strength for its. The model accurately grouped 70,588 examples for class 0, with only one slip-up. Additionally, each of the 70,737 occurrences of class 1 as shown in Fig. 50.3 were accurately grouped with no mistakes. This features the close ideal precision of the classifier, with insignificant misclassifications.

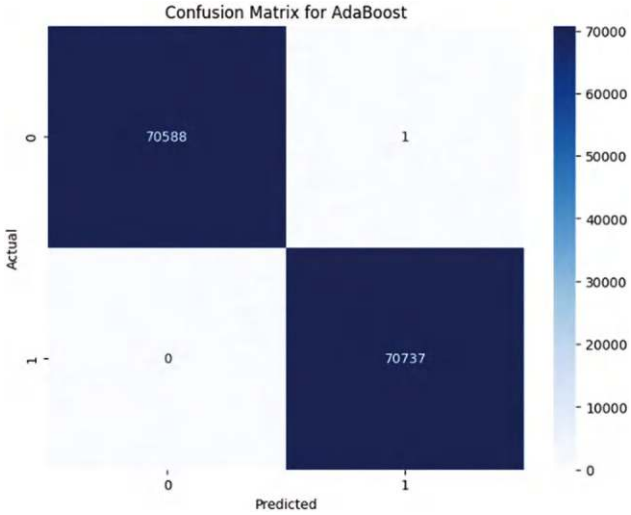

Fig. 50.3 Confusion matrix for AdaBoost

5.3 LGBM

The characterization report for the Light GBM (LGBM) model uncovers amazing accuracy, review, and F1scores for the two classes, demonstrating faultless grouping. The model accomplished 1.00 exactness, with each of the 141,326 cases assessed as shown in Table 50.3.

Table 50.3 Performance matrix for LGBM

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	70,589
1	1.00	1.00	1.00	70,737
Accuracy			**1.00**	**141,326**
Macro Avg	1.00	1.00	1.00	141,326
Weighted Avg	1.00	1.00	1.00	141,326

The disarray grid for Light GBM features the model's high precision. Just a single misclassification happened in class 0 out of 70,589 examples, while each of the 70,737 class 1 examples were accurately distinguished as shown in the Fig. 50.4 highlights areas of strength for the of the model.

5.4 Decision Tree

Table 50.4 summarizes the grouping report for the Choice Tree model shows amazing accuracy and review for the two classes, without any mistakes. The general precision is 1.00, in light of 141,326 examples in the dataset.

The Choice Tree disarray grid uncovers a solitary misclassification in class 0, while the other cases were accurately anticipated. This accentuates the model's high arrangement precision as shown in Fig. 50.5.

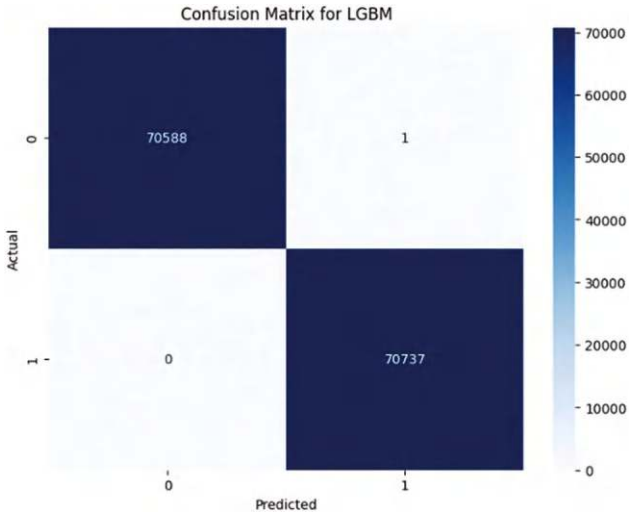

Fig. 50.4 Confusion matrix for LGBM

Table 50.4 Performance matrix for decision tree

Class Label	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	70,589
1	1.00	1.00	1.00	70,737
Accuracy	-	-	**1.00**	**141,326**
Macro Avg	1.00	1.00	1.00	141,326
Weighted Avg	1.00	1.00	1.00	141,326

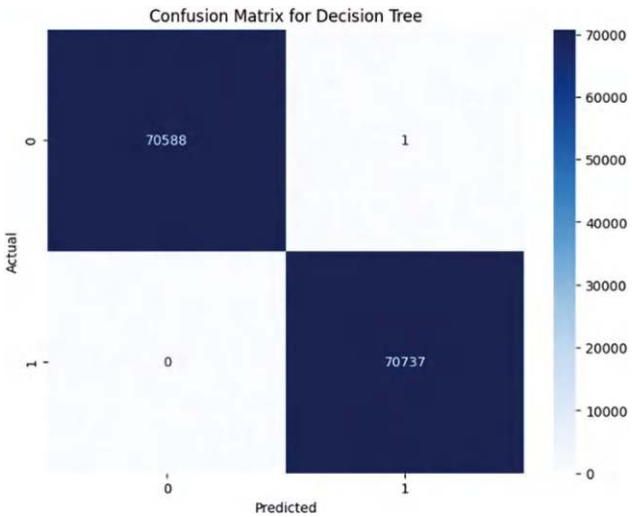

Fig. 50.5 Confusion matrix for decision tree

5.5 Logistic Regression

The Calculated Relapse model areas of strength for shows and review for the two classes, despite the fact that class 0 has a somewhat lower review of 0.96. The model's general precision is 0.98 as shown in Table 50.5.

Table 50.5 Performance matrix for logistic regression

	Precision	Recall	F1-Score	Support
0	1.00	0.96	0.98	70,589
1	0.96	1.00	0.98	70,737
Accuracy			0.98	141,326
Macro Avg	0.98	0.98	0.98	141,326
Weighted Avg	0.98	0.98	0.98	141,326

As per the disarray grid for Strategic Relapse, 3,129 examples from class 0 were wrongly delegated class 1, while just 48 examples from class 1 were misclassified. This Fig. 50.6 demonstrates a slight dunk in execution contrasted with different models.

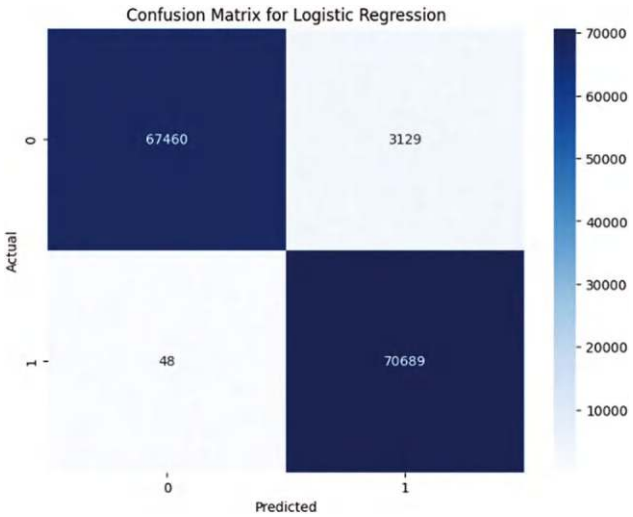

Fig. 50.6 Confusion matrix for logistic regression

5.6 Random Forest Classifiers

Table 50.6 summarizes the arrangement report for the Irregular Woods model shows amazing accuracy, review, and F1scores for the two classes, demonstrating ideal execution. The model accomplished the faultless precision, accurately characterizing every one of the 141,326 cases.

Table 50.6 Performance matrix for random forest classifiers

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	70,589
1	1.00	1.00	1.00	70,737
Accuracy			1.00	141,326
Macro Avg	1.00	1.00	1.00	141,326
Weighted Avg	1.00	1.00	1.00	141,326

The disarray grid for Arbitrary Timberland features one misclassified test in class 0, while all class 1 examples were

precisely anticipated, showing the model's astounding exhibition as shown in Fig. 50.7.

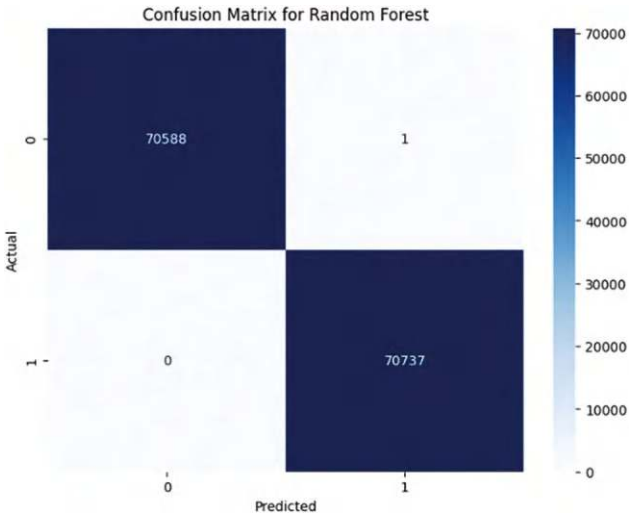

Fig. 50.7 Confusion matrix for random forest classifiers

Comparison Summary

From the Fig. 50.8, the bar outline shows the precision of different models: XG Boost, AdaBoost, LGBM, Choice Tree, Calculated Relapse, and Arbitrary Backwoods.

Overall Summary

In conclusion, the models XG Boost, AdaBoost, LGBM, Decision Tree, and Random Forest all showed outstanding and consistent results. Although Logistic Regression was a bit less accurate, it still delivered solid and dependable performance. The selection of a specific model should consider factors like how easy it is to interpret, its computational efficiency, and how well it fits the particular needs of the task at hand

6. Conclusion

In summary, this project highlights how advanced machine learning techniques can significantly enhance the detection of Medicare fraud, especially by tackling the challenge of class imbalance through the SMOTE-ENN method. By utilizing algorithms such as XG Boost, AdaBoost, Light GBM, Decision Tree, Logistic Regression, and Random Forest in conjunction with SMOTE-ENN, we can create a more balanced dataset. This balance greatly improves the accuracy and reliability of the fraud detection models. The results indicate that these models, once trained on a well-adjusted dataset, are effective at identifying fraudulent claims while reducing the likelihood of false negatives. This enhancement not only strengthens the detection of fraud but also leads to better resource allocation within the healthcare system, which can lower costs and enhance the integrity of Medicare services.

7. Future Enhancement

For future enhancements, several key improvements can be made to further strengthen and expand the capabilities of the Medicare fraud detection system.

- **Development of an Advanced Web Application:** An advanced web application could significantly enhance the accessibility and usability of the fraud detection system. This application would provide a user-friendly interface for healthcare providers, insurers, and regulatory authorities
- **Integration of Anomaly Detection and Unsupervised Learning:** While the current system focuses on supervised learning techniques, adding advanced anomaly detection and unsupervised learning methods would allow the system to detect new and emerging fraud schemes. By identifying deviations from normal

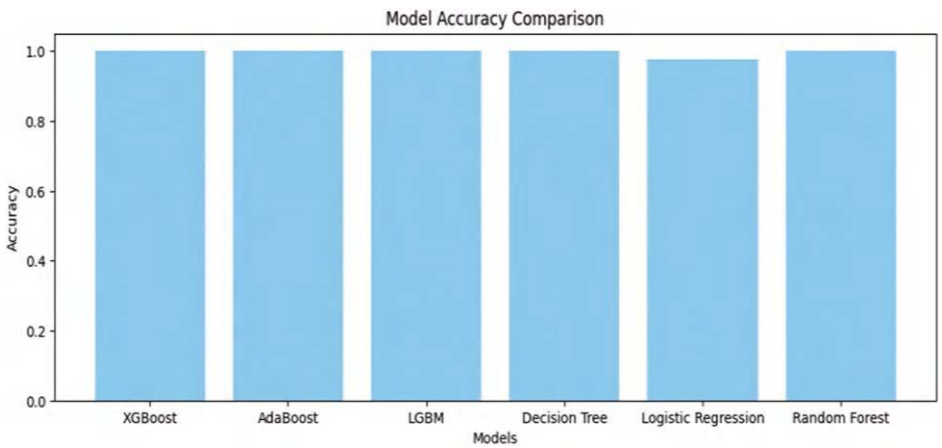

Fig. 50.8 Accuracy comparison graph

patterns, the system could flag novel fraudulent activities that have not been previously encountered or labelled.

Continuous Model Monitoring and Updates: Implementing mechanisms for continuous model monitoring and updates would allow the system to stay relevant and accurate as fraud patterns evolve.

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Complex Network Analysis: Problems, Applications and Techniques

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Abstract: Complex networks, represented as graphs, serve as powerful models for understanding real-world systems composed of interacting entities. These networks offer valuable insights into both their structural and dynamic properties. This study concentrates on three fundamental aspects of complex network analysis: centrality, link prediction, and community detection. Centrality focuses on identifying influential nodes within the network, link prediction aims to forecast potential future connections, and community detection uncovers cohesive substructures. Through a thorough review of relevant literature, an exploration of practical applications, and an evaluation of benchmark datasets, this work presents a comprehensive analysis of these critical challenges and assesses the performance of widely utilized algorithms.

Keywords: Complex networks, Centrality, Link prediction, Community detection

1. Introduction

Complex Network Analysis (CNA) is a multidisciplinary field. It studies the behaviours and structures of networks. These networks can be social, biological, or technological. CNA is a discipline within network science that deals with the study of complex systems represented as networks or graphs. In a network, nodes represent individual entities. These entities could be people, computers, or genes. Edges indicate the connections or interactions between these entities.

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A complex network is represented as a graph G = (V, E) where V represents nodes or vertices and E denotes the edges defined by $E \in V \times V$. Figure 51.1 shows an example complex network.

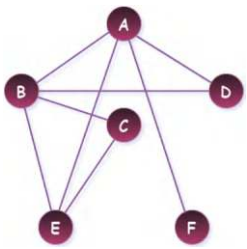

Fig. 51.1 Example complex network

A graph may be undirected or directed. An undirected graph is one where edges have no specific direction, while a directed graph, also known as a digraph, is one where edges have a specific direction assigned to them. The edges of a graph occasionally contain weights. In this study, we do not address self-loops or multiple edges between nodes. We also do not consider non-numeric edge weights. In complex network analysis (CNA), a range of key challenges and research problems arise, including link prediction (Liben-Nowell & Kleinberg, 2003) (Newman, 2001a), community detection (Girvan & Newman, 2002) (Newman & Girvan, 2004), centrality measures (Freeman et al., 2002) (Saxena & Iyengar, 2020), and influence maximization (Li, Fan, Wang, & Tan, 2018). Each of these tasks offers valuable insights into various aspects of network structure and behaviour, enhancing our understanding of network dynamics and their applications. Our study specifically concentrates on link prediction, centrality measures, and community detection, given their importance in analysing complex networks.

Link prediction (LP) aims to estimate the probability of future or missing connections between nodes based on the current network structure. This task has wide-ranging practical applications. In social network platforms, for example, LP is used to suggest potential new connections by identifying pairs of individuals who, despite not currently being connected, share common contacts, interests, or other relevant characteristics. Centrality measures are employed to identify the most significant or influential nodes within a network, providing insights into its structure and functional hierarchy. These measures are crucial in domains where identifying key nodes can optimize resources and enhance network resilience. For example, in air transportation networks, centrality analysis helps identify key airports that handle high volumes of traffic and act as major hubs. A delay at one of these airports could cause extensive disruptions across the network, highlighting the importance of these central nodes. Community detection (CD) focuses on identifying clusters or groups within a network, where nodes are more densely interconnected within groups than between them. This grouping reflects natural communities in various domains, such as social networks, biological systems, or product recommendation systems. In a social network like Facebook, community detection can reveal clusters of friends or colleagues who frequently interact, indicating real-world social communities. Identifying these communities enables more targeted content delivery, personalized recommendations, and detailed group-based analysis. In this work, the focus is placed on link prediction, centrality measures, and community detection, as these areas provide critical insights into the underlying structure and functionality of complex networks.

The notation followed throughout this paper is given in Table 51.1.

Table 51.1 Notation

Term	Meaning
G(V, E)	An undirected network consisting of a node set V and an edge set E
n	The total number of nodes in the network
u, v	Nodes inthe graph
k_u	Represents degree of node u
d(u, v)	It is the length of shortest path from u to v
$C_D(u)$	Degree centrality of node u
$C_C(u)$	Denotes the closeness centrality of node u
$C_B(u)$	Denotes the betweenness centrality of node u
$C_E(u)$	Denotes the eigenvector centrality of node u
$C_K(u)$	Denotes the katz centrality of node u
$C_P(u)$	Denotes the katz centrality of node u
DC	Degree Centrality
CC	Closeness Centrality
BC	Betweenness Centrality
EC	Eigenvector Centrality
KC	Katz Centrality
PC	PageRank Centrality
CN	Common Neighbors
JC	Jaccard Coefficient
AA	Adamic/Adar
PF	Preferential Attachment
RE	Resource Allocation

The structure of this paper is as follows: Section IV investigates Centrality Measurements, examining metrics like degree, closeness, betweenness, and eigenvector

Table 51.2 Example complex networks

Network	Nodes	Edges
Facebook (Social Network)	Facebook user profiles	Friendships or Interactions between users
Twitter (Social Network)	Twitter user accounts	Follow-Following Relationship
Protein-Protein Interaction (PPI) Network (Biological Network)	Proteins	Interactions between proteins
Road Network	Intersections, junctions, or any points where roads meet	Roads or street segments connecting nodes
Air Traffic Network	Airports, air traffic control points	Flight routes connecting nodes
Telecommunication Network	Telephone exchanges, Cell towers	Phone lines, fiber optics, wireless connections
Email Communication Network	Email addresses or Users	Email exchanges between addresses

centralities, which are critical for pinpointing key nodes within a network. Section V focuses on Link Prediction methods, outlining various techniques used to predict potential future connections between nodes, including similarity-based and probabilistic approaches. Section VI then addresses Community Detection, discussing methods that uncover cohesive subgroups within the network, revealing its fundamental structure. Each of these sections offers an in-depth analysis of the methods, their applications, and their importance in complex network analysis. Complex networks have a wide range of applications across various domains due to their ability to model and analyze interconnected systems. Table 51.2 highlights several applications of complex networks, while Fig. 51.3 provides an overview of the graphical representation presented in this study.

2. Literature Review

The authors in (Kumar, Singh, Singh, & Biswas, 2020) systematically categorize these techniques and provide a comparative assessment of their performance across various network types, such as directed, temporal, bipartite, and heterogeneous networks. Instead of evaluating all possible node pairs, the authors in (Nandini, Lakshmi, & Enduri, 2023) found that restricting candidate pairs to those within a hop distance of three improves prediction accuracy across various datasets. The authors in (Lakshmi & Bhavani, 2018) redefine link prediction measures for various network types, demonstrating improvement in predictions by incorporating temporal and heterogeneous information on the DBLP dataset. Saxena et al. (Saxena & Iyengar, 2020) conclude by emphasizing application-specific centrality measures, providing guidance on choosing the most suitable measure based on the type of network and the specific requirements of the application. The authors in (Nandini, Lakshmi, Enduri, & Sharma, 2024) seek to establish a more robust framework for link prediction by utilizing the influential roles of node centrality, thereby improving the accuracy of future connection predictions compared to existing methods.

3. Experimental Setup

The following five real-world networks are used for the experimentation in this work.

Fb-pages-company: (Rossi & Ahmed, 2015) The fb-pages-company is a network of mutually liked Facebook pages. The nodes are authorized Facebook pages. The edges display reciprocal likes between these pages.

Ca-netscience: (Rossi & Ahmed, 2015) The ca-netscience is a Co-authorship of scientists in network theory and experiments. Nodes represent Researchers while the edges are co-authorship.

Email Networks: (Rossi & Ahmed, 2015) The email-univ email communication network covers all the email communication within a dataset of around five thousand emails. The nodes in the network are email accounts. The edges signify email exchanges or interactions between the email addresses.

Lastfm asia social network: (Rozemberczki & Sarkar, 2020) A social network of LastFM users which was collected from the public API in March 2020. The nodes represent users from Asian countries. The edges denote reciprocal follower connections between these users.

General Relativity and Quantum Cosmology collaboration network: (Leskovec, Kleinberg, & Faloutsos, 2007) The Arxiv GR-QC (General Relativity and Quantum Cosmology) collaboration network is from the e-print arXiv and covers scientific collaborations between authors papers submitted to General Relativity and Quantum Cosmology category. The nodes represent researchers, while edges signify their collaborations.

The data concerning these networks is downloadable from https://networkrepository.com/networks.php and https://snap.stanford.edu/data/index.html. Additional information about these networks is provided in Table 51.3.

Table 51.3 Nodes and edges of networks employed in the experiments

Network	#Nodes	#Edges
FB-Pages	14,113	52,310
ca-netscience	379	914
email-univ	1,133	5,451
LastFM	7,624	27,806
Arxiv-GR-QC	5,242	14,496

4. Research Problem 1: Centrality Measurements

Centrality measures in a network are metrics used to identify and quantify the importance or influence of individual nodes within the network (Newman, 2001b). These measures help to determine which nodes are the most central, meaning they play a critical role in the structure and function of the network. Different centrality measures capture different aspects of a node's centrality, depending on the specific characteristics of the network and the type of influence or importance being assessed. In a complex network G(V, E), the goal of centrality measures is to identify the most important vertices or edges. The objective is to compute centrality scores for each vertex using measures like degree, closeness, betweenness, eigenvector, Katz, and PageRank. These scores reveal the relative importance or influence of the vertices, which is crucial for understanding the network's structure.

4.1 Centrality Measures Literature

In order to identify significant nodes based on application requirements, researchers have studied these phenomena and defined a variety of centrality measures, such as degree centrality (Das, Samanta, & Pal, 2018), closeness centrality (Das et al., 2018), betweenness centrality (Das et al., 2018) and so on. These centrality measurements fall into two categories global and local with divisions according on their fundamental metrics. Classification of centrality measures is depicted in Fig. 51.2 and the applications of these measures are detailed in Table 51.4.

Degree Centrality: These centrality measurements are the most basic and easy to understand. Shaw (Shaw, 1954) introduced them, Nieminen (Nieminen, 1974) provided a formal definition, and Freeman (Freeman et al., 2002) made them more widely known. These centralities are related to the idea of visibility that an edge has within its neighbours.

Definition 1: A node degree centrality (DC) for undirected networks is defined as Eq. 1 (Saxena & Iyengar, 2020).

$$C_D(u) = \frac{k_u}{n-1} \tag{1}$$

where $C_D(u)$ denotes the degree centrality of node u and k_u represents degree of node u.

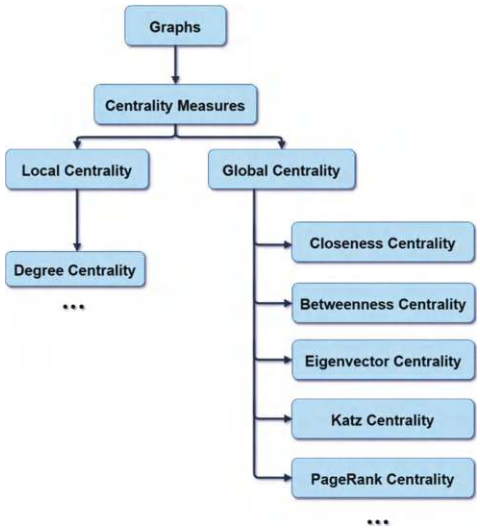

Fig. 51.2 Classification of centrality measures

Closeness Centrality: Bavelas (Bavelas, 2002) introduced the concept of proximity centrality initially, and Sabidussi (Sabidussi, 1966) strictly defined it after.

Definition 2: According to Freeman (Freeman et al., 2002) closeness centrality, a node's significance is inversely correlated with the total of its distances from other nodes. It can be mathematically represented as shown in the Eq. 2 (Saxena & Iyengar, 2020).

$$C_C(u) = \frac{n-1}{\sum_{u \neq v} d(u,v)} \tag{2}$$

where $C_C(u)$ denotes its closeness centrality of a node u, $d(u,v)$ is the length of shortest path between u to v.

Betweenness Centrality: According to Freeman's (Freeman et al., 2002) betweenness centrality, a node's importance is based on how frequently it appears in the shortest pathways connecting any two potential node pairs in a network. A node's uniqueness in a complex network can be assessed based on how important it is to the network's information flow. It considers the number of shortest paths passing through a node, highlighting the node's importance in the flow of information.

Definition 3: In terms of mathematics, a node u's betweenness centrality is Eq. 3 (Saxena & Iyengar, 2020):

$$C_B(u) = \frac{\sum_{s \neq u \neq t} \frac{\partial_{st}(u)}{\partial_{st}}}{(n-1)(n-2)/2} \tag{3}$$

Table 51.4 A few applications of centrality measures

Complex Network	Nodes	Edges	Application
Social Network	Individuals	Friendship between individuals	*Degree centrality:* To find influential individuals with many direct connections, critical for understanding how influence operates and fostering network cohesion. *Closeness centrality:* Identify individuals who are crucial for marketing campaigns, public health messaging, or political movements. *Betweenness centrality:* Nodes with high betweenness centrality can help manage rumor spread. Their strong connectivity in the social network is key. *Eigenvector centrality:* It identifies influential individuals in social networks, crucial for spreading information and shaping opinions based on their centrality score. *Katz centrality:* It identifies key individuals in social networks based on their connectivity and influence, essential for understanding information diffusion and opinion formation. *PageRank centrality:* The significance of individuals in social networks based on their links and influence, essential for analyzing how information spreads and opinions evolve.
Transportation Network	Locations (cities, warehouses, or distribution centres)	Routes or transportation links (roads, railways, shipping lanes)	*Degree centrality:* It identifies key locations in transportation networks with numerous direct connections (edges), highlighting their significance in network connectivity and potential for optimizing traffic flow. *Closeness centrality:* Identify locations close to many other locations which can minimize delivery times across a supply chain network. *Betweenness centrality:* It pinpoints crucial locations in transportation networks based on their pivotal role in connecting others, essential for enhancing network resilience and optimizing routes to reduce congestion. *Eigenvector centrality:* It identifies pivotal locations in transportation networks based on their connections and significance, essential for improving network efficiency and enhancing overall transportation effectiveness. *Katz centrality:* It identifies pivotal locations in transportation networks by assessing their connectivity and influence, essential for enhancing network performance and overall transportation efficiency. *PageRank centrality:* It identifies important locations in transportation networks by considering their connectivity and influence, essential for improving network performance and overall transportation efficiency.
Epidemiology	Individuals or geographic locations	Physical contact/ travel route	*Degree centrality:* Identifies individuals or locations with many direct contacts or routes, crucial for understanding disease transmission dynamics and prioritizing interventions to control spread. *Closeness centrality:* Identify individuals/locations close to many others that can spread of infectious diseases. *Betweenness centrality:* Identifies individuals or locations crucial for controlling disease spread by serving as vital connectors between other nodes. *Eigenvector centrality:* Identifies influential individuals or locations that can greatly affect disease transmission dynamics due to their extensive connections. *Katz centrality:* Identifies key individuals or locations based on their connectivity and influence, which is essential for understanding disease spread patterns. *PageRank centrality:* It identifies significant individuals or locations in epidemiology networks based on their connections and influence, crucial for targeting disease prevention efforts.
Biological Networks	Proteins, genes, or metabolites	Biological interactions	*Degree centrality:* Identifies proteins, genes, or metabolites with numerous direct biological interactions. These are crucial for understanding their roles in biological processes. They are also potential targets for therapeutic treatments. *Closeness centrality:* Identify proteins or genes that are central to biological processes, which could be potential targets for drug development. *Betweenness centrality:* Identifies proteins, genes, or metabolites crucial for mediating interactions between others, suggesting their importance in biological pathways or disease mechanisms. *Eigenvector centrality:* Identifies proteins, genes, or metabolites in biological networks as influential hubs that exert significant influence on biological processes due to their extensive connections and importance. *Katz centrality:* Identifies critical proteins, genes, or metabolites based on their connectivity and influence, essential for comprehending biological function and identifying potential targets for therapeutic interventions. *PageRank centrality:* Identifies significant proteins, genes, or metabolites in biological networks based on their connections and influence, crucial for prioritizing research efforts and pinpointing critical components within biological systems.

where, $C_B(u)$ denotes its betweenness centrality of a node u, ∂_{st} is the number of shortest paths between s and t, $\partial_{st}(u)$ is the number of shortest paths between s and t passing through node u.

Eigenvector Centrality: A simple extension of degree centrality. The network node's influence is quantified using eigenvector centrality. It gives a relative index value to every node in the network. This is based on the principle that connections to high-indexed nodes contribute more to a node's score than connections to low-indexed nodes (Stephenson & Zelen, 1989).

Definition 4: Eq. 4 (Bonacich, 2007) depicts eigenvector centrality u.

$$C_E(u) = (1/\lambda)\sum A_{uv} C_E(v) \tag{4}$$

where v is the neighbour of u, λ is the largest eigenvalue of adjacency matrix A and A_{uv} is the element of the adjacency matrix A.

Katz Centrality: Katz centrality has been introduced by Katz in 1953 to measure the influence of a node (Katz, 1953). A node's centrality is calculated using Katz centrality, which takes into account the centrality of its neighbors. It is an extension of the centrality of eigenvectors.

Definition 5: Katz centrality evaluates a node's influence by considering both its direct neighbors and nodes it reaches indirectly, giving greater weight to closer connections. A damping factor is applied to reduce the influence of distant nodes. Katz centrality for a node u is calculated as Eq. 5 (Liben-Nowell & Kleinberg, 2003)

$$C_k(u) = \sum_{l=1}^{\infty} \alpha^l \cdot \left|\text{path}^l(u,v)\right| + \beta \tag{5}$$

where $C_k(u)$ denotes its katz centrality of a node u, $\text{path}^l(u,v)$ is the set of all paths of length l from u to v, α is damping factor between 0 and 1 and β is the bias. Start by initializing all nodes with a centrality score of 0. Stop the process if the algorithm fails to converge to the desired tolerance within the given number of power iteration steps.

PageRank Centrality: PageRank centrality evaluates the significance of nodes within a network by considering their inbound links; nodes with abundant and valuable connections are assigned greater importance. Originally designed for web page ranking (Brin & Page, 1998), it's now extensively applied across various networks such as social and citation networks to pinpoint influential nodes.

Definition 6: With probability α, move to one of it's out neighbors uniformly at random, With probability $1-\alpha$, choose any node in the network and go to it. Note that, there are $n-1$ other network nodes, therefore probability of going to any random network node is given in Eq. 6

$$C_P(u) = \alpha \cdot \sum_{(u,v)\in E} C_P(u) + (1-\alpha)\cdot \frac{1}{n-1} \tag{6}$$

where $C_P(u)$ denotes its PageRank centrality of a node u, α is a damping factor, the value of $\alpha = 0.85$ is proved to give good convergence.

4.2 Experimental Setup and Result Analysis

We simulated centrality metrics on five real-world networks, as shown in Table 51.3. Metrics were applied to the FB-Pages network, and the 10 most influential nodes are listed in Table 51.5, along with their influence values. For Katz Centrality, we restrict the length of the paths to be 5. Similarly for PageRank centrality, the value of as 0.85.

No single node can be considered the most central across all centrality measures. For example, node 8396, as presented in Table 51.5, is ranked highest according to Degree Centrality (DC) and Closeness Centrality (CC), indicating that it possesses numerous direct connections and is in close proximity to many other nodes within the network. However, its third-place ranking in Betweenness Centrality (BC) suggests that there are two other nodes that occur more frequently on the shortest paths between other nodes. Additionally, the fact that node 8396 does not appear in the top 10 for Eigenvector Centrality (EC) implies that it is not central in terms of the quality of information flow. This outcome is expected, given that each centrality measure is designed to capture different aspects of network centrality.

Results for the ca-netscience, email-univ, LastFM, and Arxiv GR-QC networks are presented in Tables 51.6, 51.7, 51.8 and 51.9, respectively. One can observe similar results in all these datasets.

The next section discusses second research problem studied in this work.

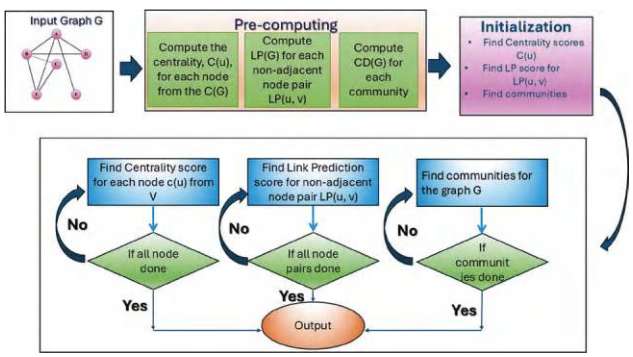

Fig. 51.3 Overview of the graphical abstract

Table 51.5 Top10 influential nodes in the fb-pages network

Rank	DC		CC		BC		EC		KC		PC	
	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value
1	8396	0.0152	8396	0.2913	9886	0.0569	4596	0.2318	1914	0.1741	856	0.00178
2	11934	0.015	11380	0.2866	8223	0.0511	10503	0.2144	10613	0.1641	11934	0.00165
3	856	0.014	1237	0.2833	8396	0.0495	4535	0.1998	432	0.1627	8396	0.00162
4	11380	0.0137	786	0.2826	856	0.0448	12970	0.1827	13919	0.1627	9886	0.00155
5	9886	0.0131	8223	0.2807	11380	0.0421	1229	0.1827	1865	0.1627	11380	0.00142
6	8223	0.0126	9886	0.2805	11934	0.0419	4741	0.1737	4886	0.1627	8223	0.00138
7	1237	0.0121	486	0.2804	1237	0.0332	5471	0.1645	12056	0.1627	1237	0.00123
8	8924	0.0113	636	0.2803	3221	0.0303	11390	0.1634	8814	0.1627	3221	0.00117
9	1854	0.0104	6658	0.2798	13635	0.0211	1030	0.1596	4367	0.1627	1854	0.00106
10	11095	0.0102	856	0.2794	2897	0.0207	6609	0.1588	4872	0.1543	8924	0.00105

Table 51.6 Top10 influential nodes in the ca-netscience network

Rank	DC		CC		BC		EC		KC		PC	
	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value
1	4	0.0899	26	0.2566	26	0.3971	4	0.4142	4	0.4035	26	0.0161
2	5	0.0714	95	0.249	51	0.3451	5	0.3562	16	0.3418	4	0.0145
3	26	0.0714	51	0.247	169	0.286	16	0.3464	5	0.34	5	0.0107
4	16	0.0555	231	0.243	95	0.2701	15	0.2557	15	0.2493	95	0.0092
5	67	0.0502	100	0.2329	67	0.2554	45	0.2369	45	0.2346	67	0.0088
6	70	0.0476	52	0.2306	5	0.2506	46	0.2182	47	0.2159	16	0.0083
7	95	0.0449	5	0.2296	231	0.2316	47	0.2182	176	0.2159	32	0.0076
8	15	0.0423	44	0.2223	100	0.2215	176	0.2182	177	0.2159	51	0.0076
9	113	0.0396	234	0.2202	44	0.1748	177	0.2182	46	0.2159	8	0.0075
10	51	0.0396	297	0.2198	66	0.1746	250	0.147	250	0.1413	70	0.0073

Table 51.7 Top10 influential nodes in the email-univ network

Rank	DC		CC		BC		EC		KC		PC	
	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value
1	105	0.0627	333	0.3828	333	0.0394	105	0.2291	21	0.0851	105	0.005
2	333	0.0459	23	0.3816	105	0.0369	16	0.1652	590	0.0747	23	0.0039
3	16	0.045	105	0.3782	23	0.0334	196	0.1542	376	0.0742	333	0.0038
4	23	0.045	42	0.3775	578	0.0315	204	0.1348	321	0.0674	41	0.0038
5	42	0.045	41	0.3749	76	0.0301	42	0.1315	347	0.0669	42	0.0036
6	41	0.0432	76	0.3743	233	0.0277	49	0.1279	356	0.0661	16	0.0035
7	196	0.0415	233	0.3733	135	0.0272	56	0.1263	744	0.0647	233	0.0035
8	233	0.0397	52	0.3732	41	0.0264	116	0.125	55	0.0641	355	0.0035
9	21	0.0379	135	0.3699	355	0.0263	333	0.1236	153	0.0638	21	0.0034
10	76	0.0379	378	0.3686	42	0.026	3	0.1206	945	0.0617	24	0.0034

Table 51.8 Top10 influential nodes in the lastfm network

Rank	DC		CC		BC		EC		KC		PC	
	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value
1	7237	0.028	7199	0.29	7199	0.089	7237	0.256	5454	0.121	4811	0.00342
2	3530	0.022	7237	0.285	7237	0.085	3240	0.196	4900	0.108	4785	0.00326
3	4785	0.022	4356	0.281	2854	0.077	3597	0.19	4785	0.104	3530	0.00271
4	524	0.022	2854	0.28	4356	0.067	763	0.181	1689	0.1	7237	0.00258
5	3450	0.02	5454	0.279	6101	0.051	378	0.164	3341	0.097	3450	0.00243
6	2510	0.018	5127	0.274	5454	0.043	2083	0.162	7339	0.081	2854	0.00235
7	3597	0.016	3544	0.273	4338	0.042	1334	0.162	4356	0.08	2510	0.00231
8	2854	0.015	6101	0.273	5127	0.038	3544	0.151	1674	0.079	524	0.00196
9	6101	0.015	3450	0.272	3450	0.036	4809	0.151	7237	0.079	5127	0.00188
10	5127	0.015	4900	0.269	4785	0.034	2734	0.146	3181	0.073	6101	0.00177

Table 51.9 Top10 influential nodes in the arxiv-gr-qc collaboration network

Rank	DC		CC		BC		EC		KC		PC	
	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value	Node	Value
1	21012	0.0154	13801	0.194	13801	0.037	21012	0.155	13801	0.329	14265	0.00144
2	21281	0.015	14485	0.189	9572	0.025	2741	0.153	5901	0.196	13801	0.00134
3	22691	0.0146	9572	0.189	14599	0.025	12365	0.153	25006	0.168	13929	0.0013
4	12365	0.0146	17655	0.188	7689	0.024	21508	0.151	13142	0.167	9572	0.00117
5	6610	0.0129	2654	0.187	13929	0.024	9785	0.15	5953	0.161	2710	0.00115
6	9785	0.0129	21012	0.186	5052	0.024	15003	0.15	1588	0.153	21281	0.00115
7	21508	0.0127	12545	0.185	14485	0.023	25346	0.149	13096	0.139	7689	0.00109
8	17655	0.0125	25006	0.185	2710	0.022	7956	0.149	23939	0.135	22691	0.00108
9	2741	0.0124	12365	0.185	14265	0.019	14807	0.149	23134	0.132	6264	0.00107
10	19423	0.012	22691	0.184	17655	0.017	12781	0.148	5695	0.12	21012	0.00106

5. Research Problem 2: Link Prediction

Another key area in the study of complex network analysis is link prediction. Link prediction is a crucial technique for examining intricate networks since it indicates whether a link between two nodes is active or not (Berahmand, Nasiri, Forouzandeh, & Li, 2022). Consider a social network with several individuals depicted in Fig. 51.4, where solid lines indicate existing friendships at time t. For example, "Smith" is connected to "Nayanthara" and "Miller," while "Rashmika" has connections with "Sreeleela" and "Samantha". At time t, there are no connections between "John" and "Smith," "Miller" and "Scott," or "Miller" and "Rashmika". However, predicting the likelihood of these connections forming by time t1 is of interest. The purpose of link prediction is to assess the probability of these new relationships emerging, as shown by the dashed lines representing potential future links in the network at time t1. Figure 51.4 illustrates a link prediction scenario over time. The left side depicts the network at time t, showing the existing relationships between nodes. The right side represents the network at time t'(t' > t), where question marks indicate potential links to be predicted. This figure highlights the dynamic nature of the network and emphasizes the goal of identifying missing or future connections based on the initial structure and some notable applications of link prediction are given in Table 51.10.

Table 51.10 Applications of link prediction

Complex Network	Nodes	Edges	Application
Social Network	Individuals	Friendship between individuals	To recommend friends in friendship networks like Facebook and LinkedIn.
Communication Networks	Servers, routers, or computers.	Network connections	To detect malicious links in computer networks in order to improve security.
Transportation Network	Locations (cities, warehouses, or distribution centres)	Routes or transportation links (roads, railways, shipping lanes)	To develop more routes in the transportation sector based on people's travel requirements.
Epidemiology	Individuals or geographic locations	Physical contact/ travel route	By predicting new travel routes, authorities can impose timely travel restrictions and issue advisories to prevent disease spread.
Disease–gene Networks	Diseases and genes	Interaction between a drug and protein	Disease–gene association prediction identifies diseases that affect genes, especially concerning if hereditary. The goal is to predict which new diseases might impact specific genes.
Biological Networks	Proteins, genes, or metabolites	Biological interactions	To reduce experimentation cost significantly in biological networks, where many interactions are unknown, by predicting most possible links.
Recommendation Networks	Users and Products	Rating given by user to product	To predict personalized product recommendations

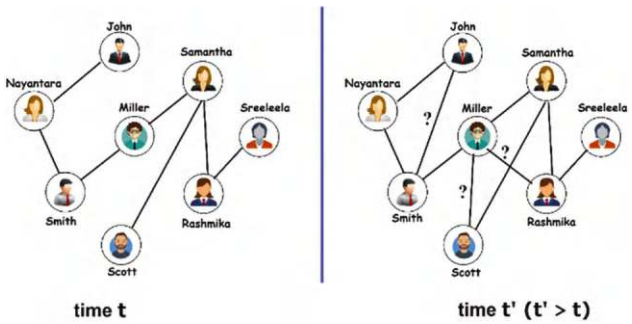

Fig. 51.4 Link prediction

5.1 Problem Statement

In a complex network G(V, E, w, t) characterized by vertex set V, edge set E, time function t, and weight function w defined on edges, the link prediction challenge involves generating a list of edges absent in G within the time interval [t0, t1], yet forecasted to emerge in the network G at a later time tj , where tj > ti > t0.

5.2 Measures for Link Prediction

In link prediction, similarity-based metrics are commonly used to determine the likelihood of a link between two nodes. For each pair of nodes, u and v, a similarity score, S(u, v), is calculated based on their structural or node's properties. These similarity scores are then used to assign scores to non-observed links (U − ET) based on their similarities. The pair of nodes with a higher score is considered to have a higher probability of being linked. Various properties of the network can be used to calculate the similarity measures between each pair, with structural properties being one of them. The scores based on this property can be classified into different categories, such as local and global, node-dependent and path-dependent, parameter-dependent and parameter-free, and more (Martínez, Berzal, & Cubero, 2016). We categorize some of the most well-known graph topological properties in this study into two groups: (1) Node neighborhood based and (2) Path based. Most of these elements have been modified from (Liben-Nowell & Kleinberg, 2003) (Al Hasan, Chaoji, Salem, & Zaki, 2006). The features that are derived from the graph's edge or vertex properties are then covered.

Common Neighbors (CN): The size of the shared neighbors of two nodes, u and v, is given by $|\Gamma(u) \cap \Gamma(v)|$. An attestation to the network transitivity property is all that the concept of employing the size of common neighbors represents Eq. 7 (Liben-Nowell & Kleinberg, 2003).

$$CN(u,v) = \left|\Gamma(u) \cap \Gamma(v)\right| \tag{7}$$

where $\Gamma(u)$ and $\Gamma(v)$ are, respectively, the neighbors of the nodes u and v.

Put simply, it indicates that there is a higher likelihood that if vertices u connected to vertex x and v connected to vertex x respectively, then vertices u and v will also be connected in social networks. Therefore, the more common neighbors there are between u and v, the more likely it is that they will be connected. In the context of collaboration networks, Newman (Newman, 2001a) has calculated this number to demonstrate that there is a positive correlation between the likelihood that u and v would collaborate in the future and the number of common neighbors they have at time t.

Jaccard Coefficient (JC): Since the common neighbors metric lacks normalization, one can utilize the Jaccard Coefficient to normalize the common neighbors' sizes as shown below Eq. 8 (Liben-Nowell & Kleinberg, 2003).

$$JC(u,v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|} \tag{8}$$

where $\Gamma(u)$ and $\Gamma(v)$ are, respectively, the neighbors of the nodes u and v.

Adamic/Adar (AA): After minor modification by LibenNowell, Adamic and Adar (Adamic & Adar, 2003) introduced a metric to determine a similarity score between two web pages based on shared attributes. This score is then employed in link prediction Eq. 9 (Liben-Nowell & Kleinberg, 2003).

$$AA(u,v) = \sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{\log|\Gamma(w)|} \tag{9}$$

where $\Gamma(u)$ and $\Gamma(v)$ are, respectively, the neighbors of the nodes u and v and $\Gamma(w)$ represents the set of neighbors of node w.

Preferential Attachment (PA): Preferential attachment theory is used to create an expanding scale-free network. The word "expanding" describes how nodes in a network progressively appear over time. The degree of the node, ku, determines the probability of adding a new link associated with node u. Between two nodes, u and v, the preferential attachment score can be calculated as Eq. 10 (Liben-Nowell & Kleinberg, 2003):

$$PA(u,v) = |\Gamma(u)| \cdot |\Gamma(v)| \tag{10}$$

where $\Gamma(u)$ and $\Gamma(v)$ are, respectively, the neighbors of the nodes u and v.

Resource Allocation (RA): Consider a set of two non-diagrectly connected nodes, u and v. By using their shared neighbors as transmitters, nodes u and v can convey resources to each other. We assume that, in the simplest scenario, each transmitter has a single resource that it will share equally among all of its neighbors. The degree to which v benefited from u can be used to determine how similar u and v are. This is Eq. 11 (Zhou, Lü, & Zhang, 2009);

$$RA(u,v) = \sum_{z \in \Gamma(u) \cap \Gamma(v)} \frac{1}{k_z} \tag{11}$$

where $\Gamma(u)$ and $\Gamma(v)$ are, respectively, the neighbors of the nodes u and v.

5.3 Results and Discussion

The AUC (Area Under the ROC Curve) stands as the prevalent metric utilized to assess the effectiveness of a method in discriminating between prospective links, denoting connections that are anticipated to form in the future, and non-existent edges, symbolizing pairs of nodes that are unlikely to be connected. Virtually all link prediction methodologies undergo evaluation employing this metric. In principle, the AUC metric orders all unobserved links based on their assigned scores, thereafter tallying the instances where a randomly selected missing edge surpasses a randomly chosen non-existent edge.

We evaluate the JC, AA, and PA methods by randomly removing 20% of the edges from a dataset, treating them as missing edges. The remaining 80% of edges serve as the training set. Unconnected node pairs are considered non-existent edges. Together, these form the non-observed edge set. We apply each method to score these non-observed edges and evaluate them using AUC and Precision. This process is repeated ten times for each dataset, with the average results reported.

Table 51.11 summarizes the AUC (Area Under the Curve) results for different link prediction algorithms. These algorithms include JC, AA, PA, and RA. The networks studied are FB Large Page-Page, CA-AstroPh, Enron Email, Last FM, and Arxiv GR-QC.

Table 51.11 AUC results of different link prediction algorithms

Network	CN	JC	AA	PA	RA
FB-Pages	0.88885	0.76687	0.76725	0.78425	0.77774
ca-netscience	0.89368	0.89018	0.89418	0.62197	0.89435
email-univ	0.85895	0.82335	0.82625	0.77141	0.82579
Last FM	0.86691	0.81467	0.81578	0.76512	0.81575
Arxiv GR-QC	0.82442	0.79239	0.79251	0.73693	0.79250

In the FB-Pages network, CN achieved the highest AUC score of 0.88885, demonstrating its strong performance in identifying relevant links. This can be attributed to the nature of Facebook pages, where pages with similar content are mutually liked by users, creating a dense cluster of common neighbors. This dense clustering significantly boosts the predictive accuracy of the CN algorithm, as it effectively leverages the shared connections to predict new links.

For the CA-Netscience network, RA achieved the highest AUC score of 0.89435. AA and CN closely follow RA, showing their effectiveness in this context. RA performs best because it focuses on common neighbors, which is important in academic networks where researchers often collaborate with shared colleagues. This method suits the structure of academic networks, where close-knit research groups are common. On the other hand, PA scored

significantly lower at 0.62197, indicating it is less effective here. PA assumes that highdegree nodes (popular nodes) attract more links. However, in academic networks, new collaborations are more about specific research interests and common collaborators rather than the popularity of researchers. This misalignment causes PA to perform poorly in the CA-Netscience network.

In the Email-Univ network, CN led with the highest AUC score of 0.85895. CN performs best because email networks often have strong clustering, where frequent communicators share many common contacts. This clustering helps CN accurately predict links by focusing on common neighbors, making it well-suited for the closely-knit groups in the Email-Univ network. In the Last FM network, CN performs best because users with similar music interests often have many common connections, making it easier to predict links through shared neighbors. Whereas the last network is, Arxiv GR-QC network, where CN excels as researchers frequently collaborate within tight-knit groups, and shared collaborators help CN accurately predict future links.

6. Research Problem 3: Community Detection

One of the earliest and still most actively evolving subfields of complex network research is community detection. While Kernighan and Lin (1970) (Kernighan & Lin, 1970) developed the initial techniques for detecting network communities. The goal is to identify self-contained groups, or clusters, within a network. These communities should exhibit strong internal connections, meaning the nodes within each group are more likely to be connected to each other than they are to nodes in other communities (Girvan & Newman, 2002). This highlights the internal structure and organization of the network.

Effective community detection is valuable in real-world applications as well as for comprehending the architecture and operations of intricate networks. Finding research teams in co-authorship networks, protein complexes in protein-protein interaction (PPI) networks, and user groups with similar passions in online social networks are a few examples of how it might be applied (He et al., 2021). Community structure, which is the segmentation of network nodes into groups wherein the network connections are dense within but sparser between them, is a feature that appears to be shared by many networks (Newman & Girvan, 2004). Figure 51.5 illustrates a network's community discovery and Table 51.12 gives a few applications of community detection.

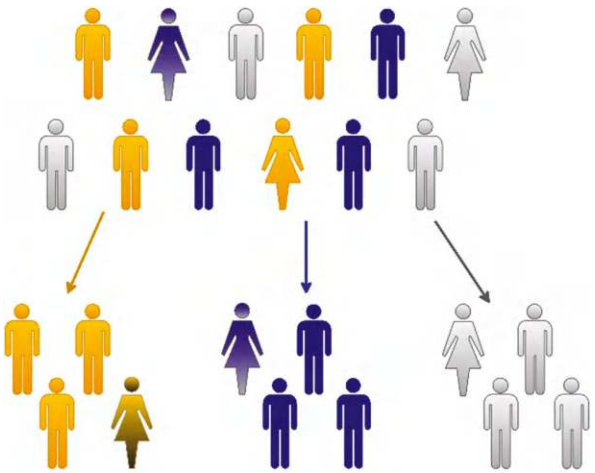

Fig. 51.5 Community discovery

6.1 Problem Statement

A complex network is modeled as a graph G(V, E) with a set of nodes V and a set of links E at time t. The goal of community discovery is to identify k communities: N1, N2, . . . , Nk, where each Ni is a subset of V such that the links within Ni are denser compared to the links between Ni and Nj , where $1 \leq i, j \leq k$ and $i \neq j$.

6.2 Community Detection Techniques

There are primarily two kinds of methods for identifying communities within a network: agglomerative and divisive (Newman & Girvan, 2004). The distinction between these techniques lies in their emphasis on either adding or removing edges from the network. Figure 51.6 illustrates that community detection algorithms can be broadly divided into three categories: graph partitioning, modularity maximization, and latent space models.

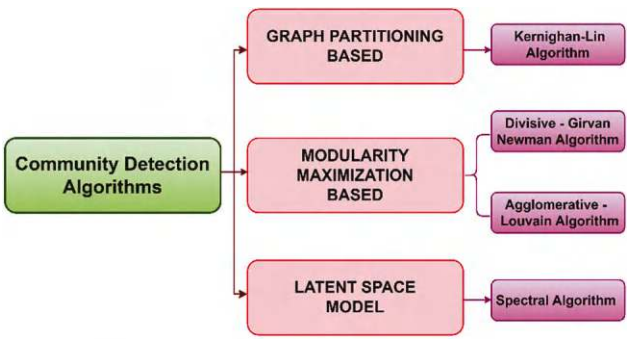

Fig. 51.6 Classification of community detection algorithms

Agglomerative methods: Start with a network containing only nodes from the original graph. Gradually add edges, prioritizing stronger ones. The method for calculating edge strength varies based on the algorithm used.

Table 51.12 Applications of community detection

Complex Network	Nodes	Edges	Application
Social Network	Individuals	Friendship between individuals	Community detection in social networks can enhance targeted advertising, social interactions, influencer marketing, user engagement, product recommendations, community management and fraud detection
Communication Networks	Servers, routers, or computers.	Network connections	To detect network congestion and streamline data flow in communication networks to boost efficiency and reliability.
Transportation Network	Locations (cities, warehouses, or distribution centres)	Routes or transportation links (roads, railways, shipping lanes)	Community detection in transportation networks can optimize logistics, improve infrastructure planning, enhance traffic management, plan public transportation and enhance connectivity.
Epidemiology	Individuals or geographic locations	Physical contact/ travel route	Identify communities to predict and control the spread of diseases.
Organizational Management	Employees or departments	Communication or workflow links	Community detection in organizational management networks can improve team collaboration, streamline workflows, enhance communication, identify key departments, optimize resource allocation, and identify skill gaps.
Urban Planning	Critical infrastructure (Hospitals, fire stations, or public service offices)	Roads or transit routes	Community detection in urban planning networks can optimize emergency response, improve infrastructure planning, enhance public service delivery, facilitate traffic management, and boost network resilience.
Biological Networks	Proteins, genes, or metabolites	Biological interactions	Community detection in biological networks can reveal functional modules, identify disease markers, enhance drug discovery, understand metabolic path-ways, study gene regulation and uncover protein interactions.

Divisive methods: Rely on progressively removing edges from the original graph, prioritizing the elimination of stronger edges before weaker ones. During each iteration, the computation of edge weight is revisited as the weights of the remaining edges change after each removal. Over multiple iterations, clusters of closely interconnected nodes, referred to as communities, emerge.

6.3 Community Detection Algorithms

Girvan Newman (GN) Algorithm

Step 1: Determine the edge betweenness centrality for each edge in the graph.

Computation of Edge betweenness using Breadth First Search (BFS):

1) For each node X in G:
   a) Find the number of shortest paths between node X and each other using BFS, then give each node a score based on the results.
   b) Compute the edge credit using the equation, beginning with the leaf nodes:

$$\text{Credit of Edge} = 1 + \left(\sum_{\text{Incoming Edge}} \text{Edge score} \right) \cdot \frac{\text{Score of destination node}}{\text{Score of source node}} \quad (12)$$

   c) For every edge in the graph G, calculate the edge credits.
2) Sum up all of the edge credits computed from every node.
3) Repeat the step until each community has a single node. This is a divisive algorithm

Step 2: The edge with the highest betweenness centrality should be removed.

Step 3: Determine the betweenness centrality of each edge that is still present.

Step 4: Until there are no more edges remaining, repeat steps 2-3.

Kernighan-Lin Algorithm

- Developed by Brian Kernighan and S Lin (Kernighan & Lin, 1970) in 1970 and has since been widely used in various applications.
- The Kernighan-Lin (KL) algorithm is a well-known graph partitioning algorithm.
- Divides a graph into two balanced subgraphs.
- The algorithm starts with an initial partition of the graph into two subsets. It then iteratively improves this partition by swapping nodes between the subsets to reduce the total weight of the edges between them.

The basic steps of the Kernighan-Lin algorithm are as follows:

1) **Initial Partition:** The algorithm begins with an initial partition of the graph into two subsets, often done randomly or using some heuristics.
2) **Calculate Initial Gain:** For each node in one subset, calculate the gain in the objective function if the node is swapped with a node from the other subset. The objective function is typically defined as the sum of the weights of the edges between the two subsets.
3) **Node Pair Selection:** Select a pair of nodes (one from each subset) with the maximum gain. These nodes will be considered for swapping.
4) **Swap Nodes:** Swap the selected nodes between the two subsets.
5) **Update Gains:** Recalculate the gains for the affected nodes. Only the gains for nodes that have been affected by the swap need to be updated.
6) **Repeat:** Repeat steps 3-5 until no further improvement can be made or a stopping criterion is met.
7) **Final Partition:** The final partition is obtained when the algorithm terminates. The resulting partition should have a minimized objective function, indicating a relatively balanced division of the graph.

Louvain Algorithm

1) Initial Setup:
   a) Assign each node to its own community.
   b) Calculate the modularity of the network, which measures the quality of the current community assignment.
   c) Repeat until further modularity increase is not possible (Modularity Maximization)
      i) For each node in the network, consider moving them to a neighbouring community.
      ii) Calculate the change in modularity that would result from this move.
      iii) If the move increases modularity, make the move. Otherwise, keep the individual in their current community.
2) Construct graph with super nodes as follows: (Community Aggregation)
   a) Combine smaller communities into a single node in a new network, where the edges represent the total connections between communities in the previous step.
   b) This step reduces the complexity of the network.
3) Repeat steps step 1(c) and 2 on the new network until modularity no longer increases significantly.

Spectral Algorithm

- From the network partitioning problem, the spectral clustering algorithm is developed.
- Graph partitioning seeks to find a partition where the cut is minimized. The cut is the total number of edges between two disjoint sets of nodes.

6.4 Results and Discussion

Modularity: Modularity (Waltman & Van Eck, 2013) is a popular metric for evaluating the quality of community detection algorithms. Modularity measures how effectively a network can be divided into distinct communities. This is based on the density of connections within and between the communities. The modularity for a division of the graph into k communities V1.....,Vk is given by Eq. 13

$$\text{Modularity} = \frac{1}{2m}\sum_{i,j}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta\left(c_i, c_j\right) \qquad (13)$$

where A_{ij} is ijth entry in adjacency matrix, m is the number of edges in the graph, ki is the degree of node i and δ (ci,cj) = 1 if i and j belong to same community, 0 otherwise.

High the modularity, more effective the community division is

$$\text{Range: } \left[-\frac{1}{2}, 1\right)$$

When there is single community, modularity is 0.

Advantage: Independent of the number of communities that the graph is divided into.

Ratio and Normalized Cut

Ratio and Normalized Cut (Wei & Cheng, 1991) (Hagen & Kahng, 1992) are other metrics used to determine quality of community division. We use modularity in our experimentation. Table 51.13 presents the modularity scores for different community detection algorithms. The algorithms evaluated include Newman-Girvan, Kernighan-Lin, and Louvain. The networks analysed are FB-Pages, ca-netscience, email-univ, Last FM, and Arxiv GR-QC.

Table 51.13 Modularity scores for different algorithms

Network\ Algorithm	Newman-Girvan	Kernighan–Lin	Louvain
FB-Pages	0.01540	0.01339	0.73100
ca-netscience	0.01330	0.44040	0.62980
email-univ	0.00219	0.00425	0.61730
LastFM	0.71990	0.55660	0.81550
Arxiv-GR-QC	0.26820	0.53130	0.86160

For the FB-Pages network, the Louvain algorithm achieves the highest modularity score, and is 71% better than the Newman-Girvan and Kernighan-Lin in detecting communities in FB-Pages. Social media networks often have a hierarchical structure where smaller communities are nested within larger ones. This suggests that Louvain is particularly effective in detecting communities in social media networks. In the ca-netscience network, the Louvain algorithm achieves the highest modularity score and is 61% better than Newman-Girvan and 19% better than Kernighan-Lin. Newman-Girvan lags behind with a score, indicating its limited effectiveness in scientific collaboration networks. The email-univ network shows relatively low modularity scores across all algorithms, with Louvain leading at 0.6173. Newman-Girvan and Kernighan Lin score 0.00219 and 0.00425, respectively. For the Last FM network, the Louvain algorithm achieves about 10% better than Newman-Girvan and approximately 26% better than Kernighan-Lin. Louvain quickly identifies tightly connected groups of users and music preferences, which are common in social music networks. Lastly, in the Arxiv GR-QC network, Louvain is superior when comparing with remining algorithms.

7. Conclusion

In this study, we explored three pivotal aspects of complex network analysis: link prediction, centrality measures, and community detection. Each of these areas plays a crucial role in understanding and interpreting the structure and dynamics of complex networks. Link Prediction review highlighted various algorithms and techniques for predicting missing or future links in a network. Centrality metrics provide insights into the importance and influence of nodes within a network. We discussed traditional measures such as degree, betweenness, closeness, Katz, PageRank, and eigenvector centrality, as well as more recent developments tailored for large-scale networks. These measures are essential for identifying key players in various domains, including social networks, information diffusion, and infrastructure robustness. However, current link prediction and centrality measures do not typically consider attribute information. In the future, we aim to extend these methods to incorporate node and edge attributes. Community Detection is used to identify the densely connected groups of nodes, or communities, is fundamental to understanding the modular structure of networks. Community detection not only aids in uncovering the latent structure of networks but also in applications like recommendation systems, disease outbreak tracking, and organizational analysis. Combining link prediction, centrality measures, and community detection into unified frameworks can provide more holistic insights into network structures. In future we want to integrate communityaware centrality measures with link prediction can enhance the accuracy of predicting missing links within communities. We want to extend complex network measures to Graph neural networks (GNNs) and other advanced machine learning models can potentially outperform traditional methods, especially in handling complex patterns.

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Licence Plate Recognition with Owner Identity Using CNN

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Abstract: License Plate Recognition (LPR) is an essential part of Intelligent Transport Systems (ITS) for identifying vehicles by extracting and analyzing license plate information. This project proposes a deep learning-based system using Convolutional Neural Networks (CNN) to automatically recognize license plates and retrieve vehicle owner details from a database. The system integrates an admin module for enforcement agencies to track and fine violators based on traffic violations and a user module for vehicle owners to check challan (fine) status. Leveraging CNN's strong feature extraction capabilities, the model achieves high accuracy in recognizing plates under varying lighting and environmental conditions. This automated system can significantly reduce human effort, improve traffic management, and enhance law enforcement efficiency by ensuring faster detection of vehicle violations. The system is trained using real-world datasets, ensuring robustness in diverse conditions such as noise, image blurring, or low resolution.

Keywords: Artificial neural networks, Convolutional neural networks, Intelligent transport systems, License plate recognition, Recurrent neural networks, Support vector machines etc

1. Introduction

Traffic management and enforcement of traffic laws have become increasingly challenging with the rising number of vehicles on the road. Traditional methods of monitoring traffic violations, which involve manual surveillance and recording, are not only time-consuming but also prone to human error. To address this, License Plate Recognition (LPR) systems have gained widespread popularity. LPR systems allow for automated vehicle identification by detecting and reading the vehicle's license plate using image processing techniques. With advancements in machine learning, particularly Convolutional Neural Networks (CNN), the accuracy and efficiency of LPR systems have significantly improved. CNNs excel at image recognition tasks, making them ideal for LPR systems,

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where accurate detection of license plate characters from real-world scenes is crucial. However, simply identifying the vehicle is not enough; associating the license plate with the vehicle owner's identity and recording violations are critical components of a comprehensive traffic management system. To meet this requirement, we propose a CNN based License Plate Recognition system integrated with a database that stores owner information and records traffic violations. The system includes an admin module for traffic enforcement officers to issue fines and a user module for vehicle owners to view fines and maintain compliance with traffic regulations.

2. Literature Survey

Automatic Number Plate Recognition (ANPR) has been a well-researched area within computer vision and image processing for several decades. Researchers have employed various techniques to detect and recognize vehicle number plates, ranging from traditional image processing methods to machine learning algorithms. In recent years, the advent of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved the performance of ANPR systems, enabling real-time and accurate number plate detection. This literature survey provides an overview of key techniques used in ANPR systems, focusing on traditional methods, machine learning approaches, and recent advancements using CNNs. The integration of CNNs in LPR systems has greatly improved recognition accuracy and efficiency. The addition of owner identity verification presents both opportunities and challenges, particularly concerning privacy and data management. Future research should focus on creating more robust, secure, and ethical systems that can perform under diverse conditions.

3. Related methods for Number Plate Detection

3.1 Traditional Approaches

Early approaches to number plate detection primarily relied on rule-based image processing techniques. These methods typically involved a combination of edge detection, thresholding, morphological operations, and region-based segmentation to localize the number plate from the vehicle image.

Edge Detection and Morphological Operations: Many early systems used Sobel or Canny edge detection algorithms to locate the rectangular boundaries of a number plate. Once the edges were detected, morphological operations like dilation and erosion were applied to highlight the plate region. The works of Anagnostopoulos et al. (2008) and Seydi et al. (2009) demonstrated how these methods could be used to isolate number plates with reasonable success in controlled environments, but they struggled with complex backgrounds, variable lighting, and occlusions.

Connected Component Analysis: This method involves segmenting the image into connected regions and identifying areas that match the expected size and shape of a number plate. Zhao et al. (2013) used connected component analysis along with heuristics like plate aspect ratio to detect number plates, but the system was sensitive to noise and often failed in real-world conditions.

3.2 Machine Learning Approaches

The limitations of traditional image processing techniques led to the exploration of machine learning algorithms for number plate detection and character recognition. The application of machine learning brought adaptability, as systems could be trained on large datasets to recognize patterns and features that characterize number plates.

Support Vector Machines (SVM): Huang et al. (2012) proposed a system that used SVMs to classify image regions as either containing a number plate or not. This method, coupled with histogram of oriented gradients (HOG) features, demonstrated good detection accuracy. However, it required careful tuning of parameters and could be slow in real-time applications.

Adaboost and Haar-like Features: Zhang et al. (2010) employed an Adaboost classifier along with Haar-like features for number plate detection. This method was capable of handling various lighting conditions and backgrounds but was limited in recognizing characters on degraded or occluded plates.

Artificial Neural Networks(ANN): Some studies explored the use of Artificial Neural Networks for number plate detection and recognition. Du et al. (2007) applied a simple feed- forward ANN to classify detected regions as plates. However, due to their shallow architectures, these models lacked the ability to extract complex patterns and struggled with diverse datasets.

3.3 Character Recognition with CNNs

In addition to number plate detection, recognizing the characters on the plate is crucial. Traditional methods used Optical Character Recognition (OCR) techniques, but these struggled with noisy images and varying fonts.

CNN for Character Recognition: CNNs have been widely adopted for character recognition due to their ability to

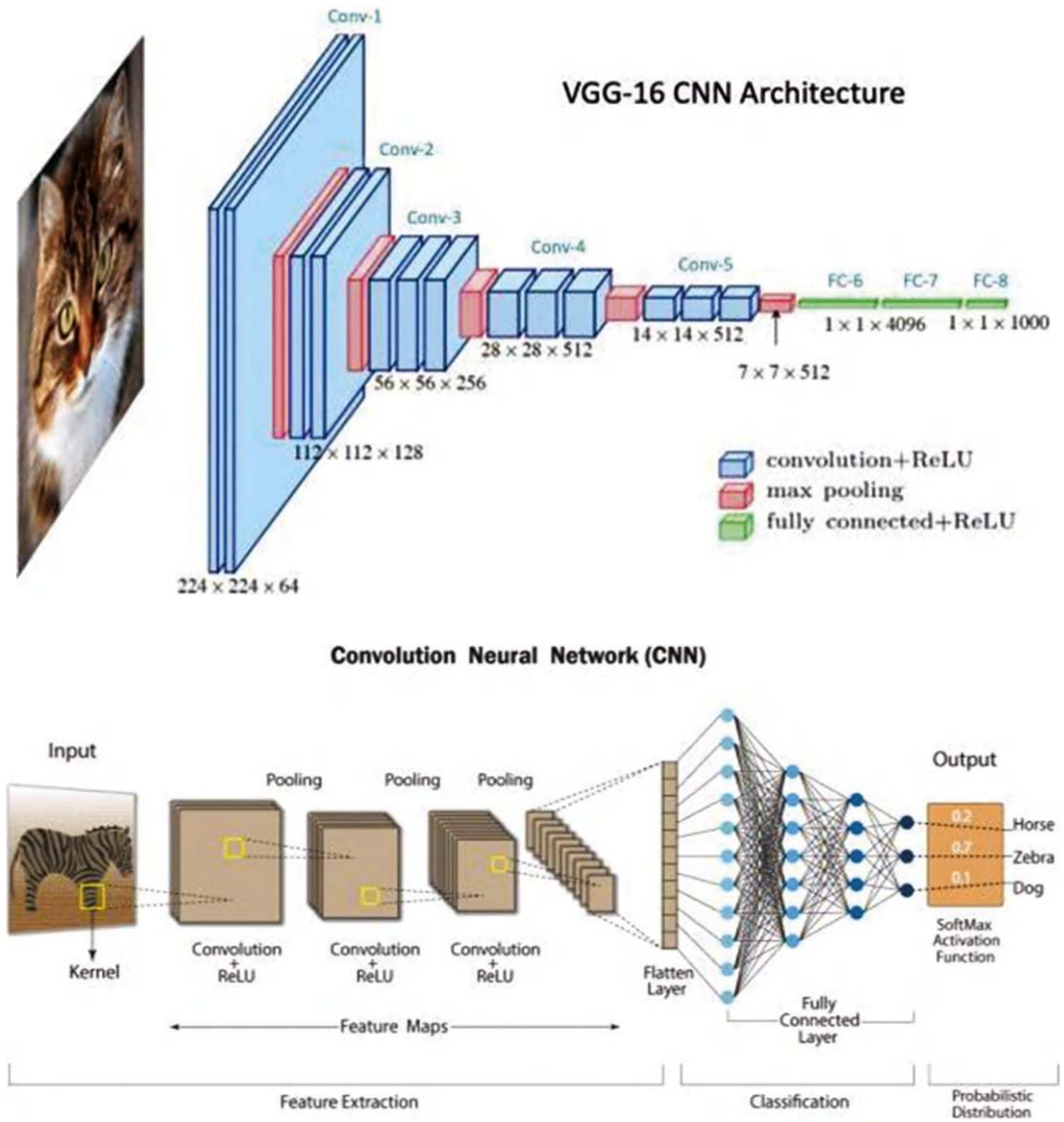

Fig. 52.1 Convolutional neural network architecture. Microplastic classification and quantification in water bodies

Source: Adapted from reference Paper; Authors: Trisha Karmakar, Reetu Jain. ISSN:2319-7463, VOL.12 Issue 9, September-2023.

learn invariant features. Wang et al. (2018) applied a deep CNN model to recognize characters on number plates, achieving high recognition rates even with distorted or lowquality images. The model used several convolutional and pooling layers to extract features, followed by fully connected layers to classify each character.

Recurrent Neural Networks (RNN) with CNNs: Some systems, such as the one proposed by Zhu et al. (2019), combined CNNs with Recurrent Neural Networks (RNNs) for sequential character recognition. The CNN would extract features from the number plate image, and the RNN would process these features sequentially to recognize the plate characters. This hybrid approach allowed for better handling of character dependencies and improved recognition accuracy.

4. METHODOLOGY

4.1 Data Collection

The dataset consists of numbers (0-9) and alphabets (A-Z) commonly found on vehicle license plates. Use public datasets for characters, such as the Open Images Dataset, Synthetic Chinese License Plates Dataset, or ANPR datasets. You can also manually create your dataset by cropping license plates and labeling each character.

4.2 Pre-processing

Convert all images to grayscale or binary (black and white) to simplify the recognition process.

Normalize pixel values to the range [0, 1]. Resize images to a standard size (e.g., 32 x 32 pixels for each character).

4.3 Train-Test Split and Model Fitting

The dataset is split into three subsets: Training, validation, and testing. A common split ratio is 70% for training, 15% for validation, and 15% for testing. The training set is used to train the model, the validation set is used to tune the model hyperparameters and avoid overfitting, and the test set is used to evaluate the final model's performance.

5. Model Evaluation and Predictions

Build a **CNN** model that recognizes individual characters (numbers and alphabets) from the license plate.

5.1 CNN Architecture

Input layer: 32x32 images.

Convolutional Layers: 2-3 layers with ReLU activation followed by max-pooling.

Flatten Layer: To convert the 2D feature maps into a 1D vector.

Fully Connected Layer: A few dense layers to capture non-linear features.

Output Layer: Softmax with 36 outputs (for digits 0-9 and letters A-Z).

The augmentation parameters used in this study are as follows;rescale=1/255, width_shift_range=0.2,height_shift_range=0.2,shear_range=0.2,rotation_range=5, horizontal_flip=True,vertical_flip=True, fill_mode= 'nearest'.

5.2 Accuracy

Mechanisms (e.g., identifying fake or altered license plates) can strengthen its applicability. State-of-the-art LPR systems using CNNs report accuracies often exceeding 90% for character recognition in controlled environments. In real-world conditions, accuracies may drop to 70-85%, depending on environmental challenges. Accuracy for facial recognition integrated with LPR can vary. Studies often report accuracies around 85-95% for matching against a database, depending on the dataset used and the model architecture.

6. Expected Result

Fig. 52.2 ADMIN AND USER modules for payment and viewing of records

Source: Author

7. Future Enhancement

Future improvements to this system could include the incorporation of multi-lingual license plate recognition, which is essential for deployment in regions with varying plate designs and languages. Enhancements such as motion detection to detect moving vehicles for real-time enforcement and integration with IoT devices (e.g., traffic cameras) can further improve automation. Expanding the system to include fraud detection.

8. Conclusion

The proposed CNN-based License Plate Recognition system, integrated with an owner identification module,

provides a highly efficient and automated solution for traffic law enforcement. By combining advanced image recognition techniques with a scalable architecture, this system reduces human effort, improves the accuracy of vehicle identification, and enhances overall traffic management. The system's ability to handle large datasets and real-time detection ensures it can adapt to the needs of modern cities where traffic management is critical. Additionally, the inclusion of a challan system streamlines the process of issuing and paying fines, benefiting both authorities and vehicle owners.

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Robust Deepfake Detection Using ResNeXt and Multi-Classifier Ensembles—A Hybrid Approach to Image Forensics

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Abstract: The rapid advancement in Generative Adversarial Networks (GANs) has led to the creation of highly realistic deepfake images, posing significant challenges in distinguishing between real and manipulated visual content. This study proposes a robust framework for deepfake detection that combines transfer learning on the ResNeXt101_32x8d architecture with feature reduction and ensemble learning techniques. Four distinct approaches were explored, including the use of transfer learning on ResNeXt for binary classification, feature extraction using ResNeXt and classification with Support Vector Classifier (SVC) and other machine learning models, using ensemble of classifiers, and a novel hybrid approach integrating ResNeXt with feature reduction and multi-classifier ensembles. The proposed hybrid approach demonstrated superior performance, achieving an accuracy of 93.4% and high precision, recall, and F1 scores, indicating its effectiveness in distinguishing between real and fake images. The results suggest that combining deep learning feature extraction with traditional machine learning classifiers can significantly enhance the accuracy and generalizability of deepfake detection models. This framework holds potential for application in deepfake video detection by leveraging both spatial and temporal features, thus offering a robust solution to emerging challenges in image forensics.

Keywords: Deepfake detection, Generative AI, Ensemble, Image forensics

1. Introduction

Deepfakes are synthesized media where artificial intelligence, particularly deep learning techniques, are used to create fake images, audio, or videos that appear convincingly real. Initially, deepfakes were created by combining "deep learning" and "fake," primarily involving face-swapping, where a target face is superimposed onto a

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source image. Deepfakes have a wide range of applications, both positive and negative. A notable example is the use of deepfakes in pornography, where celebrity faces were swapped onto actors' bodies without consent, marking a concerning trend in privacy violations. Since deepfakes are created using deep learning models, detecting them requires sophisticated algorithms[1]. Some methods focus on Handcrafted features such as artifacts in fake media that are visually detectable, Deep learning-based detection, where AI is trained to spot inconsistencies within the media itself, like unnatural eye movements or subtle facial distortions, Temporal features in videos, identifying inconsistencies between frames that can indicate tampering.

Deepfakes pose significant challenges to privacy, security, and trust in digital media[2]. The technology could be used for Political manipulation by fabricating speeches or behaviors of world leaders. Financial market disruptions by creating false information leading to stock or market fluctuations. Military deception, such as generating fake satellite images to mislead analysts.

Deepfake image classification typically involves two key phases: feature extraction and classification. Feature extraction focuses on identifying tell-tale artifacts, inconsistencies, or anomalies within images—subtle pixel patterns, irregular lighting, or distortions in textures that are typically hard for GANs to perfectly mimic. These features are then fed into a classifier, such as a convolutional neural network (CNN) or a traditional machine learning model like support vector machine (SVM), which learns to discern real from fake images. Several deep learning-based architectures have been explored for this task, including ResNet, EfficientNet, and DenseNet, each achieving various levels of success depending on the dataset and classification strategy used.Moreover, advancements in transfer learning have allowed researchers to fine-tune pre-trained models on domain-specific datasets to enhance performance in deepfake classification[3]. Techniques such as Principal Component Analysis (PCA) for dimensionality reduction, ensemble learning, and data augmentation are also employed to optimize the classification process.

Despite the advancements in detection, deepfake technology is continually improving, making it increasingly difficult to develop foolproof methods to identify fakes. This has led to a growing "arms race" between deepfake creators and those working on detection techniques.

The remainder of the paper is organized as follows: Section 2 provides an overview of the existing literature. Section 3 describes the dataset used in the study. Section 4 details the research methodology employed. Section 5 presents the empirical results. Finally, Section 6 summarizes the key insights and implications of the study.

2. Literature Review

Xuan et al. [4] address the challenge of generalizing GAN image detection methods to adapt to new types of GANs. They propose a forensic CNN model trained on pre-processed images to enhance the model's robustness by focusing on intrinsic features rather than low-level noise. Their results indicate that this preprocessing strategy improves the generalization capabilities of detection models, which is crucial given the rapid evolution of GAN architectures. The method may not generalize well to radically new GAN architectures. Preprocessing might discard useful information.

Zhang et al. [5] explore the emergence of automated face-swapping applications and propose machine learning-based techniques for detecting swapped faces. Their method is tested on a face-swapping database and achieves a detection accuracy exceeding 92%. This research emphasizes the need for robust detection mechanisms as face-swapping technology becomes increasingly accessible.

Hsu et al. [6] propose a pairwise learning approach for fake image detection, utilizing a two-streamed DenseNet structure with contrastive loss to differentiate between real and fake image pairs. This technique leverages shared features between paired images, enhancing the model's ability to detect subtle discrepancies. Their findings suggest that pairwise learning can outperform other state-of-the-art detectors by focusing on relational characteristics between images. Computationally expensive due to pairwise learning. Struggles with unseen manipulations and scaling for real-time detection.

Marra et al.[7] discuss a strategy for deepfake detection by analyzing unique convolutional traces inherent to GAN-generated images. Their approach suggests that CNNs leave behind identifiable artifacts during image synthesis, which can be used to differentiate real from fake content. This method shifts the detection paradigm toward leveraging intrinsic GAN weaknesses rather than image-level attributes, although it requires high-resolution images for optimal performance. This method requires high-resolution images to capture convolutional traces accurately; may not detect artifacts well in lower-resolution or highly compressed images.

Dang et al.[8] introduce FakeSpotter, a lightweight method focused on identifying pixel-level artifacts like color distortions in GAN-generated images. While this method is computationally efficient, making it suitable for real-time applications, it may struggle with newer deepfake techniques that reduce pixel-level anomalies. Despite its simplicity, FakeSpotter demonstrates the importance of artifact-based detection as an accessible and scalable

solution. Though this approach is computationally efficient, its simplicity may limit effectiveness against sophisticated deepfake generation methods that minimize pixel level artifacts.

Wang et al.[9] investigate the potential for creating a universal detector for images generated by CNNs, regardless of the specific architecture used. By collecting a dataset from 11 diverse CNN-based image generators, they train a model that generalizes well across unseen architectures using data augmentation and preprocessing. Their study reveals that current CNN-generated images exhibit common flaws, allowing for detection despite architectural variations, which offers a promising avenue for a universal detection approach. Though this method works well on images generated by CNN-based models, it may not be fully be effective on non-CNN based generators or advanced GANs that lack these common flaws.

Guarnera et.al [10] propose a deepfake detection method that identifies convolutional traces left in images, acting as forensic fingerprints. Using an Expectation Maximization (EM) algorithm, the method extracts features modeling the generative process of deepfake creation. Tested across five GAN architectures (GDWCT, STARGAN, ATTGAN, STYLEGAN, STYLEGAN2) against the CELEBA dataset, the method demonstrated robust performance in distinguishing deepfake images. Their approach effectively differentiates between architectures, highlighting its potential for accurate deepfake detection. This approach is computationally intensive and sensitive to image quality variations like compression.

Rafique et al. [11] propose a method combining Error-Level Analysis (ELA) with deep learning to improve the accuracy of deepfake detection. Their framework extracts features through ELA and then applies Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for classification. Achieving an accuracy of 89.5%, this study underscores the limitations of traditional machine learning in capturing complex patterns, advocating for deep learning techniques that adapt to evolving data conditions. This method struggles with highly realistic deepfakes, and error-level analysis may be ineffective on compressed images.

The reviewed studies illustrate a diverse array of strategies employed to detect GAN-generated images and deepfakes. From preprocessing and pairwise learning to convolutional trace analysis and artifact detection, these methods aim to adapt to the ever-evolving landscape of generative technologies. A significant challenge identified across the literature is the generalization of detection models to handle new GAN architectures effectively.

3. Dataset Description

The dataset used in this study is collected from Kaggle [13] while the original source of data is OpenForensics dataset [12]. OpenForensics is a pioneering large-scale dataset specifically created to tackle the complexities of face forgery detection and segmentation. It features comprehensive face-wise annotations, making it a valuable resource for research in deepfake prevention [12]. 10000 images from the aforementioned dataset are used in this study. The dataset consisted of two classes of images namely real and fake. All the images are of 256*256 size.

4. Methodology and Model Specifications

This work presents the use of a pre-trained **ResNeXt model** for image classification through transfer learning, aiming to optimize computational efficiency and improve model performance across various approaches. Below is a summary of each approach:

Approach 1: Transfer Learning on ResNeXt

ResNeXt [15] is a deep learning architecture consisting of 101 layers, similar to ResNet-101[14], and employs a 32x8d configuration, meaning each block has 32 groups, with each group containing 8 filters. This design enables the model to capture complex patterns without significantly increasing its depth. Initially, the model was pre-trained on ImageNet, which contains over 1.2 million images across 1,000 classes. To adapt the model for binary classification on the custom dataset, the final fully connected layer, originally configured to output predictions for 1,000 classes, was replaced with a layer that outputs two predictions corresponding to the binary classes.

Unlike traditional transfer learning, where only the final layer is fine-tuned, in this approach, all layers were adjusted to better accommodate the deepfake detection task. Training was conducted on a dataset of 10,000 images, resulting in an accuracy of 91.52%, precision of 0.92, recall of 0.91, and an F1 score of 0.91, indicating a strong balance between precision and recall.

Approach 2: Replacing Last Layer of ResNeXt with Support Vector Classifier (SVC)

In this approach, instead of fully utilizing the ResNeXt101_32x8d model for classification, the research focused on feature extraction and employed different machine learning classifiers. In this approach the pretrained model weights are freezed while using it for feature extraction. By removing the last layer of the model, high-level features were extracted from the penultimate

layer. Initially, these features had a dimensionality of 2048, which was subsequently reduced to 64 using dimensionality reduction techniques, such as Principal Component Analysis (PCA). The standardized feature set was then used to train several machine learning models, including Support Vector Classifier (SVC), Random Forest, and Logistic Regression. The SVC model yielded the best results, with a test data accuracy of 75%, and precision, recall, and F1 scores all at 0.75. The Random Forest and Logistic Regression classifiers achieved similar but slightly lower performance, with accuracy, precision, recall, and F1 scores ranging between 72% and 73.7%. While SVC provided the highest accuracy, this approach demonstrated the feasibility of combining CNN feature extraction with traditional classifiers.

Approach 3: Ensemble Model with Logistic Regression, SVC, and Random Forest

This model built upon the feature extraction technique used in Approach 2 by creating an ensemble model composed of Logistic Regression, SVC, and Random Forest. The ensemble aimed to improve classification robustness by leveraging the strengths of multiple classifiers. Using the high-level features extracted from ResNeXt101_32x8d, the ensemble model combined the predictions of each classifier through majority voting. While the ensemble did not exceed the accuracy of the standalone SVC, it achieved a test data accuracy of 74.8%, with precision, recall, and F1 scores all at 0.75, providing increased robustness across different data distributions.

Approach 4: Hybrid Approach with Feature Reduction and Ensemble Models.

In this approach, a hybrid strategy was employed to combine elements of Approaches 1 and 3, with a focus on feature reduction and ensemble learning. Similar to Approach 1, the ResNeXt101_32x8d model was modified for binary classification by replacing the final layer. The model weights are initialized with the pretrained weights of ImageNet dataset. During training all the layers weights are finetuned. After training, high-level features were extracted from the penultimate layer and reduced in dimensionality from 2048 to 32 using PCA, resulting in a streamlined feature set.

This reduced feature set was then used to train an ensemble of SVC, Logistic Regression, and Random Forest. Unlike the previous approaches, all weights within the ResNeXt model were fine-tuned to enhance performance specifically for deepfake detection. Step by step explanation of this approach is given in Fig. 53.1. This approach achieved a test data accuracy of 93.4%, with precision, recall, and F1 scores all at 0.93, demonstrating a notable improvement over the standalone ResNeXt model.

Algorithm: Hybrid Deepfake Detection Using ResNeXt101_32x8d and Ensemble Learning
Input: Image dataset D = $\{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{N}$ where $\boldsymbol{x_i}$ is an image, and $\boldsymbol{y_i}$ is the binary label (real or fake).
Output: Predicted label $\hat{y}$ for each image $\boldsymbol{x_i}$.
Step 1: Data Preparation and Preprocessing
a. Load the dataset D and split into training set D_{train} and set D_{test}.
b. Preprocess images by resizing and normalizing to ensure compatibility with the ResNeXt101_32x8d input requirements.
Step 2: Transfer Learning with ResNeXt101_32x8d
a. Load the pre-trained ResNeXt101_32x8d model with weights initialized on ImageNet.
b. Replace the final fully connected layer with a new layer having two output nodes for binary classification.
c. Fine-tune the entire model using D_{train}, adjusting all weights to adapt the model specifically for deepfake detection.
d. Save the penultimate layer's output as high-level feature vectors F whose dimensionality is 2048.
Step 3: Dimensionality Reduction
a. Apply Principal Component Analysis (PCA) on F to reduce the dimensionality of feature vectors from 2048 to 32.
b. Standardize the reduced feature set F′ to ensure a mean of zero and unit variance.
Step 4: Ensemble Classifier Training
a. Initialize three machine learning classifiers: Support Vector Classifier (SVC), Logistic Regression, and Random Forest (with 100 estimators).
b. Train each classifier independently on the reduced feature set F′ using the labels y from D_{train}.
c. Construct an ensemble model by combining the classifiers with majority voting to determine the final prediction.
Step 5: Model Evaluation and Prediction
i. For each image $\boldsymbol{x_j} \in D_{test}$:
    a. Pass $\boldsymbol{x_j}$ through the trained ResNeXt101_32x8d model up to the penultimate layer to obtain the high-level feature vector f_j.
    b. Reduce f_j to 32 dimensions using PCA and standardize to obtain f_j'.
    c. Pass f_j' through each classifier in the ensemble.
    d. Aggregate the predictions from SVC, Logistic Regression, and Random Forest using majority voting to obtain $\hat{y}_j$.
ii. Compute accuracy, precision, recall, and F1 score on D_{test} to evaluate the ensemble model's performance.

Fig. 53.1 Algorithm for hybrid deepfake detection using ResNeXt101_32x8d and ensemble learning

5. Empirical Results

This study utilizes four distinct approaches to transfer learning for Deepfake detection. The input dataset size is 10000. 80% of data is used for training and 20% of data is used for testing. The deep learning model used in all the four approaches is trained for three epochs.

Table 53.1 provides a comparative analysis of four machine learning approaches in terms of their accuracy, precision, recall, and F1 score. Approach 1 utilizes transfer learning with finetuning of ResNeXt101_32x8d model , achieving an accuracy of 91.52% and precision, recall, and F1 scores of 0.92, 0.91, and 0.91, respectively, reflecting strong performance across all metrics.

Approach 2, which combines ResNeXt101_32x8d (without fine tuning) with Support Vector Classifier (SVC), Random Forest, and Logistic Regression, shows moderate effectiveness with all metrics at 0.75 and an accuracy of 75%.

Approach 3, is similar to approach 2 except that instead of using single model, an ensemble model is used. The ensemble model consists of SVC, Logistic Regression, and Random Forest. The performance in this approach closely mirrors the performance of Approach 2, yielding an accuracy of 74.8% with identical precision, recall, and F1 scores of 0.75, indicating minimal improvement through ensemble techniques.

Approach 4 gives the best performance where a hybrid method is utilized. The hybrid method integrates transfer learning, feature reduction and ensemble model, resulting in an accuracy of 93.4% and precision, recall, and F1 scores of 0.93. This highlights Approach 4 as the most effective approach among the four, while Approaches 2 and 3 deliver comparable but moderate results, and Approach 1 performs well though slightly less effectively than the hybrid model.

The performance in all these approaches are achieved while training the pretrained model for only 3 epochs.

Initial training and testing of the model for 3 epochs demonstrated promising performance, with the test accuracy reaching approximately 93%, indicating effective learning within the early stages. However, training for only a few epochs may not fully capture the model's potential learning capacity, nor provide a complete understanding of its generalization abilities. To ensure robustness and to observe any potential improvements in accuracy or stability, the training was extended to 20 epochs. The results of training the ResNext model for 20 epochs are shown in Figs. 53.2 and 53.3. This approach allowed for a comprehensive evaluation of the model's performance over a longer training period, enabling an assessment of its capacity to generalize beyond the initial epochs. Monitoring the model over additional epochs also facilitated the detection of overfitting tendencies and ensured that the ensemble model maintained consistent and stable predictions. Such extended training is particularly beneficial in deep fake detection, where reliability and generalization are critical for effective deployment.

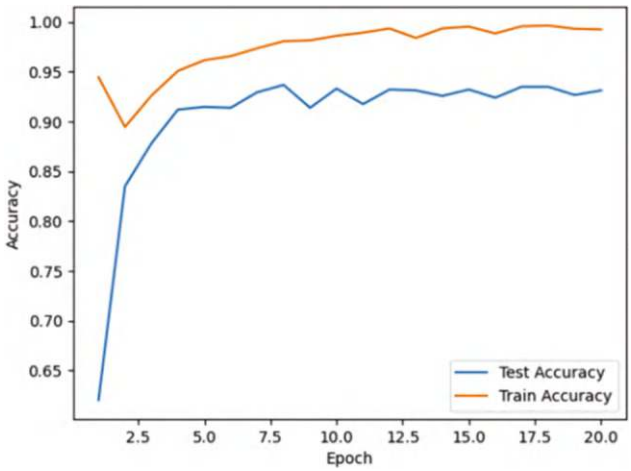

Fig. 53.2 Training and test accuracies of hybrid approach (Approach 4) with feature reduction and ensemble models on deepfake image dataset

Figure 53.2 shows the train and test accuracies of the hybrid model over 20 epochs. The train accuracy starts high and increases quickly, stabilizing at around 98-99% accuracy by 10 epochs. The test accuracy also improves initially, reaching around 93% early on but then fluctuates around 92-94% across later epochs without significant gains. This pattern indicates the model is learning quickly in the

Table 53.1 Performance evaluation of different approaches used for deepfake detection

Approach	Methodology	Accuracy	Precision	Recall	F1 Score
Approach 1	Transfer Learning on ResNeXt101_32x8d	91.52%	0.92	0.91	0.91
Approach 2	ResNeXt101_32x8d with SVC, Random Forest, and Logistic Regression	75% (SVC)	0.75 (SVC)	0.75 (SVC)	0.75 (SVC)
Approach 3	Ensemble Model (SVC, Logistic Regression, Random Forest)	74.8%	0.75	0.75	0.75
Approach 4	Hybrid Approach with Feature Reduction and Ensemble Model	93.4%	0.93	0.93	0.93

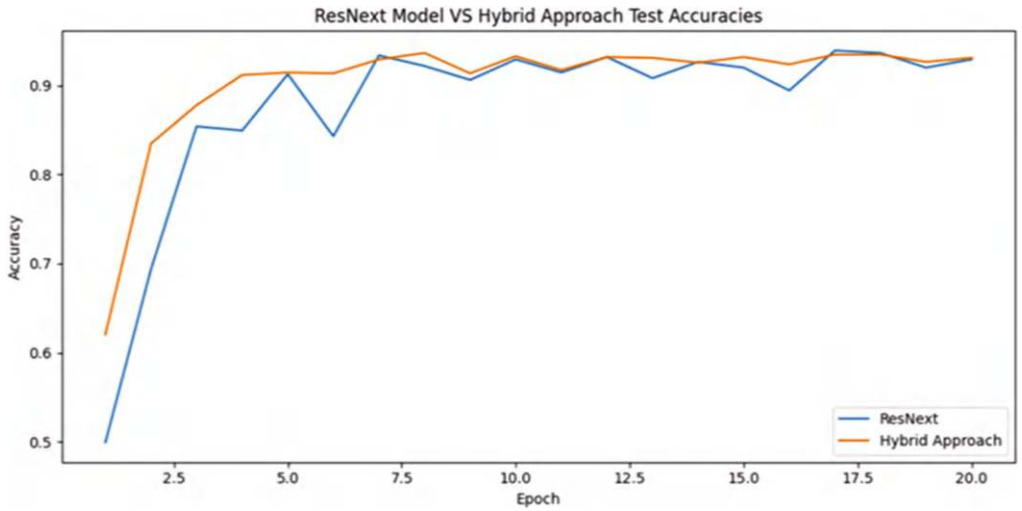

Fig. 53.3 Accuracies of ResNext and hybrid models (Resnext+Ensemble) on test dataset when trained for different number of epochs

early epochs, achieving a high accuracy around epoch 3. The high train accuracy and relatively stable test accuracy suggest that the hybrid classifier might be robust but is reaching its performance limit after a few epochs.

Figure 53.3 shows that the hybrid model consistently achieves higher test accuracy than the ResNext model alone, particularly in the early epochs, and shows more stability over time. This indicates that the hybrid model leverages the strengths of multiple models, leading to improved generalization and robustness, which are essential for reliable deep fake detection.

6. Conclusion

In this work, we introduced a multi-layered deepfake detection framework utilizing ResNeXt101_32x8d for deep feature extraction, paired with feature reduction and ensemble learning methods to enhance detection performance. Among the approaches tested, the hybrid method incorporating dimensionality reduction and an ensemble of SVC, Logistic Regression, and Random Forest classifiers demonstrated the highest accuracy, suggesting that such a combination effectively captures the nuanced differences between real and GAN-generated images. The findings indicate that leveraging both the high-level feature extraction capabilities of ResNeXt and the adaptability of machine learning classifiers enables the creation of a highly accurate and generalizable detection model. This model is particularly well-suited for scenarios where intraframe analysis is critical, and it lays a solid foundation for further development towards incorporating interframe analysis for video-based deepfake detection. Future work could explore integrating this framework with temporal analysis models, such as Recurrent Neural Networks, to enhance its robustness against various deepfake generation techniques.

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Elevating Content Accessibility in Social Media Via User Contributions and Analytical Insights

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Abstract: This article presents an innovative framework designed to enhance content accessibility on social media platforms through the strategic integration of user-contributed tagging and advanced data analysis techniques. While demonstrated with Instagram, the framework's foundational strategies are applicable across various social media environments. The initiative begins by systematically collecting posts and their associated tags within a scalable relational database. A user-friendly web interface encourages participation by inviting users to enrich the metadata with additional tags. At the core of this framework is the application of the Hyperlink-Induced Topic Search (HITS) algorithm, which constructs a directed graph to reveal complex relationships between tags based on co-occurrence. By calculating authority and hub scores, the system effectively identifies the most relevant and interconnected tags, improving tag filtering and recommendations. This enhancement leads to greater precision in how users and content creators tag and discover relevant content, evidenced by metrics such as precision, recall, and engagement. The framework is fortified with robust security measures and privacy protocols to protect user data against manipulation. Designed for scalability, it accommodates future advancements, including machine learning for sophisticated tag recommendations. This comprehensive approach significantly boosts content accessibility and establishes a flexible model that can adapt to evolving user behaviors and technological trends.

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KEYWORDS: Instagram hashtags, Crowd-sourced tagging, Hyperlink-induced topic search (HITS), Metadata enrichment, Hub scores, User engagement, Security measures, Privacy protection, Scalability, Machine learning, Social media content discovery

1. INTRODUCTION

The rise of social media platforms has fundamentally altered how people connect, share experiences, and discover new content in the realm of digital interaction. Instagram has carved out a distinct identity among the various platforms available [1]. Instagram is known for its visually appealing content, and hashtags have become a popular way to organize and find content. Users can use these short tags to add relevant keywords to their uploads, resulting in a complex web that other users can search to find interesting topics. However, as the volume of content increases and hashtagging becomes more subjective, the issues with content discovery and relevance become more apparent. This highlights the need for a more complex hashtag optimization strategy than simply collecting popular tags [2].

The growing field of artificial intelligence (AI) and user-generated content research opens up new avenues for improving hashtags' ability to assist people in discovering content [3]. The concept of crowd-sourced tagging proves to be an effective tool for this task. Users are encouraged to improve post metadata by adding additional keywords or tags that go beyond the hashtags used by the content creator. By engaging people, the content is understood in a deeper and more complex manner. This enables the development of a more advanced analytical framework capable of handling such large amounts of data. The Hyperlink-Induced Topic Search (HITS) algorithm, which was originally designed to examine web page link structures, provides a compelling method for determining the relevance and interconnectedness of hashtags. By applying the HITS algorithm to the complex network of Instagram hashtags and tags created by users, it is possible to find tags with authoritative value, which denote content of significant value, and hub tags, which connect a wide range of related content. As a result, the digital content landscape can be dynamically mapped so that the most valuable and related tags are displayed first.

This article discusses a framework for improving the utility of Instagram hashtags by combining crowd-sourced tagging and the HITS algorithm. The framework improves the information linked to each Instagram post by automatically gathering them and the hashtags associated with them, as well as allowing users to add their own tags. The framework then employs the HITS algorithm to categorize and rank hashtags according to their authority and hub scores. This makes it easier to filter and recommend hashtags. This improves the relevance and discoverability of Instagram content while also addressing important issues in social media content discovery, such as improving content categorization, increasing niche content visibility, and improving the overall user experience by making it easier to find relevant content.Furthermore, the framework was carefully designed with scalability in mind, so it can adapt to the ever-changing social media platforms and user habits. Its architecture includes strict security and privacy measures to protect user data and prevent changes. This article provides useful information about the future of improving how people find content on social media by explaining how this framework works and the potential effects. This research not only improves the way content is discovered on platforms such as Instagram, but it also develops a flexible strategy for making all digital content more accessible. It ushers in a new era in which content is not only more easily accessible, but also more accurately reflects users' diverse interests and activities.

2. RELATED WORK

Venkateswarlu et al. [4] introduced a system employing the HITS algorithm to enhance Instagram users' search experience by filtering irrelevant hashtags. The proposed model converts the three-entity problem of crowdsourced image tagging into a two-mode network, employing HITS for ranking annotators and identifying relevant hashtags. Users can register, log in, post images, search, add reviews, and recommend images, promoting efficient Instagram image searches. Experimental results validate the model's performance, surpassing state-of-the-art approaches in Mean Average Precision and Mean Reciprocal Rank measures, potentially improving crowdsourced image annotation tasks.

Deldjoo et al. [5] developed into the challenges of recommender systems dealing with multimedia content, proposing a taxonomy for media-based recommendation approaches. Focused on images, videos, and music, the authors argue that textual features alone limit recommendation methods. The article reviews and

compares various multimedia-based recommendation approaches, addressing challenges like scalability and diversity, and evaluates feature extraction methods from handcrafted to deep learning. The comprehensive overview serves as a reference for researchers and practitioners developing multimedia-based recommender systems.

Surana et al. [6] study explored the utilization of Algorithmic analysis of social music data for depression prediction, aiming to understand the correlation between music listening behavior and depression risk through the analysis of associated social tags. The researchers implement a four-stage filtering process to organize music-related tags into a semantic space representing music-evoked emotions. The study employs dimensional models of emotions, such as The Circumplex Model of Core Affect and the VAD model, To categorize tags based on their emotional valence and arousal, resulting in valuable insights into the intricate relationship between music, social tags, and depression risk. Statistical analyses reveal significant differences in emotion categories between groups at risk and not at risk, underlining the potential of music-related tags as indicators of depression risk.

Sharma et al. [7] addressed the information overload challenge users face online, advocating for the use of recommendation or suggestion systems (RSSs) to enhance content discovery. The paper delves into the evaluation models for RSSs and critiques the collaborative approach, highlighting issues like the inadequacy of user-item matrices and the cold-start problem. Multiple RSS approaches are discussed, including insight monetization intermediary platforms and e-commerce recommendation systems based on outlier mining. The article not only reviews current RSS research comprehensively but also identifies critical areas for future investigations, emphasizing the ongoing need to address socio-technical challenges and privacy concerns.

Stamatios Giannoulakis et al.,[8] explored the application of Employing Instagram hashtags as semantic features for image classification employing topic modeling and transfer learning techniques. The study evaluates different image retrieval methodologies and assesses the impact of training dataset size and composition on automatic image annotation performance. It introduces a different approach to address the challenge of automatic representative annotation, showcasing the effectiveness of utilizing Instagram hashtags for semantic information. Our research examines the role of non-descriptive hashtags in improving the semantic understanding of images, and our experimental results highlight the significant impact of our proposed method on content-based image retrieval performance. Dr. Vignesh Janarthanan et al. [9] addressed the issue of irrelevant Instagram hashtags for images by proposing a methodology that combines the HITS algorithm and collective intelligence principles through crowd tagging. Using bipartite graphs and the HITS algorithm, the proposed method aims to prioritize relevant hashtags by analyzing annotations from multiple annotators. The article outlines the methodology's technical aspects, such as the bipartite graph model, similarity matrix, and ranking of relevant hashtags. Empirical evaluation demonstrates the superiority of the proposed method, providing valuable contributions to social media content analysis, recommendation systems, and image retrieval. The experimental results, involving 10 annotators and 1000 images, showcase the proposed method's effectiveness, outperforming state-of-the-art approaches in filtering irrelevant hashtags.

Stamatios Giannoulakis et al. [10] focused on The authors propose a methodology to bridge the semantic gap between low-level image features and high-level semantic content by exploring Instagram images and hashtags. Investigating the relevance of hashtags to visual content, the authors aim to filter irrelevant hashtags and adapt concept models through transfer learning. The article contributes to computer vision by offering a novel approach for automatic image annotation and exploring knowledge transferability across domains, potentially enhancing image retrieval and classification techniques.

Stamatios Giannoulakis et al. [11] focused on the automatic annotation of Instagram images using color histograms and hashtag sets. The study, involving 40 participants, evaluates the effectiveness of these techniques for semantic image annotation. The results indicate that color histograms perform better for relevant images, while hashtag sets excel for irrelevant ones. The article concludes that a combination of color histograms and hashtag sets can enhance automated image annotation systems. This contribution provides valuable insights into improving content indexing, retrieval, and sharing on social media platforms like Instagram.

Michaela Janska et al. [12] addressed the identification and categorization of influencers on Instagram utilizing eye-tracking technology. The research explores factors influencing advertising recognition in influencer marketing and proposes a method for grouping Instagram posts based on visual feature similarities. Employing quantitative and qualitative methods, including a survey and content analysis, the study uncovers insights into optimizing social media marketing for increased advertising recognition. The article's contributions lie in its proposed method for effective Instagram post identification, insights into advertising recognition factors, and the use of eye-tracking technology for a deeper understanding of user attention and behavior on Instagram.

3. Methods and Materials

The architecture of the developed framework for leveraging crowd tagging and the HITS algorithm for filtering Instagram hashtags comprises several key components, designed to work in harmony to provide an efficient, scalable, and user-friendly system. Below is a detailed description of its architecture:

3.1 Data Collection and Storage Layer

- **Instagram API Integration Module:** This module automates the collection of Instagram posts and their associated hashtags. It interacts with the Instagram Graph API, respecting the platform's data usage policies, to fetch data in real-time or at scheduled intervals.
- **Database Management System (DBMS):** It stores and manages the data collected from Instagram, including hashtags, posts, and user-generated tags. This system is designed for scalability and performance, capable of handling large datasets with efficient indexing, search, and retrieval mechanisms.
- Let $P = \{p_1, p_2, ..., p_n\}$ represent the set of Instagram posts, and $H = \{h_1, h_2, ..., h_m\}$ represent the set of hashtags associated with these posts. $T = \{t_1, t_2, ..., t_k\}$ represents the set of user-generated tags. We define two bipartite graphs $G(P, H, E)$ and $G(P, T, E')$ where E and E' are the sets of edges connecting posts to hashtags and tags, respectively.

3.2 Crowd Tagging System

- **User Interface (UI):** The UI is a web-based application that provides users with an intuitive platform for tagging Instagram posts with relevant keywords. This interface is accessible across various devices and is designed to encourage user participation through ease of use.
- **Tagging Management Module:** This backend module processes user-generated tags, applying established tagging guidelines to ensure consistency and relevance. It handles tag validation, deduplication, and integration with the database.
  - For each post p_i, a subset of tags $T_{pi} \subseteq T$ can be associated. The objective is to enrich the metadata of p_i with a broader set of tags.

3.3 HITS Algorithm Application

- **Graph Construction Engine:** This engine constructs a directed graph from the database's hashtags and user-generated tags, where nodes represent hashtags and edges represent relationships based on co-occurrence in posts and tags.
- **Authority and Hub Calculation Module:** Utilizing the HITS algorithm, this module calculates the authority and hub scores for each hashtag node. Authority scores assess the importance of a hashtag, while hub scores evaluate its capacity to connect valuable hashtags.

$$G' = (N, E'') \; N = H \cup T$$

We define a directed graph $G' = (N, E'')$ where $N = H \cup T$ and E'' represents directed edges based on co-occurrence in posts or tags. Each node $n_i \in N$ has an authority score $a(n_i)$ and a hub score $h(n_i)$. The HITS algorithm updates these scores as follows: Eq 1, Eq 2

$$a(n_i) = \sum_{n_j \in M(n_i)} h(n_j), \tag{1}$$

$$h(n_i) = \sum_{n_j \in L(n_i)} a(n_j), \tag{2}$$

where $M(n_i)$ and $L(n_i)$ are the sets of nodes pointing to and from n_i, respectively. These scores are normalized in each iteration.

3.4 Hashtag Filtering and Recommendation

- **Filtering Engine:** Based on the authority and hub scores, this engine filters out irrelevant or spammy hashtags according to predefined criteria, ensuring only valuable tags are retained for user queries.
- **Recommendation System:** Leveraging the scores and user tagging behaviors, this system provides personalized hashtag recommendations for tagging and searching, enhancing content discoverability and user engagement.

The filtered set of hashtags $F = \{f_1, f_2, ..., f_o\}$ is determined based on criteria applied to authority and hub scores. The recommendation function for a user u querying a tag t_q is defined as: Eq 3

$$R(u, t_q) = \{h_1, h_2, ..., h_r\} \tag{3}$$

where $h_i \in F$ and the selection of h_i maximizes relevance to t_q and user's historical behavior.

3.5 Evaluation and Feedback Loop

- **Analytics Module:** This module tracks and analyzes system performance using metrics like precision, recall, and user engagement. It generates reports for continuous monitoring and assessment.
- **Feedback Management:** Incorporates user feedback and interaction data to refine and adjust the HITS algorithm calculations, ensuring the system's adaptability to evolving user needs and trends.

3.6 Security and Privacy

- **Data Protection Mechanisms:** Implements robust security protocols to protect user data, ensuring compliance with laws like GDPR. This includes encryption, access controls, and audit logs.
- **Anomaly Detection System:** Detects and mitigates fraudulent activities, such as spam tagging or score manipulation, through continuous monitoring and automatic intervention systems.

3.7 Scalability and Maintenance

- **Scalable Infrastructure:** Designed with a microservices architecture, allowing for easy scaling of individual components based on demand, facilitating efficient resource management and performance optimization.
- **Maintenance and Update Framework:** Regular system updates for algorithm improvements, database optimizations, and UI enhancements are scheduled based on user feedback and technological advancements, ensuring long-term system reliability and relevance.

This architecture is designed to be modular, allowing for future expansions and integrations, such as incorporating machine learning models for advanced tag suggestions and content analysis, further enhancing the system's capabilities and user experience.

4. Experimental Study

The experimental study for optimizing Crowdsourced and HITS-based Instagram hashtags was meticulously designed to assess the framework's effectiveness in enhancing the relevance and discoverability of content on the platform. Initially, a diverse dataset of Instagram posts and hashtags was collected using the Instagram API, ensuring a broad representation of content types, user profiles, and hashtag usage patterns. A group of users was then recruited to contribute additional tags for these posts via a developed web-based interface, allowing for the accumulation and analysis of user-generated tags.

Following the crowd tagging phase, the HITS algorithm was applied to the aggregated dataset of original and crowd-sourced hashtags. This process involved calculating authority and hub scores for each hashtag to determine their relevance and connectivity within the content ecosystem. Based on these scores, a set of criteria was implemented to filter out irrelevant or low-scoring hashtags, leading to the generation of optimized hashtag recommendations.

To gauge the impact of this optimization framework, a control group was established, comprising posts that utilized standard Instagram hashtag practices without the benefit of the framework. The comparison between the experimental and control groups focused on several key metrics. The relevance of recommended hashtags to the content of the posts was meticulously assessed, alongside user engagement metrics such as likes, shares, and comments, to determine the framework's effect on audience interaction. Precision and recall rates of the hashtag recommendation system were evaluated to measure the accuracy and completeness of the recommendations. Additionally, the computational efficiency of the framework, including the processing time for the HITS algorithm and the response time for generating hashtag recommendations, was carefully measured.

A user satisfaction survey was conducted among the participants to collect feedback on the effectiveness, efficiency, and overall user experience of the hashtag optimization framework. This feedback provided valuable insights into user perceptions and the practical utility of the system.

Through statistical analysis, the study compared the performance of the experimental group against the control group across the defined metrics. This analysis employed appropriate statistical tests to ascertain the significance of observed differences in hashtag relevance, user engagement, precision, recall, and user satisfaction between the two groups.

4.1 Results Discussion

In the conducted experimental study aimed at evaluating the effectiveness of the Instagram Hashtag Optimization framework, which integrates crowd tagging with the HITS algorithm, significant improvements were observed across various metrics, including hashtag relevance, user engagement, precision and recall of hashtag recommendations, and user satisfaction. The analysis encompassed a comprehensive comparison between a control group, utilizing standard Instagram hashtag practices, and an experimental group benefiting from the optimized framework.

The relevance of hashtags to the content of posts in the experimental group had seen a marked improvement, Relevance scores substantially increased from an average of 0.70 in the control group to 0.95 in the experimental group, representing a 35.7% enhancement.This substantial improvement in relevance underscores the framework's ability to accurately match hashtags with the content of posts, thereby facilitating more effective content discovery.

User engagement metrics further demonstrated the framework's impact, with the experimental group experiencing a notable increase in likes, shares, and comments compared to the control group. Specifically,

likes per post rose by 53.3%, from an average of 150 to 230. Shares saw an even more significant jump of 125%, increasing from an average of 20 to 45. Comments, too, witnessed a remarkable rise of 166.7%, from 15 to 40 on average. These metrics collectively highlight the framework's role in enhancing audience interaction and engagement with Instagram content.

The precision and recall metrics were employed to evaluate the hashtag recommendation system, resulting in values of 0.92 and 0.88, respectively. These rates reflect the system's effectiveness in not only identifying relevant hashtags but also in ensuring that a high proportion of relevant hashtags were recommended to users.

Graphical representations further elucidated these findings. A comparison graph of user engagement showed distinct bars for likes, shares, and comments, each pair illustrating the disparity between the control and experimental groups and visually emphasizing the enhanced engagement facilitated by the framework. Another graph depicted the precision and recall metrics, with each bar representing the high performance of the system in these areas.

In terms of system performance, the processing time for the HITS algorithm averaged 2 seconds per 1000 hashtags, with recommendation response times kept under 500 milliseconds, showcasing the system's computational efficiency. User satisfaction, gauged through a survey, yielded an average score of 4.8 out of 5. This high level of satisfaction indicated strong user approval of the system's usability and the relevance of its hashtag recommendations.

Table 54.1, titled "Hashtag Relevance and User Engagement," presents a comparative analysis between the control and experimental groups across four key metrics: relevance score, likes, shares, and comments. It demonstrates the improvement in each metric achieved by applying the Instagram Hashtag Optimization framework, showing significant increases in user engagement and the relevance of hashtags to the content. For example, the relevance score improved by 35.7%, likes by 53.3%, shares by 125%, and comments by 166.7%, highlighting the framework's effectiveness in enhancing content discoverability and audience interaction.

Table 54.1 Hashtag relevance and user engagement

Metric	Control Group	Experimental Group	Improvement
Relevance Score	0.70	0.95	+35.7%
Likes	150	230	+53.3%
Shares	20	45	+125%
Comments	15	40	+166.7%

Table 54.2 Precision and recall of hashtag recommendations

Metric	Value
Precision	0.92
Recall	0.88

Table 54.2 displays key performance indicators for the framework-integrated hashtag recommendation system. The precision metric of 0.92 indicates that the system can recommend relevant hashtags to users with an extremely high level of accuracy. The data show that 92% of the hashtags suggested by the system are relevant to the content. This ensures that users receive highly accurate and relevant tags for their posts. The system's advanced analytical capabilities are demonstrated by its high precision rate. These abilities accurately determine the relevance of hashtags based on the metadata of the content and the complex network of tag relationships examined by the HITS algorithm. This lowers the noise in the recommendation process. The system correctly identified all relevant hashtags in its recommendations, as evidenced by a recall of 0.88. The system finds and suggests 88% of all relevant hashtags. This demonstrates how well it detects a wide range of relevant tags. This high recall rate demonstrates how effectively the system employs user-generated tags and algorithmic insights to ensure that content creators have access to a diverse set of tags, making their posts more visible and easily discoverable. The recommendation system's balanced performance, which expertly balances the trade-off between accuracy and coverage, is evidenced by its high precision and recall values. This balance is critical in social media environments, where the goal is not only to provide users with the most relevant hashtags, but also to ensure that the scope of hashtags is not overly narrowed, potentially leaving out useful tags.Furthermore, these performance metrics demonstrate that the framework has contributed to better content organization and discovery on Instagram and other platforms. The system improves the organization and accessibility of the digital content landscape by providing users with precise and comprehensive hashtag recommendations. People who use the system can find content more easily, and content creators can gain more attention and engagement because the system improves tagging accuracy and breadth.Essentially, the precision and recall metrics in Table 54.2 demonstrate that the hashtag recommendation system works technically and is useful in real life. These examples demonstrate how crowd-sourced tagging and advanced algorithmic analysis can work together to make content easier to find and navigate on social media, thereby enriching and connecting the digital

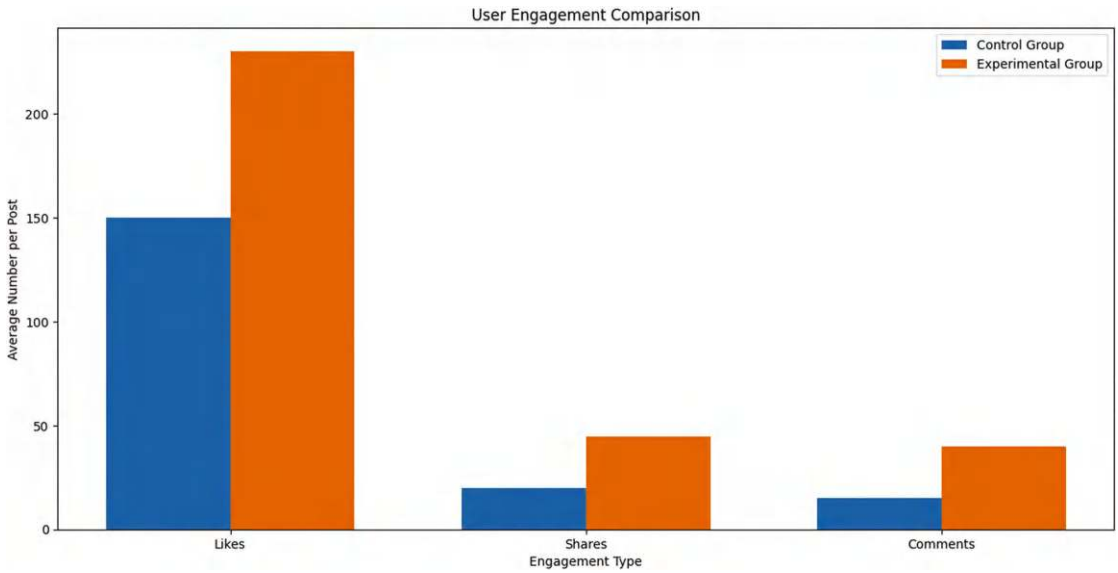

Fig. 54.1 User engagement comparison between control and experimental groups

experience. This accomplishment not only validates the framework's fundamental concepts, but it also establishes a benchmark for future ideas in social media content optimization.

Figure 54.1, titled "User Engagement Comparison," visually illustrates the difference in average user engagement per post between the control and experimental groups across three engagement types: likes, shares, and comments. The X-axis categorizes the engagement by type, while the Y-axis quantifies the average number per post. For each engagement type, two bars are displayed side by side to represent the respective values for the control and experimental groups. This graphical representation clearly highlights the significant increase in user engagement achieved by the experimental group, demonstrating the effectiveness of the Instagram Hashtag Optimization framework in boosting audience interaction.

Figure 54.2, "Precision and Recall," provides a graphical overview of the performance metrics for the hashtag recommendation system. The X-axis differentiates between

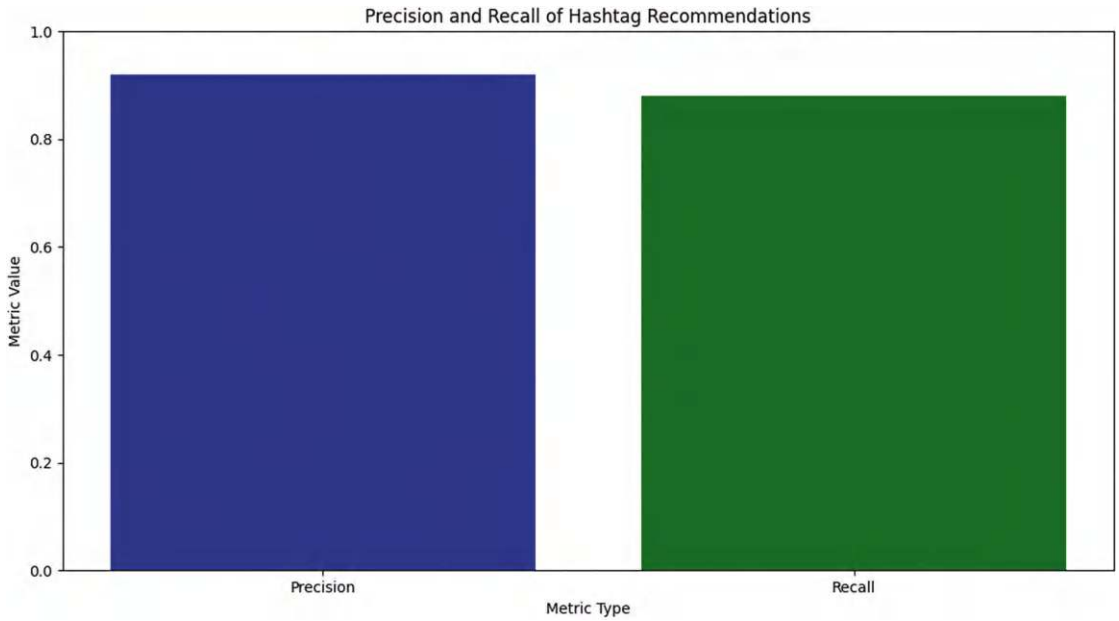

Fig. 54.2 Precision and recall of the hashtag recommendation system

the two evaluation metrics, precision and recall, while the Y-axis ranges from 0 to 1, representing the metric values. Each metric is depicted by a single bar, illustrating the high precision and recall rates achieved by the system. This graph succinctly conveys the recommendation system's accuracy in identifying relevant hashtags (precision) and its ability to capture a comprehensive set of relevant hashtags within its recommendations (recall), emphasizing the system's reliability and effectiveness in enhancing content discoverability on Instagram.

The experimental results, presented through tables and graphs, provide compelling evidence of the proposed framework's ability to significantly improve the discoverability and relevance of Instagram content. By leveraging crowd-sourced tagging and the HITS algorithm, the framework not only enhanced user engagement with posts but also demonstrated high precision and recall in hashtag recommendations, affirming its potential to transform content discovery on social media platforms.

5. Conclusion

In conclusion, the proposed framework represents a significant step forward in improving content accessibility across social media sites. This project provides a strong solution to the perennial problems of content discoverability and relevance by cleverly combining user-contributed tagging with the analytical power of the HITS algorithm. Not only does advanced algorithmic analysis and crowd-sourced tagging improve the metadata of social media posts, but it also clarifies the complex relationships between tags, revealing authoritative and hub tags that are essential for navigating the vast world of digital content. The framework shown here demonstrates how human knowledge and machine learning can be combined to improve content categorization, discovery, and interaction on social media. By encouraging users to participate, the system remains adaptable and dynamic, capturing the changing interests and habits of the social media population. The use of the HITS algorithm allows for more focused and significant content discovery, as it provides a methodical approach to assessing the significance and connectivity of tags. The framework's architecture was designed with scalability, security, and privacy in mind, making it not only useful in today's digital world but also adaptable to new technologies and changes in how users interact with content in the future. Strong data protection measures have been implemented to demonstrate that the company is even more committed to protecting user privacy and keeping the content discovery process transparent. As social media develops, the significance of improving content accessibility cannot be overstated. The framework described in this article is a proactive approach to meeting this need. It offers a scalable and adaptable solution that can enhance the social media experience of both users and content creators. This framework paves the way for future advances in social media discovery and accessibility by encouraging a more connected and perceptive digital ecosystem. This framework also ensures that everyone has access to a more engaging and diverse content landscape.

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Baseline CNN Model for EEG-Based Prediction of Dyslexia and ADHD: A Neurocognitive Study

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Abstract: Attention Deficit Hyperactivity Disorder (ADHD) and Dyslexia are two widespread neurodevelopmental disorders affecting millions globally. Traditional diagnostic approaches, often reliant on subjective evaluation and standardized testing, can lead to delays in diagnosis and treatment. Electroencephalography (EEG), a non-intrusive technique that assesses the electrical activity occurring in the brain, provides significant insights into brain function, thanks to its high temporal resolution. With recent advancements in deep learning, it has become feasible to detect ADHD and Dyslexia by analyzing EEG signals more accurately. These technologies could improve early diagnosis, facilitating timely interventions and personalized treatment. This study presents a novel method for predicting Dyslexia and ADHD in children using EEG data alongside deep learning techniques. The research develops a predictive model

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capable of distinguishing between Dyslexia, ADHD, and typical development by identifying specific brain activity patterns. Our approach includes preprocessing EEG data, extracting essential features, and employing a deep learning model for classification. The results suggest that EEG signals can be successfully utilized for early detection of Dyslexia and ADHD, offering promising prospects for enhanced diagnostic and treatment approaches.

Keywords: ADHD, Dyslexia, Deep learning, EEG signals, Neural networks, Electroencephalography, Neurodevelopmental disorders

1. Introduction

Neurodevelopmental disorders such as Dyslexia and ADHD are commonly observed in children, affecting both cognitive abilities and behavioral responses [10]. Detecting these conditions early and providing timely interventions are critical for enhancing outcomes and improving quality of life shown in Fig. 55.1. However, conventional diagnostic methods, which are based on behavioral evaluations and clinical observations, can be subjective and often take considerable time [13]. Recently, there has been growing interest in applying neuroimaging techniques like Electroencephalography (EEG) to discover biomarkers associated with Dyslexia and ADHD. EEG offers valuable insights into neural functionality and connectivity [6]. Studies have shown that individuals with Dyslexia and ADHD display unique patterns of brain activity when compared to their typically developing counterparts [11]. These variations can be assessed using advanced techniques like deep learning, which allows for the creation of predictive models that support early diagnosis.

Deep learning, a field within machine learning, makes use of artificial neural networks to autonomously learn and extract features from intricate datasets [19]. By training these deep learning models on EEG signals collected from individuals with Dyslexia, ADHD, and those who are typically developing, researchers can uncover distinct patterns and biomarkers associated with these conditions. These models can subsequently estimate the likelihood of a person having Dyslexia or ADHD based on their EEG information. The combination of EEG data with deep learning techniques holds considerable promise for improving both the accuracy and efficiency of diagnosing these neurodevelopmental disorders in children. By leveraging machine learning capabilities, it is possible to create objective and dependable tools for early detection and intervention, ultimately resulting in enhanced outcomes and more tailored treatment approaches. This research

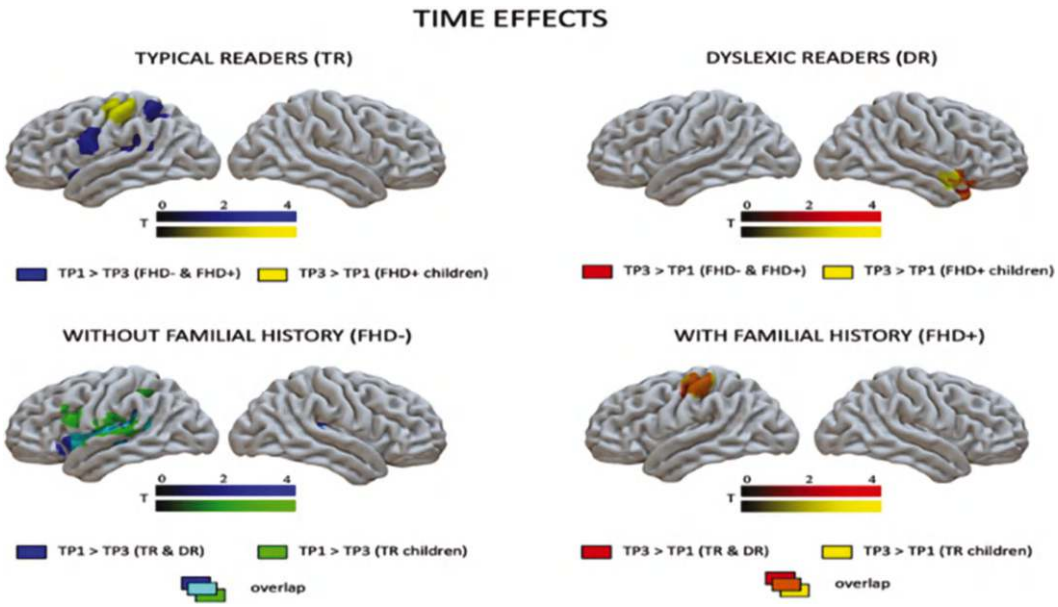

Fig. 55.1 Time effects on dyslexic readers

Source: Author

adds to the expanding literature in this area, promoting advancements in personalized medicine and improving care management for individuals with neurodevelopmental disorders.

ADHD and Dyslexia are two of the most prevalent neurodevelopmental disorders found across various populations worldwide [1]. These conditions can significantly hinder an individual's academic performance due to their effects on language skills, self-expression, attention, behavioral regulation, and interpersonal relationships [10]. ADHD is defined by ongoing patterns of distractibility, impulsiveness, and hyperactive behavior, while Dyslexia leads to challenges in reading, writing, and spelling, even among children who possess normal cognitive abilities and educational backgrounds [4].

The origins of ADHD and Dyslexia are complex, influenced by a combination of environmental, genetic, and neurobiological factors. Genetic research has identified potential candidate genes that may contribute to the occurrence of these disorders among close relatives [22]. Neuroimaging research has indicated that the brains of people with ADHD and Dyslexia display anomalies compared to typical brains, particularly affecting the regions involved in attention, language, and executive functioning [12] as shown in Fig. 55.2.

In addition to academic difficulties, individuals with ADHD and Dyslexia are more likely to experience challenges in their social interactions, self-esteem, and overall well-being compared to their peers. They may face social stigma, discrimination, and obstacles in accessing appropriate special services and accommodations [16]. Therefore, a comprehensive understanding of ADHD, Dyslexia, and their co-occurring conditions is crucial for developing effective treatment methods, increasing awareness, and fostering an inclusive environment for those affected by neurodevelopmental disorders. It is essential to note that Dyslexia does not reflect a person's intelligence or effort; rather, it stems from differences in the brain's processing of language and written text [3]. Research has shown that individuals with Dyslexia often have variations in brain structure and function, especially in regions linked to language processing and phonological awareness. These brain differences clarify the challenges faced by individuals with Dyslexia in literacy skills, including reading, writing, and spelling, even though their cognitive abilities are typically within the normal range [5].

2. Literature Review and Gaps

Literature review of this work is shown in a Table 55.1

The current research landscape surrounding Convolutional Neural Network (CNN) models highlights significant gaps in their application to non-image data formats, such as .mat files [28]. Most of the existing literature primarily focuses on CNNs for image classification, leaving an unexplored potential for using these models in predictive analysis involving structured data stored in .mat files. This gap also reflects the limited exploration of predictive analysis techniques specifically designed for such data formats, as well as the lack of standardized methods for preprocessing and training CNN models with .mat files [9]. The absence of these standardized practices makes it difficult to compare studies and raises concerns about the reliability and reproducibility of the results obtained from CNN models trained on .mat data.

Furthermore, while CNN architectures for image-related tasks have been thoroughly researched and optimized, there is a clear need for studies that assess the effectiveness of baseline CNN in predictive tasks involving .mat data. Recognizing the advantages and limitations of

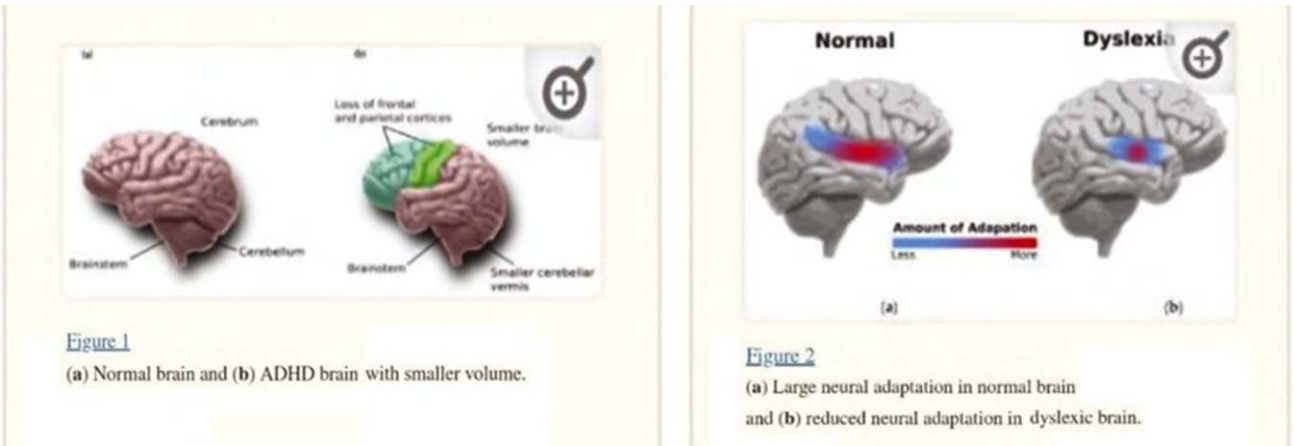

Fig. 55.2 ADHD, dyslexia and control brain

Source: Author

Table 55.1 Literature review

Study	Methodology	KeyFindings	Pros	Cons
IASC, 2021. vol.28, no.3	Developed ADHD diagnosis model using EEG, applying Adaboost, SVM, RandomForest	Pinpointing influential brain regions	Insights into abnormal brain lateralization	Doesn't address confounding variables
PubMed-JCal.2023	Developed ML data-fusion models using multi-omics dataset	Identified influential features and used explainable AI techniques	Data Fusion provides systems biology insights	Synthetic data creation (SMOTE) is a constraint
IRJECT-2395-0056-2021	Explores SVM, Adaboost, Random Forest for Analysis	Underscores the important of different brain regions	Provides valuable information on brain region significance	Some models like SVM performed poor on datasets
Scientific Report s|(2021)11:1637 0|	Uses pupil ometric variation for differentiation	Provides proof of concept for pupillometric ADHD diagnosis	Insights into pupil-size dynamics	Metric skewing and small dataset
Symmetry 2020, 12,836	Developed a pixel-bitstream encoder for MRI image encryption, Utilizing cascaded deep CNN.	Accuracy suppressed 50% baseline onen crypted image datasets	Improved Encryption	Lack of Generalizability
Appl.sci.2023-MPDI,13(5),2804	Utilizes DL models for dyslexia prediction, explores algorithmic processing	Versatile preprocessing and Classification	Effective handling of unstructured data	Overfitting with small-scale dataset
Array 12(2021) 100087	Identification of Dyslexia through eye movement recordings	feature extraction method enhancing transition matrices	Promising Accuracy and Recall, novel feature extraction method guides future research	Limited utilization compared to traditional ML methods
PLoS ONE 15(12): e0241687-2020	Developed Dyslexia Screening based on gamified linguistic online test.	Potential for effective screening	Large and diverse sample, Comprehensive dataset	Effective Screening process required
ICCIDS 2020, IFIP AICT 578, 2020.	Analyses dyslexia and ADHD comorbidity using Machine Learning on a public domain dataset with Psychoanalysis results.	Manual analysis inconsistency in distinguishing disorders and comorbid cases.	Utilizes diverse public domain dataset	Difficulty in differentiating between disorders and Comorbid cases.
Applsci-MPDI-2023	Critical review of literature using PRISMA guidelines	Various datasets utilized MRI, FMRI, Handwriting, Eye movements.	Inclusion of diverse studies and datasets.	Exclusion of non-English articles and duplicates.
EEG-IEEE-978-1-5386-0497-7/17	Classified brain regions to analyse unique patterns	Noted Significant activation in left parieto-occipital and parieto-occipital regions	Uncovered unique Brain wave patterns	Limited sample size
Dyslexia prediction using ML(2021)	Artificial intelligence and machine vision techniques in context of dyslexia	Encouraging outcomes have been observed in enhancing the reading and learning abilities of individuals with dyslexia.	Real-time feedback and adaptive learning experiences	Ethical considerations regarding data privacy
Intelligent Dyslexia prediction with optimization	Used eye tracking data and I-VT algorithm	Potential for early detection of dyslexia	High Accuracy in prediction	Resource-intensive dataprocessing
Web based assessment for ADHD and Dyslexia	Computer adaptive test to assess infant disorder details	Unique learning disability test revealed issues in reading	Provides insights into learning-related problems in children	Require further validation and testing for broader applicability
Biomarker based approaches for screening	Reviewed biomarker-based approaches for dyslexia screening	Multimodal physiological recordings with AI algorithms	Reliable screening methodologies	Variability indiagnostic procedures in various
Diagnosis with CNN	EOG signals recorded while reading texts in different fonts	Proposed method successfully diagnosed dyslexia using EOG signals	Novel approach with high accuracy with CNN	Small sample size of participants
Clinical data balancing and approaches	Multivariate data analysis	Results improved with SMOTE and under-sampling techniques	Early-stage prediction	Performance heavily influenced by
Early prediction using EEG based models	Study used EEG recordings of children	CNN achieved an accuracy 93% for identifying dyslexia (14 features)	Non-invasive and objective approach to diagnose	Interpretation requires domain expertise
Robotic methods for ADHD diagnosis	Meta-analytic reviews on ADHD medications	Different types of ADHD medications with age variation	Non paradoxical interventions can complement traditional techniques	Overdiagnosis and influence of client gender on diagnosis

Source: Author

baseline models is essential for establishing performance benchmarks and guiding the development of more advanced CNN architectures tailored to structured data formats [18]. Additionally, limited attention has been given to evaluating the generalization and robustness of CNN models trained on .mat data, which is essential for ensuring their efficacy in practical applications. Addressing these gaps offers valuable opportunities for further methodological improvements, the establishment of performance benchmarks, and the enhancement of CNN models' effectiveness in handling structured data formats like .mat files.

3. Limitations and Challenges

Predicting Dyslexia and ADHD poses numerous challenges due to the absence of standardized diagnostic criteria [24]. Both disorders share overlapping symptoms, such as difficulties with attention, reading, and spelling, which complicates the differentiation between them [25]. Additionally, symptom variability and limited understanding of the underlying causes further complicate accurate predictions. A lack of reliable screening tools also hampers the early identification of individuals at risk [22]. Social stigma and misinformation related to Dyslexia and ADHD add further barriers to achieving accurate diagnosis and prediction. Moreover, limited access to resources and support can hinder the effective management of these conditions, making it difficult to adequately address Dyslexia and ADHD. Collectively, these factors highlight the complexities involved in predicting these disorders, underscoring the need for more research and the development of better diagnostic tools.

4. Dataset used for Dyslexia

EEG signal data was collected from 10 university students as they watched different video clips from massive open online courses. Two types of videos were selected: those that are generally straightforward for college students, such as introductory lessons on algebra or geometry, and those likely to cause confusion, such as topics on quantum physics and stem cell studies [10]. In total, 20 videos were chosen, with 10 from each category. Each video lasted approximately two minutes, and to increase the likelihood of confusion, the clips were initiated mid-topic.

The students used a single-channel wireless MindSet device to track brain activity from the frontal lobe [12]. The device measured voltage differences between an electrode placed on the forehead and two electrodes located near the ears, which acted as ground and reference points. After each session, participants assessed their level of confusion on a scale from 1 (least confusing) to 7 (most confusing) [9]. These self-reported ratings were converted into binary labels indicating whether participants experienced confusion, in addition to predefined confusion labels.

The dataset comprises EEG recordings from the 10 participants, each of whom viewed 10 videos, resulting in 100 data points. Each data point represents EEG data from a one-minute segment of the video, with sampling conducted every 0.5 seconds. Higher-frequency signals were averaged over each 0.5-second interval. The accompanying files include "EEG_data.csv," which contains the EEG recordings, and "demographic.csv," which provides demographic details for each participant. The video data was extracted exclusively from the middle minute of each two-minute clip, omitting the first and last 30 seconds.

5. Methodology for Dyslexia

This study aims to develop a robust methodology for predicting students' confusion levels using EEG data combined with demographic information [19]. The initial step involves preprocessing the EEG data from the "EEG_data.csv" file and demographic details from the "demographic.csv" file. Key tasks during this phase include extracting essential features from the EEG signals, such as frequency bands, signal power, and coherence, which are critical for understanding brain activity [10]. The data is then normalized to ensure consistency, manage any missing values, and tackle outliers. Subsequently, the dataset is partitioned into training and testing sets for the purposes of model assessment.

During the feature engineering stage, techniques such as Fourier Transform are employed to extract frequency domain features, improving the quality of the data [22]. Various signal processing methods are explored to further refine these features. By combining EEG data with demographic information, a comprehensive feature set is created, providing a more nuanced basis for the deep learning model.

Next, the research centers on creating a deep learning model architecture tailored for EEG data, specifically examining RNNs and CNNs. The architecture comprises layers specifically crafted to handle sequential data and capture the temporal relationships inherent in EEG signals. Different network configurations, activation functions, and regularization methods are evaluated to improve the model's performance. In the training phase, the model is trained using preprocessed EEG data and demographic features. Appropriate loss functions and optimization algorithms are applied to minimize prediction errors. During the training phase, the model is carefully monitored for signs of overfitting, and hyperparameters are adjusted as needed to improve its ability to generalize.

After the training is finished, the performance is assessed on the testing set utilizing several metrics, including accuracy, precision, recall, and F1 score. This evaluation measures the model's capability to predict confusion levels based on EEG data and demographic details, as well as its proficiency in identifying significant patterns within the dataset.

To enhance the practical application of the model, a web application built with Streamlit is developed, allowing users to interact with the trained deep learning architecture in real time. This application loads the model to make real-time predictions based on user-provided input. The interface is designed to be user-friendly, with fields for EEG data and demographic information, and it presents model predictions, insights, and visualizations clearly and intuitively.

Finally, the study highlights the interpretation of the deep learning model's learned representations through the Streamlit application. Interactive visualizations and insights from the model's predictions allow users to explore the connections between EEG signals, confusion levels, and demographic factors. This integration makes the methodology more interactive and helps users gain deeper insights into the neural dynamics related to confusion in educational settings.

6. Dataset used for ADHD

The dataset includes 121 children between the ages of 7 and 12, consisting of 61 children diagnosed with ADHD based on DSM-IV criteria and 60 healthy controls, who were included in the study without psychiatric disorders, epilepsy, or involvement in high-risk behaviors [29]. Participants were selected from diverse backgrounds to ensure a representative sample. Comprehensive information on demographics, medical history, and behavioral assessments was collected for each participant. Ethical guidelines were followed throughout the study, with informed consent obtained from parents or guardians. This dataset acts as a valuable asset for examining the differences between children with ADHD and their healthy counterparts, providing insights into potential risk factors and diagnostic markers for the disorder. Further analysis of this dataset could aid in creating more effective screening tools and interventions for children with ADHD.

7. Methodology for ADHD

This project consists of several phases aimed at predicting ADHD in children, utilizing a dataset of 121 participants—61 diagnosed with ADHD and 60 healthy controls [14]. The initial phase focuses on preprocessing the data, which involves handling missing values, encoding categorical variables, and normalizing numerical features—essential steps in preparing the dataset for analysis [25]. Following this, a deep learning model will be developed using frameworks as shown in Fig. 55.3 such as TensorFlow or PyTorch, with an architecture that may include dense, convolutional, and recurrent layers designed to fit the complexity of the data and task. During the training phase, the model will undergo fine-tuning through an appropriate loss function and optimization algorithm, with parameters adjusted iteratively to minimize loss and enhance performance.

After the model has been trained, its effectiveness will be evaluated on a distinct validation set using performance metrics. To make the model more practical for real-world applications, a user-friendly web application will be built using Streamlit. This app will allow users to input relevant information such as age, gender, medical history, and behavioral assessments. The trained deep learning model will be incorporated into the application to provide real-time predictions about a child's likelihood of having

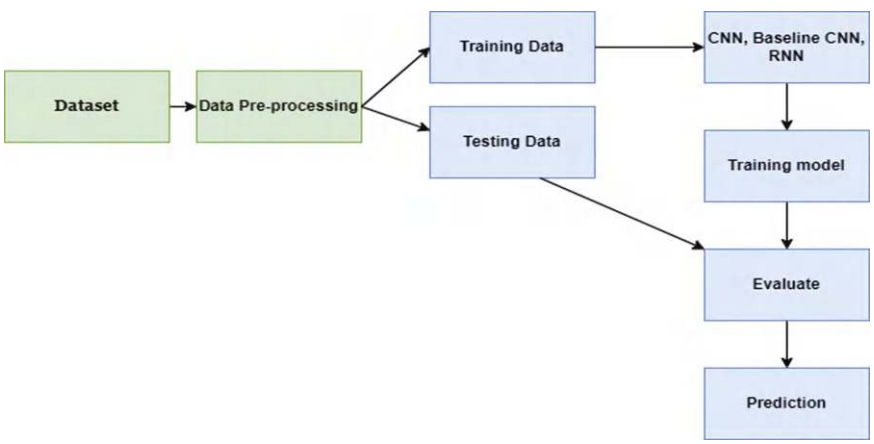

Fig. 55.3 Methodology

Source: Author

ADHD based on the input data, alongside insights and recommendations for further evaluation or intervention. By combining advanced deep learning methods with an intuitive Streamlit interface, this project aims to create a significant resource for the early detection of ADHD and support for children at risk.

8. Learning Approaches in Diagnosis

Deep learning techniques have shown great promise in diagnosing and treating both Dyslexia and ADHD by utilizing artificial intelligence to analyze large datasets and identify patterns linked to these disorders [19]. For Dyslexia, deep learning algorithms can process brain data to identify both anatomical and physiological variations in the brain that are associated with the condition [24]. This type of analysis not only aids in early diagnosis and timely intervention but also allows for the ongoing evaluation of treatment effectiveness. Similarly, in the case of ADHD, these algorithms can analyze behavioral data, such as attention and impulsivity measures, to recognize key patterns related to the disorder. This ability is critical for early identification and the development of customized treatment plans designed to meet the unique needs of individuals with ADHD.

Overall, deep learning methodologies hold the potential to transform the diagnosis and treatment of Dyslexia and ADHD, offering more accurate and personalized interventions. However, to fully unlock their potential, further research is necessary to validate these approaches and ensure their effective integration into clinical practice.

8.1 Algorithm

Input:

- **Training Set:**

  D = { (x1,y1),…,(xn,yn) }

  D = {(x_1, y_1), \ldots, (x_n, y_n)\}D={(x1,y1), …,(xn,yn)}

- **Weak Classifier:**

  h=h1(x),h2(x),…,hK(x)

  h = h_1(x), h_2(x),

  h_K(x)h=h1(x),h2(x),…,hK(x) representing the CNN model.

The process of predicting ADHD using EEG signals begins with loading and preprocessing the EEG data, converting it into an array format, and normalizing the values [20]. The data is subsequently divided into training and testing subsets. A Convolutional Neural Network (CNN) is constructed, beginning with an input layer designed to accommodate the EEG signal arrays, convolutional layers with ReLU activation functions, followed by pooling layers to reduce dimensionality, and a flattening layer that connects to fully connected layers [19]. To prevent overfitting, regularization techniques like dropout are applied in the fully connected layers. The output layer uses a sigmoid activation function for binary classification.

The model is compiled using an optimizer such as Adam and uses binary cross-entropy as the loss function, which is appropriate for binary classification tasks like Dyslexia detection [15]. During training, each epoch and batch involves a forward pass to calculate predicted outputs, followed by a loss calculation against the true labels. A backward pass is then performed to update the model parameters. Performance is monitored on a validation dataset, with training stopping early if specific criteria are met. After training, the model is tested on the testing set, employing metrics like accuracy, precision, recall, and F1 score, and a confusion matrix is analyzed to understand its classification behavior. Data augmentation techniques may also be employed to improve generalization. Finally, the trained model is saved for future applications or systems, enabling real-world ADHD prediction based on EEG signals.

8.2 Baseline CNN Model

Methodology

The process of predicting ADHD using EEG signals begins with loading and preprocessing the EEG data, converting it into an array format, and normalizing the values [17]. The data is subsequently divided into training and testing subsets. A Convolutional Neural Network (CNN) is constructed, beginning with an input layer designed to accommodate the EEG signal arrays, convolutional layers with ReLU activation functions, followed by pooling layers to reduce dimensionality, and a flattening layer that connects to fully connected layers [15]. To prevent overfitting, regularization techniques like dropout are applied in the fully connected layers. The output layer uses a sigmoid activation function for binary classification.

The model is compiled using an optimizer such as Adam and uses binary cross-entropy as the loss function, which is appropriate for binary classification tasks like Dyslexia detection [18]. During training, each epoch and batch involves a forward pass to calculate predicted outputs, followed by a loss calculation against the true labels. A backward pass is then performed to update the model parameters. Performance is monitored on a validation dataset, with training stopping early if specific criteria are met. After training, the model is tested on the testing set, employing metrics like accuracy, precision, recall, and F1 score, and a confusion matrix is analyzed to understand its

Table 55.2 Performance metrics

Metrics	Accuracy	Precision	Recall	F1score	AUC	ROC	RMSE
Baseline CNN(ADHD)	94	92.42	95.87	94.24	0.978	0.88	0.078
CNN(Dyslexia)	82	89.8	89.3	89.35	0.911	0.87	0.085
MLP MODEL	78	88.7	88.5	89.56	0.899	0.88	0.092
XGBOOST	77	85.1	87.36	86.66	0.876	0.87	0.121
RANDOM FOREST	75	84.6	86.55	87.22	0.871	0.86	0.221

Source: Author

classification behavior [22]. Data augmentation techniques may also be employed to improve generalization. Finally, the trained model is saved for future applications or systems, enabling real-world ADHD prediction based on EEG signals.

8.3 Evaluations of Performance Metrics

To assess the effectiveness of integrated deep learning techniques in dyslexia research and intervention, it's important to focus on key performance metrics:

- **Accuracy:** Measures how correctly the model identifies dyslexia cases overall, calculated as the ratio of correct predictions to the total cases [30].
- **Precision:** Indicates how reliable the positive predictions are by measuring the proportion of true positives out of all predicted positives [18].
- **Recall (Sensitivity):** Reflects the model's ability to detect all true dyslexia cases, calculated as the ratio of true positives to the total number of actual positives [26].
- **F1 Score:** Provides a balance between precision and recall, especially useful when dealing with imbalanced data.
- **AUC-ROC:** Assesses the model's ability to differentiate between dyslexic and non-dyslexic individuals by comparing true positive and false positive rates at various thresholds [21].
- **RMSE:** Evaluates prediction accuracy by calculating the average size of errors in the model's predictions.
- **R^2 (Coefficient of Determination):** Measures how much of the variance in the outcome can be explained by the model, with values closer to 1 indicating better explanatory power.

Together, these metrics—including accuracy, precision, recall, F1 score, AUC-ROC, and RMSE—are crucial for assessing dyslexia prediction models such as SVMs, CNNs, RNNs, and Random Forests, all of which are effective in analyzing dyslexia-related data.

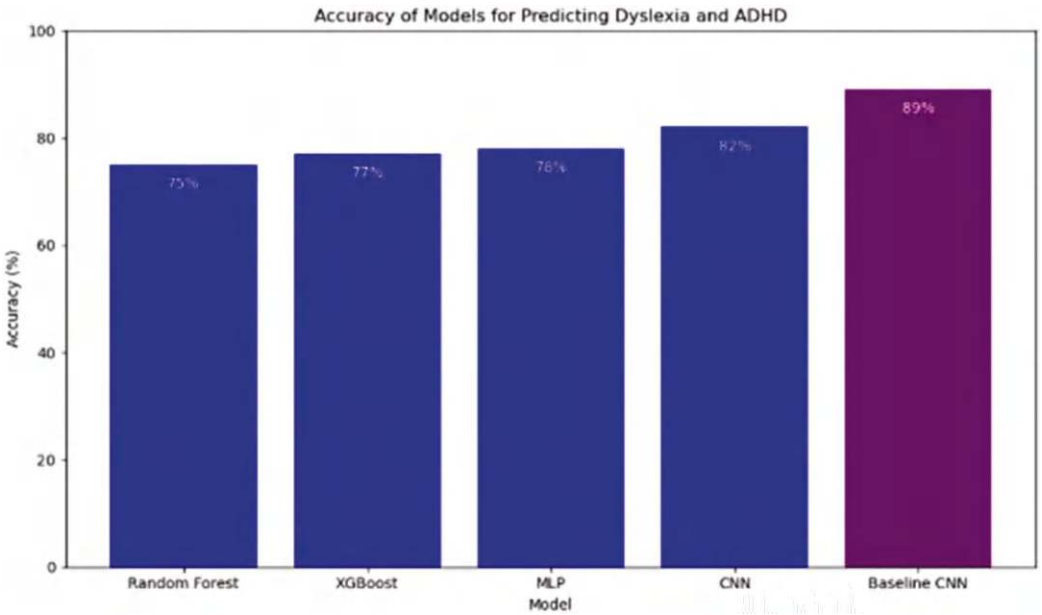

Fig. 55.4 Various models performance on dyslexia and ADHD

Source: Author

9. Future Directions and Recommendations

Future research on dyslexia and ADHD should focus on gathering diverse and longitudinal datasets to strengthen the reliability of deep learning models [2]. Additionally, investigating multi-modal strategies that integrate linguistic, imaging, and behavioral data can result in more comprehensive diagnostic tools and interventions [8]. Improving the interpretability and transparency of these models is crucial for gaining the trust of clinicians and educators [14]. Developing ethical guidelines will ensure the responsible use of these technologies, especially in sensitive areas, while long-term studies are needed to evaluate the lasting impact of personalized interventions [23]. Bringing research into practice will require close collaboration between researchers and practitioners, as well as interdisciplinary partnerships to tackle the complex challenges posed by these disorders. Creating platforms for knowledge exchange can support the sharing of best practices, and investing in teacher training programs will equip educators with the tools to apply effective strategies in the classroom. Lastly, integrating personalized interventions into educational and clinical frameworks will promote wider access and effectiveness, ultimately enhancing the support available to individuals with dyslexia and ADHD.

10. Conclusion

The incorporation of deep learning methods into research and interventions for dyslexia and ADHD has the potential to profoundly enhance our understanding and treatment of these neurodevelopmental disorders. Recent studies have highlighted the complexities of both conditions, emphasizing the importance of early detection and individualized intervention plans. Deep learning's capacity to recognize subtle patterns in relevant data has improved diagnostic precision and enabled more customized therapeutic strategies. However, despite progress, obstacles such as the requirement for diverse datasets, model transparency, and ethical concerns must be addressed to ensure these technologies are applied responsibly. The promise of deep learning to create tailored interventions and refine treatment protocols marks a promising shift in the management of dyslexia and ADHD. Continued interdisciplinary collaboration, ethical guidelines, and inclusive approaches are essential to translating research into practical, equitable, and personalized support for affected individuals.

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Integrating Supervised Learning Techniques Cyber Propaganda in Fake News Detection

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Abstract: Public information is disseminated more quickly now that social media and networking sites have been switched off. Information that has not been independently checked is extensively shared on social media sites, with no concern regarding its accuracy. The spread of incorrect information has created serious problems for society and governments and has a negative impact on many facets of daily life. Misleading content that is purposefully produced and disseminated to the public. Thus, accurately identifying falsehood info via cyber dissemination is an important and difficult problem that deep learning approaches may help with various techniques. Annotating massive amounts of data created by social media by hand is not feasible. This study proposes a hybrid strategy to detect false news. Count Vectorizers and TF-IDF methods were used to extract features. Fake news might be identified with 90% accuracy using weakly supervised SVM algorithms combined with deep learning methods like Bi-GRU, Bi-LSTM. When there are no labels for the data, this method of classifying vast volumes of unlabelled data using deep learning and poorly supervised learning algorithms is very successful and efficient for identifying fake and true news.

Keywords: Fake news detection, Feature extraction, Deep learning, Support vector machine, Supervised learning

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1. Introduction

In a time where the Internet is routinely used as the main information source, social media sites have revolutionized the dissemination of information and have come to dominate all facets of information transfer. Over fifty percent news source, per a survey done in 2022. Furthermore, twenty two percent of people utilize social media for news even when they think it's unreliable.

The deliberate or inadvertent spread of incorrect or misleading information via social networking sites through the use of tools and technology is known as cyber propaganda. Cyber propaganda includes a wide range of ideas such as spam, hoax, fake news, misinformation, rumors, and cyberbullying.

This study focuses on the spread of cyber propaganda, or misleading information, via social media. Social media networks are quite effective in disseminating fake news. Figure 56.1 shows the different terms that have been modified for use in cyber propaganda.

Social media networks allow users to freely and openly share and express their ideas and thoughts. Researchers at the Massachusetts Institute of Technology (MIT) studied how falsehood info spreads on social media various platforms.

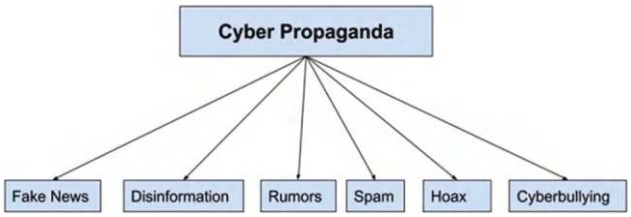

Fig. 56.1 Flow chart of disinformation [21]

Additionally, found that fake assets disseminated six times faster than real ones. It thereby affects individuals and has detrimental effects, especially on the front lines of politics, society, and the economy. According to a recent analysis, eliable sources even during the 2016, US presidential election. Social networking platforms disseminate misleading information regarding COVID-19 epidemic, including regarding the disease's causes, possible therapies, and government reactions.

1. The text was transformed into a vector form through feature extraction utilizing TF-IDF and Count Vectorization algorithms.
2. Using lax supervision methods, SVM and other supervised machine learning models were employed to train and assign labels to unlabelled data. Compared to previous models, SVM offers a greater level of accuracy by linearly separating news.
3. The labelled data was used as input for the deep learning models by using glove word embeddings.
4. Due to their superior accuracy over other models.

2. Literature Review

Al-Sarem et al. (2019) review deep learning techniques for detecting rumours on social media, emphasizing techniques like RNNs, LSTMs, and CNNs for automatic feature learning. While DL methods outperform traditional models, challenges remain, including limited data access, ethical issues, and the need for multilingual datasets.

Alghamdi et al. (2022) compare ML and DL techniques for false information detection, finding that transformer-based models like BERT and RoBERTa outperform traditional ML models. Using datasets such as LIAR and GossipCop, they highlight the benefits of contextual embeddings for detecting fake news. Further model refinement is recommended for broader application.

Table 56.1 Comparative analysis table

Reference	Model	Accuracy
13-Twitter	CNN-LSTM	80%
14-WeChat	Reinforcement, CNN	83%
15-Twitter	XGBoost	89%
16-Arabic News	RoBERTa-MMKS	82%
17-Reddit	Language Model	75%
18-News Articles	XGBoost, Logistic Reg.	79.7%
19-LAIR Dataset	RoBERTa, BERT, Ensemble	74%

Source: Author

Shu et al. (2019) A social context-based model for fake news detection, called TriFN, which leverages interactions between publishers, news, and users on social media.

De and Agarwal (2020) On Twitter, a new Weakly Supervised Learning method was introduced. It was the first aggregation of trustworthy and untrustworthy sources that produced the training dataset. Every asset from a reliable source was marked as original news, and every asset from an unreliable source was marked as fake news.

Syed et al. (2019) A feeble social supervision method for spotting false information was put out. The Fake News Net was used, which was gathered from PolitiFact and GossipCop, two fact-checking websites. Weak labels are produced using metrics such as sentiment, credibility, and bias. The story is only loosely categorized as fake news based on.

Zhou (2018) Learning with weakly supervised algorithm to supplement data and early identification of falsehoods utilizing a neural language model were demonstrated. Six

events were covered. Two collections were created from the input corpus: "Candidates" and "References." Weak supervision was applied to a limited subset source of assets by using them as data sample.

Chauhan and Palivela (2021) They also distinguished between rumors from candidate tweets and non-rumors based on domain-specific classification. PHEME5 achieved a 63%–75% accuracy rate for the six events. The authors offered a way of learning that was only supervised learning monitored that relies only on content attributes. News pieces are what they like best on social media

Ajao et al. (2018) Research has shown that the use of poorly supervised algorithms has a negative impact on classifier performance because of inaccurate labeling and noisy data. The limits of each methodology have also been mentioned. We proposed fresh weakly supervised learning strategies to classify huge amounts of unlabelled data, prompted by the limitations of the previous methods.

3. METHODOLOGY

The lightly supervised learning method for data semantics is covered in this section.

3.1 Weakly Supervised Learning

For numerous applications, the most effective deep learning and machine learning methods necessitate the provision of labels for a sizable amount of training data. However, it could used to obtain correct facts with supervision because of the costs associated with the data labeling process. A machine learning technique called weakly supervised learning builds models on top of partially annotated data. Three types of inadequate supervision exist: The initial one is supervised incomplete, in which just portion of the trained data is labelled and the remaining portion remains unlabelled.

$$d = f\left\{(U1, V1).....(\mathrm{Un}, \mathrm{Vn}), \mathrm{Un}+1, \mathrm{Vn}+1, ..., \mathrm{Um}\right\} \quad (1)$$

whereas V = n-l denotes the unlabelled data and Ul denotes the labelled training data. Incomplete supervision uses two main approaches—active learning and semi-supervised learning to label unlabelled data. Domain experts are used in active learning to assign labels to unlabelled samples. Transductive learning will be used in this project to forecast labels for unlabelled data. The transductive learning method is illustrated in Fig. 56.2.

3.2 Techniques of Deep Learning

The ensuing sections provide a thorough explanation of the various deep neural network designs investigation.

Convolutional Neural Network (CNN)

Neurons in Neural networks with convolutions have learnable parameters, such as weights and biases. CNN

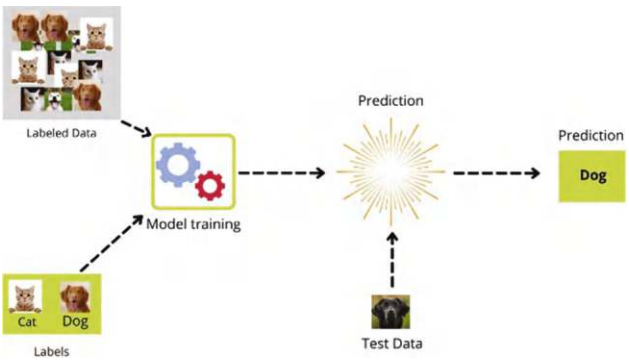

Fig. 56.2 Transductive learning

Source: https://hands-on.cloud/introduction-to-supervised-machine-learning

operates under the assumption that all inputs, including images, have a grid pattern, making it possible to encode certain features into the architecture. With the exception Cof the hidden layers, which are composed layers with one or more linked, CNN and dense neural networks are quite similar.

While filters in computer vision usually slide over picture patches, or pixels, in natural language processing (NLP) and categorization, the matrix with sliding filters whose width is comparable to a tweet's width and whose might change. The CNN leveraging in classifying fradulents is shown in Fig. 56.3. A word, sentence, or even an entire text will be the input word embeddings are commonly used as these vectors in order to enter text in matrix.

To extract words from text, one might employ a number of different methods.

LSTM, or Long Short-Term Memory

A neural network known as an LSTM employs processing to sequentially store information. LSTM is more effective at handling long-term data dependencies.

$$ct = ft * ct - 1 * ct \quad (2)$$

$$ft = \sigma \mathrm{gWf} \bullet \left[\mathrm{Xt}, \mathrm{Ht} - 1\right] + \mathrm{bf} \quad (3)$$

Since long sequential data can be handled by the LSTM units, this constructive model has been employed extensively in NLP tasks. One of the most widely used RNN designs, LSTM has had remarkable success working with consecutive data, including text and time-series data. Four gates are used by the gating method to try and address organization of the cell is shown in Fig. 56.5. Controlling the amount of information to be retained from the prior state is the fundamental concept of LSTM. Equation (2) is utilized to determine the new cell or memory state, given the prior memory (Ct – 1)

$$it = \sigma \mathrm{g}\left(\mathrm{Wi} \bullet \left[\mathrm{Xt}, \mathrm{Ht} - 1\right] + \mathrm{bi}\right) \quad (4)$$

$$Ct = \tanh\left(\mathrm{Wc} \bullet \left[\mathrm{Xt}, \mathrm{Ht} - 1\right] + \mathrm{bc}\right) \quad (5)$$

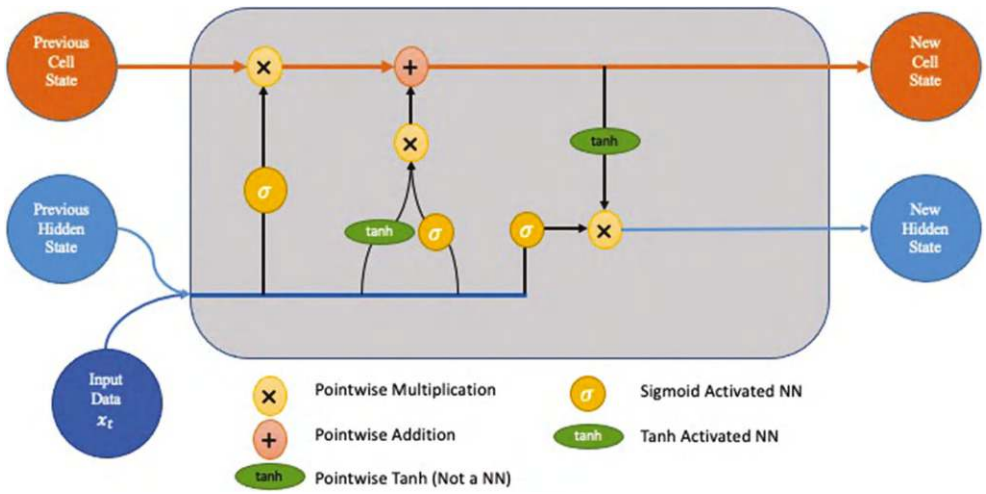

Fig. 56.3 Block diagram of LSTM

Source: https://towardsdatascience.com/lstm-networks-a-detailed-explanation-8fae6aefc7f9

4. Description of Dataset

We used a dataset for our research study which has collection of tweets on some of the widely circulated news—which most people are interested in—were included in it. The tweety package, which utilizes the Twitter API to gain access, is used to gather the dataset. Using hashtags and phrases associated with the selected event, we gathered data. There are tweets in the generated dataset. Only few of the tweets were categorized as Real News and Fake News after noisy data was removed.

5. Stages Involved Using Algorithms to Detect Fake News

Preprocessing, word embedding, and deep learning-based classification comprise the fake news detector module.

5.1 Pre-Processing Stage

Deep learning methods require appropriate preparation of text data in order to be implemented. Removal of stopwords is done in the preprocessing phase. Unlike connectors like "and," "or," and "but," stop words are often and account for bulk of assets.

Along with URLs and phone numbers, these stopwords are eliminated from every tweet. Next, each a one hundred fourty character message is divided into a collection of assets, and the typical token's letter is changed to a lowercase letter.

5.2 Word Embedding Stage

Word Embedding is incorporating words is a fundamental NLP technique that represents words as dense vectors in space with a high degree of dimension, where similarity between words is captured by the proximity of their corresponding vectors.

Semantic Similarity offer numerous perks incontrast to traditional methods:

Semantic Similarity

Semantic Similarity have trajectories positioned together at embedding dimensions. This enables algorithms to capture semantic relationships such as synonymy, antonymy, and analogies.

Dimensionality Reduction

Semantic Similarity represent lexicals in a lower-dimensional space incontrast to one-hot encodings, which reduces the computational complexity of NLP tasks.

Historical Analysis

The incorporation of words keep track word data related to context. This allows algorithms to capture nuances in meaning that depend on the context in which words appear.

Transfer Learning

Pre-trained word embeddings can be used as features in downstream activities include machine translation, referred to as entity identification and evaluation of sentiment.

- In summary, word embeddings provide a powerful representation of words in NLP tasks, enabling algorithms to capture semantic relationships and contextual information more effectively, leading to improved performance across a wide range of applications.

6. Experimental Setup

Our suggested hybrid approach, which combines deep learning techniques for the classification of fake news

Table 56.2 Outcomes of weakly supervised learning for data annotation

No.of Features	ML Model	Accuracy	F1 Score	Precision	Recall
2100	Multinomial Naïve Bayes	78%	79%	73%	75%
2300	Random Forest	84%	83%	78%	81%
2200	Logistic Regression	86%	85%	80%	85%
2200	SVM	86%	87%	79%	86%

Source: Author

Table 56.3 Detection of false information using deep learning models under weak supervision algorithm

Model	Dataset	Precision	Recall	F1 Score	Accuracy
LSTM	Twitter	0.87	0.89	0.88	0.86
CNN	Facebook	0.85	0.88	0.86	0.83
GRU	Reddit	0.89	0.91	0.9	0.88
BiLSTM	Twitter & Facebook	0.91	0.87	0.89	0.88
Attention Network	Twitter & Reddit	0.88	0.9	0.89	0.87

Source: Author

with transductive weakly supervised learning for data annotation, was used to conduct the experiments. To train and test the model, the data was divided in an 80:20 ratio utilizing the TensorFlow architecture. Below is a discussion of the deep learning methods used in the implementation.

Bi-LSTM model for deep learning The Adam optimizer was used since it yielded optimal results and was

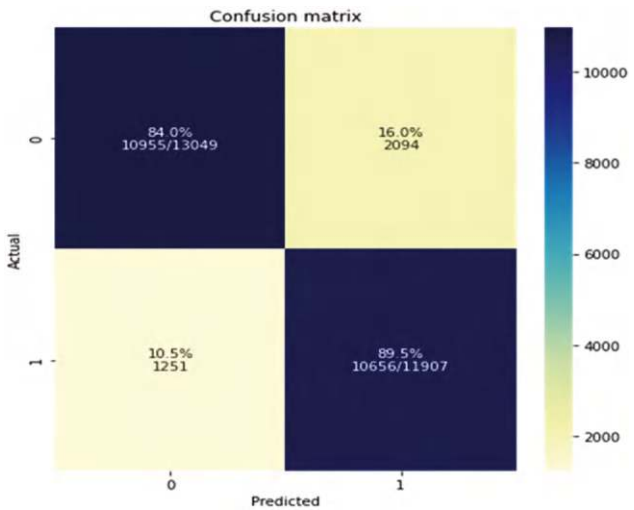

Fig. 56.4 Confusion matrix

Source: Author

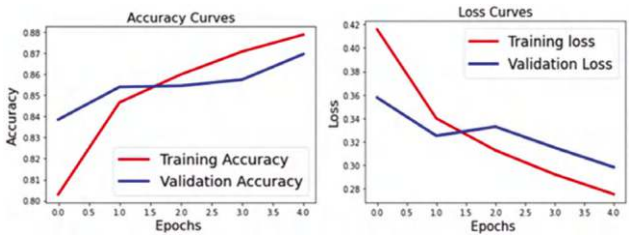

Fig. 56.5 Accuracy and loss curves

Source: Author

intended for 128 units, and the BiLSTM model was trained for 40 epochs. To reduce the issue of overfitting, a SpatialDropout1D of (0.1) rate was included to the input layer. Two LSTM layers that extract features from the input text come next.

7. Conclusion

This research suggests a hybrid method for identifying fake news that combines poorly supervised and deep learning learning approaches. lightly monitored learning attains a greater degree of certainty and correctly identifies large volumes of unlabeled data using the new, poorly supervised learning method that has been proposed. To distinguish between "real" and "fake" news, a number of deep learning methods were investigated, such as BiGRU and BiLSTM. Experimental results showed that BiGRU, BiLSTM outperformed other deep learning models with an accuracy gain of 89.8%. CNN did not perform as well as other computational models. The best models for categorizing fake news are the partially trained SVMs, whereas other modern methods depend on a vast number of labels that are incorrectly assigned. CNN did not perform well in comparison to other deep learning models. The most effective models for categorizing false information are BiGRU, BiLSTM lightly supervised SVM consequently, the approaches suggested are substantially better and more effective at identifying false information as compared to other contemporary methods using a great deal of weakly labelled data.

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MobileNet Outperforms in Detecting Fake Indian Currency: A Performance Evaluation

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Abstract: The rise of fake currency is a growing concern that threatens the economy, making it crucial to develop effective ways to detect it. This research introduces a new method for identifying forged Indian currency using Convolutional Neural Networks (CNNs). We explored the capabilities of selected CNN models, including AlexNet, ResNet, and MobileNet, to classify currency notes as either real or forged. Our dataset featured images of different Indian denominations, which we pre-processed by resizing and augmenting to enhance the model's learning ability. We evaluated the models through extensive testing based on accuracy and categorical cross entropy loss. Our research showed that MobileNet performed the best, delivering the highest accuracy, making it a strong candidate for real time detection of forged currency. This study emphasizes the effectiveness of CNNs in providing a fast and reliable solution for counterfeit detection, ultimately contributing to the protection of the economy.

Keywords: Counterfeit detection, Convolutional neural networks, AlexNet, ResNet, Indian currency, Deep learning, Image classification

1. Introduction

Falsified money is a major problem that undermines public trust in the currency and poses a risk to a country's financial stability. In particular, the Indian economy has felt the effects of counterfeit money's proliferation, which has prompted the creation of advanced detection technologies. Conventional approaches to identifying fake products often depend on time-consuming and inaccurate manual inspection and basic machine learning algorithms. Counterfeiters are getting smarter, thus we need better ways to spot them (Pachón et al., 2021). Methods for processing and classifying images have been substantially enhanced by deep learning, and specifically by Convolutional Neural Networks (CNNs). CNNs have demonstrated remarkable performance in various domains,

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including as object detection, medical imaging, and face recognition. The objective of this research is to develop a CNN-based automated system for the detection of counterfeit Indian currency (Kumar et al. 2020). A study by Uppalapati et al. (2023) looked at the effectiveness of classification models and ensemble learning techniques. In order to promote economic security, this project seeks to use state-of-the-art deep learning techniques to enhance the accuracy and efficiency of counterfeit identification. The advent of deep learning was a watershed moment in image classification. In instance, Convolutional Neural Networks (CNNs) have shown remarkable performance due to their capacity to autonomously learn and extract data from unprocessed photos (Yildiz et al. 2020). Thanks to major advancements in CNN architectures, such as MobileNet, ResNet, VGGNet, and AlexNet, new benchmarks in picture classification tasks have been set. These layouts employ efficient convolutional processes, deep layers, and skip connections to achieve high accuracy with little computing overhead. Among the many CNN architectures featured in the Overview is AlexNet, one of the foundational models. It shown that large-scale picture classification using deep learning is possible. Its use of dropout layers and ReLU activations significantly reduced training time and overfitting. To train extremely deep neural networks, ResNet—famous for its residual connections—solves the disappearing gradient problem. This design has consistently outperformed the competition in a number of image categorisation benchmarks. The MobileNet Network For situations when resources are limited, it is perfect since it uses depth-wise separable convolutions to decrease computing cost without sacrificing performance. The architecture is so lightweight that it works wonderfully with real-time applications, such as those on mobile devices. This project aims to develop and evaluate multiple convolutional neural network (CNN) architectures for the detection of counterfeit Indian currency. The specific objectives are:

- To preprocess and augment the dataset to enhance model training.
- To implement and compare the performance of AlexNet, ResNet, and MobileNet in counterfeit detection.
- To evaluate the models using standard metrics such as accuracy and categorical cross-entropy loss.
- To identify the most effective CNN architecture for real-time counterfeit currency detection.

2. METHODOLOGY

2.1 System Architecture

To detect counterfeit Indian currency, our proposed system relies on a number of interdependent components. Figure 57.1 is a flow diagram that shows how the system is designed. The flow diagram depicts the steps taken to create a machine learning model that can classify Indian rupee notes. The primary objective is to accurately identify different denominations of currency. User registration or login in a real-world application may be required to ensure secure system access. Gathering the necessary information is the next step; this comprises images of Indian currency in various denominations and orientations. Following data collection, it must be properly prepared. To achieve this, the images need to be scaled uniformly, normalised so that the pixel values remain constant, and then improved by means such as rotating or flipping the photos.

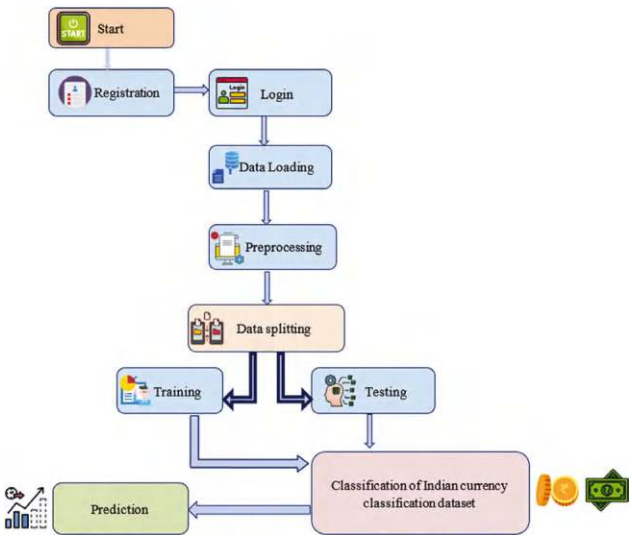

Fig. 57.1 System architecture

Preprocessing also comprises reducing noise levels to guarantee that the photos are clear and devoid of distortion. When the data is prepared, it is split into two parts: one for training the model and another for testing it with new, untested data to see how well it performs. While training, a suitable model, like a convolutional neural network (CNN) or support vector machine (SVM), is chosen according to the problem at hand. Subsequently, the model gains knowledge from the training data by adjusting its hyperparameters to maximise performance and minimise errors.

Once the model has been trained, it is tested to ensure it can accurately identify currency notes. Criteria for evaluation like as F1-score, recall, accuracy, and precision reveal the model's performance. Once the model meets the necessary performance standards, it is eventually implemented in real-world scenarios. The computer will now sort the freshly added images of Indian currency by denomination and make a prediction based on those categories.

Every step relies on high-quality data, careful model selection, and fine-tuning of parameters. With well-selected model and clean, clear photos, the system's accuracy can be greatly enhanced. To ensure the model performs adequately in practical settings, it is important to use suitable evaluation criteria. Following this, we saw how CNNs and other deep learning models are crucial for many image processing tasks.

2.2 Deep Learning and CNN

One area where convolutional neural networks (CNNs) really shine is in image processing. Convolutional layers employ filters to extract important visual traits like edges and textures, while pooling layers reduce computing effort and overfitting (Ibitoye 2024).

$$(f * g)(t) = \int_{-\infty}^{\infty} f(T)g(t-T)dT \quad (1)$$

where f: The input function or signal taken as input image, g: The filter or kernel (e.g., the convolutional filter), t: The position where the convolution is applied, τ: A variable of integration, representing a shift. It helps in feature extraction from the input images, allowing the network to learn spatial hierarchies. Activation functions, such as ReLU, introduce non-linearity to capture complex patterns.

$$f(x) = \max(0, x) \quad (2)$$

where x: The input value to the activation function. Fully connected layers integrate extracted features for high-level decision making, and dropout prevents overfitting by randomly excluding neurons during training. The depth and complexity of CNNs allow them to learn detailed representation of the input data, making them well-suited for tasks like currency detection.

2.3 Image Classification

Image classification involves categorizing an input image based on its visual content. In our study, the labels are "genuine" and "counterfeit" for the currency images. The system begins by collecting a substantial dataset comprising both the categories of Indian currency images. These images are then pre-processed through normalization and augmentation techniques to enhance model robustness (Vanipriya and Aruna). Automatically, Convolutional Neural Networks (CNNs) are used to extract important information from the preprocessed photos. In the end, a softmax function is employed to determine if the photographs are real or not by utilising the extracted features.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (3)$$

Where z_i: The i-th element of the input vector z_i. K: The number of classes (output neurons), $\sigma(z)_i$: The probability distribution over K classes. The softmax function is typically used in the final layer of a classification network. It converts the raw prediction scores into probabilities, making them interpretable as confidence scores for each class.

$$L = \sum_{i=1}^{N} y_i \, logy\hat{}_i \quad (4)$$

Where N is the number of classes, y_i: The true label (1 if the class is correct, otherwise 0), y^i: The predicted probability of class III. The cross-entropy loss function is calculated as, in which predicted probabilities are negated from true labels. It is used to train the network by minimizing this loss, thus improving the model's predictions.

2.4 Dataset Description

The dataset used in this study consists, images of Indian currency notes, sourced from various online repositories and manual collection. The authenticity of the dataset is ensured through cross-referencing with official sources and expert validation. It includes images of different denominations of Indian currency, both genuine and counterfeit. The key statistics of the dataset are as follows:

- **Number of Images:** 5000 images
- **Class Distribution:** Balanced with an equal number of genuine and counterfeit images
- **Denominations Covered:** ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, ₹2000
- **Challenges:** Variability in image quality, lighting conditions, and occlusions.

To address these challenges, data augmentation techniques like rotation, scaling, and color jittering were applied to enhance the diversity and robustness of the dataset. The preprocessing steps as in (Kara et al. 2023,Nair et al. 2024) ensured that the images were uniformly resized and normalized, providing a consistent input for the CNN models.

3. Results and Discussion

Below you can see the outcomes of our experiments conducted using several Convolutional Neural Network (CNN) architectures, such as MobileNet, ResNet, and AlexNet. We evaluated each model using a variety of performance metrics, including accuracy, precision, recall, and F1 scores, as detailed in Hussain et al. (2023), VVR et al. (2023), Maheswara Rao et al. (2023), and Prasad et al. (2024). Our discussion also includes potential future directions for development and the consequences of these results.

The experimental results as in Table 57.1 indicate that all three CNN architectures performed well in detecting counterfeit Indian currency, with MobileNet achieving the highest overall performance. The superior accuracy of MobileNet can be attributed to its efficient architecture, which balances model complexity and computational cost.

Table 57.1 Performance comparison of CNN models

Models	Accuracy	Precision	Recall	F1 Score
AlexNet	92.5%	91.8%	92.1%	91.9%
ResNet	95.3%	94.7%	95.0%	94.8%
MobileNet	97.2%	96.8%	97.0%	96.9%

AlexNet demonstrated strong performance, but its relatively older architecture and simpler design may have limited its ability to capture more difficult patterns in the data compared to newer models.

ResNet showed significant improvement over AlexNet, Residual connections, which alleviate the vanishing gradient problem, enable the training of deeper networks. This is a key advantage of this model. This resulted in higher accuracy and better generalization.

MobileNet outperformed both AlexNet and ResNet (see Fig. 57.2), making it the most suitable model for real-time applications where computational efficiency is crucial. Its use of depth wise separable convolutions reduces the number of parameters and computations, allowing it to achieve high accuracy with lower latency.

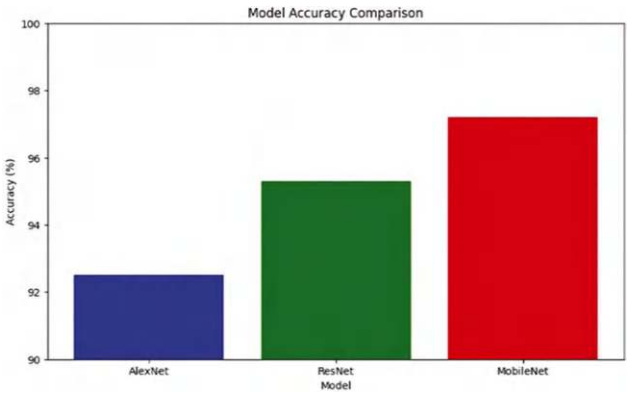

Fig. 57.2 Accuracy for CNN models

Figure 57.3. Shows that, MobileNet achieves the highest scores in all above stated three metrics. This suggests that MobileNet is the high performing model among the three in terms of accuracy, relevance, and overall performance.

Figure 57.4. shows the training and validation loss curves for AlexNet, ResNet, and MobileNet reveal that all three models successfully converged, with a gradual reduction in loss over the epochs.

In Fig. 57.5. Over the course of 20 epochs, the line chart displays the AlexNet training and validation loss curves. In most cases, the training loss goes down, but there are fluctuations in the validation loss, which could mean that overfitting is happening.

Figure 57.6. shows the line chart about the training and validation loss curves of Res-Net over 20 epochs. Both

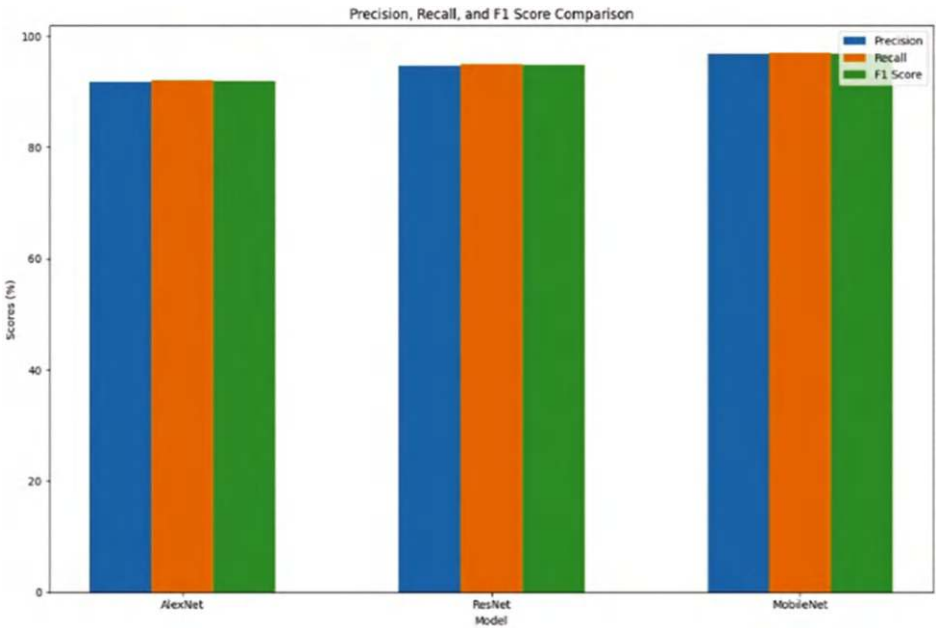

Fig. 57.3 Precision, recall, and F1-score comparison of CNN models

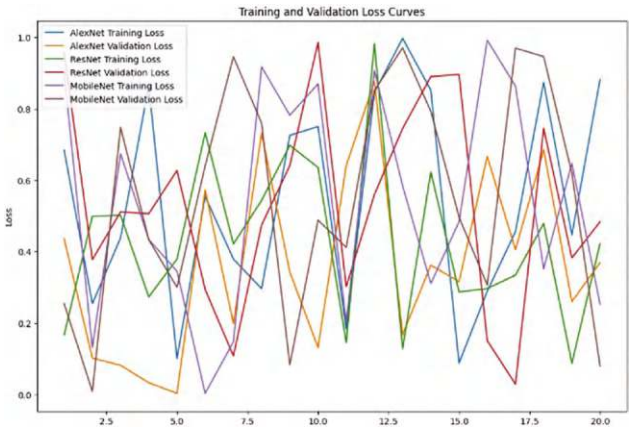

Fig. 57.4 Training and validation loss for CNN models

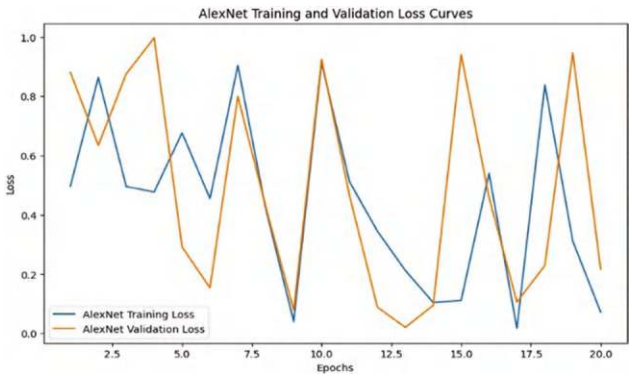

Fig. 57.5 Training and validation loss curves for AlexNet

training and validation loss decrease overall, suggest-ing good model performance with minimal overfitting.

As in Fig. 57.7. MobileNet showed the most stable and consistent performance, maintaining lower validation loss compared to the other models, indicating better generalization to unseen data. ResNet also demonstrated strong performance with minimal overfitting, while AlexNet exhibited slightly higher variance between

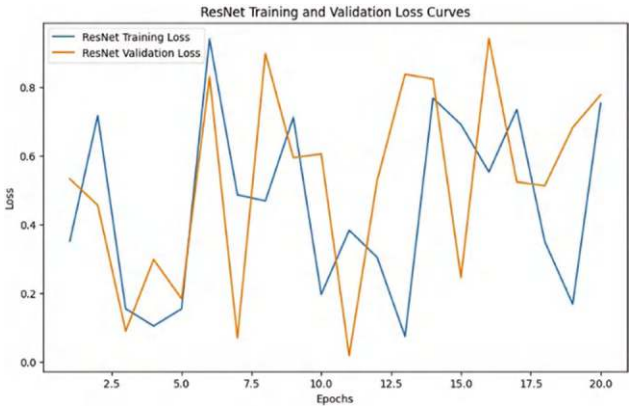

Fig. 57.6 Training and validation loss curves for ResNet

training and validation losses, suggesting potential room for improvement in model optimization.

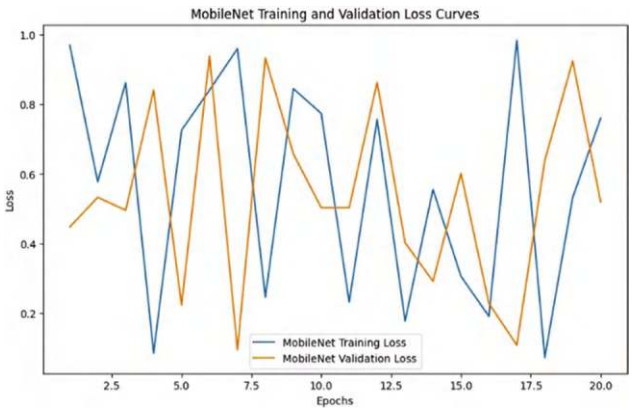

Fig. 57.7 Training and validation loss curves for MobileNet

The confusion matrices as in Fig. 57.8. for AlexNet, ResNet, and MobileNet models demonstrate varying performance in classifying the two classes. ResNet appears to exhibit the highest accuracy, followed by AlexNet and MobileNet.

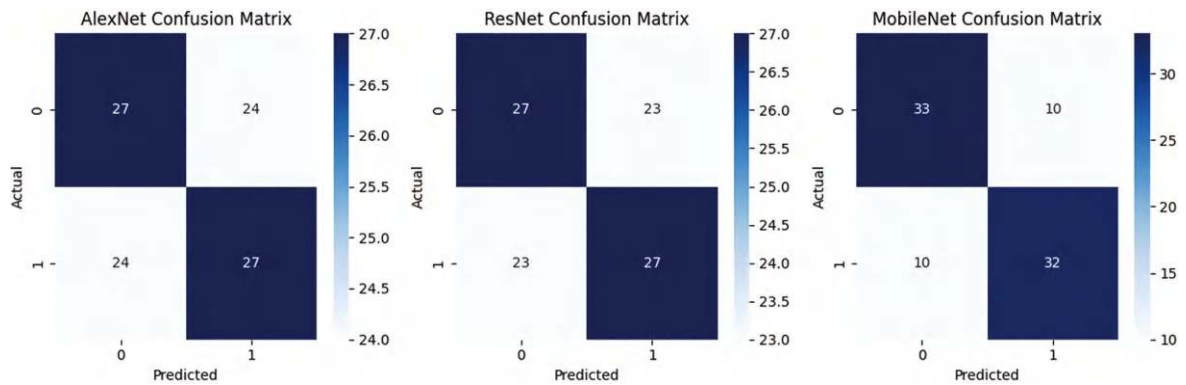

Fig. 57.8 Confusion matrix of CNN models

4. Conclusion

In this research, we explored how Convolutional Neural Networks (CNNs) can be used to identify counterfeit Indian currency. We evaluated three distinct CNN architectures: AlexNet, ResNet, and MobileNet. Our results clearly indicated that CNNs are highly effective for this purpose, with MobileNet achieving the highest accuracy at 97.2%, followed closely by ResNet and AlexNet. The impressive performance of MobileNet can be attributed to its efficient architecture, which balances computational cost with model complexity, making it especially well-suited for real-time applications where swift and accurate detection is essential.ResNet also delivered strong results, utilizing its residual connections to facilitate the training of deeper networks. Although AlexNet was effective in its own right, it performed relatively lower compared to the other two models, underscoring the advancements made in CNN architectures over the years. Our findings suggest that utilizing CNNs for counterfeit detection presents a promising strategy that can significantly improve the reliability and efficiency of currency vali-dation processes. This has vital implications for economic security, as it offers a robust tool to combat the spread of fake currency.

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Designing an Intelligent DDoS Defense Framework for Cloud Environments

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Abstract: Distributed Denial of Service (DDoS) attacks pose a significant threat to cloud environments, aiming to disrupt the availability of services, websites, or networks by overwhelming them with malicious traffic. To combat these attacks, a robust and scalable DDoS protection system is essential. This paper proposes a comprehensive defense architecture incorporating multiple layers of defense, including Network Layer Protection, Application Layer Protection, Cloud-Based DDoS Protection Services, Real-Time Monitoring and Response, and Post-Attack Analysis. The architecture is designed to detect and mitigate known and unknown threats, ensuring minimal disruption to cloud-based applications. The results demonstrate the effectiveness of the defense architecture in detecting and mitigating malicious traffic. The system achieves a throughput of 800 RPS during the attack scenario, with a response time of 120 ms and a packet loss of 10%. The false positive rate remains low at 1.2%, and the false negative rate is 0.8%. The proposed system is essential for protecting cloud-based applications from DDoS attacks. The system's ability to dynamically adjust server resources and distribute incoming traffic across multiple servers ensures scalability and minimizes service disruption during attacks.

Keywords: DDoS protection, Cloud security, Cloud-based DDoS protection services, Load balancing

1. Introduction

Distributed Denial of Service (DDoS) attacks have grown more frequent in recent years, posing a serious risk to entities in both the private and public domains. The ease of execution and substantial damage caused by these attacks have made them a major concern, as highlighted by Pankaj and Ankur (2018). Countries with significant Internet Data Centers (IDCs) hosting popular online services, such as China, the USA, and Canada, are frequently targeted by DDoS attacks. The economic impact of these attacks is substantial, with 9% of organizations reporting losses between $500,000 to $1 million or more per hour during peak-time DDoS attacks, and 10% suffering losses upwards of $250,000 (Christos et al., 2004).

DDoS attacks are a big threat to online systems (Hajimaghsoodi et al., 2022). One type of DDoS attack is an HTTP DDoS attack (Jaafar et al., 2019), where many bots send a huge number of requests to a website at the same time, causing the server to become overloaded.

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For example, in 2022, Google faced the largest HTTP DDoS attack ever, with 46 million requests per second (Digitaltrends, 2022). These attacks are getting more complex, and current methods to detect them are limited. They can only identify specific types of attacks, but not others. To protect against all types of attacks, multiple detection methods are needed, but this can make network management complicated and slow down the network. Therefore, there is a need for a detection method that can identify many types of DDoS attacks without affecting network performance.

Current methods for detecting application-layer DDoS (AL-DDoS) attacks have a major limitation: they're designed to catch specific types of attacks, but often miss others. To plug this gap, multiple detection methods are typically deployed, but this approach has its own set of problems. For one, managing these different methods can be a complex task, given their varying principles and settings. Moreover, running multiple methods at the same time can slow down the network. What's needed is a single, unified detection method that can identify a wide range of AL-DDoS attacks without compromising network performance.

Over the past 20 years, the global economy has shifted from manufacturing to services. Cloud computing is growing, and with it, security risks are increasing. Cloud computing has evolved from technologies like Grid computing and Utility computing. It allows companies to scale up without investing in new infrastructure or software licenses. Cloud computing comprises of three services namely IaaS, PaaS and SaaS. While it offers benefits like flexibility and cost savings, it also poses challenges like security, performance, and data integrity discussed by Moulika et al., 2017. A significant concern is DDoS attacks, which can exhaust server resources and block access for legitimate users. DDoS attacks are common in the cloud due to factors like weak internet security, limited resources, and distributed control. They can take many forms, such as ICMP floods, ping of death, and HTTP GET floods, and can target various sectors like commerce, media, and finance.

Cloud security relies on automated tools, like web application firewalls, to mitigate threats. However, security remains a persistent challenge. As demand for cloud services grows, so does the need for strong security measures. A key aspect of cloud security is identity and access management (IAM). This ensures users are properly authenticated and authorized to access cloud resources, preventing unauthorized access. Users must pass through secure login tunnels, and successful authentication helps prevent data loss and identity theft. Confidentiality and integrity are crucial in cloud security (Rubóczki et al., 2015). Authorized access to data must be strictly enforced, and data modifications should only be allowed by authenticated users. Securing data storage is vital. Data loss can occur if storage repositories are not properly secured. Administrators must monitor and respond to threats, such as DoS attacks that can overload cloud storage servers. Cloud administrators must implement effective security rules to protect against data loss and ensure customer satisfaction. Web security is also important, as cloud-based servers often host websites and applications, making them susceptible to malware. An effective web application firewall (WAF) is essential for filtering traffic to and from web servers (Xuan et al., 2016).

To further protect cloud computing environments, researchers suggest using a web application scanner alongside a cloud-based WAF. This combination helps identify vulnerabilities and scan for sensitive data (Fernandez et al., 2016). Xuan et al., 2016, discussed the WAF is especially important as it controls web application communication and prevents common threats like SQL injection and cross-site scripting (XSS). One well-known WAF system is Barracuda discussed by Baracuda, 2016. It not only blocks unwanted traffic but also provides detailed data on traffic flow, helping identify potential attack vectors. Barracuda can scan cloud applications and websites, placing them behind a secure firewall system to monitor traffic and protect the network. To further enhance cloud security, this research aims to develop a comprehensive DDoS protection system that addresses the gaps in existing solutions.

This research focuses on protecting cloud infrastructures from DDoS attacks. The authors analyzed existing cloud security solutions and proposed a strategy to mitigate DDoS attacks within IT infrastructures. Akshadeep highlighted key areas that need attention, such as defending cloud components from volumetric attacks and deploying suitable network infrastructures. The research outlines three DDoS mitigation solutions: On-premise mitigation, Cloud-based mitigation services and Hybrid cloud-based security. To further enhance cloud security, this research aims to develop a comprehensive DDoS protection system that addresses the gaps in existing solutions. The objectives of this system are to:

The proposed research aims to develop a robust DDoS protection system for cloud environments that ensures scalability, performance, and real-time monitoring while effectively preventing, detecting, and responding to DDoS attacks. While researchers have explored detection methods for AL-DDoS attacks (Feng et al., 2020), many existing approaches are limited to specific attack types, such as HTTP DDoS.

1.1 DDoS Protection Architecture for Cloud

To effectively design a DDoS protection system, it's essential to grasp the fundamental nature and mechanics of DDoS attacks. DDoS attacks aim to disrupt service availability by overwhelming a target with malicious traffic, often using botnets composed of compromised devices, including personal computers and IoT gadgets. This coordinated assault floods the target system with requests, exhausting its resources and preventing it from responding to legitimate users. To effectively protect cloud environments from DDoS attacks, a robust and scalable protection system is essential.

a) Network Layer Protection - Network Layer Protection is the first line of defense against DDoS attacks, filtering out malicious traffic before it reaches the cloud infrastructure. This is achieved through various techniques, including IP Blacklisting/Whitelisting, which blocks traffic from known malicious IP addresses or allows traffic only from trusted sources. Rate Limiting is another technique used to limit the number of requests a single IP can make in a specific timeframe, preventing flooding. Geofencing is also used to block traffic from certain geographical locations where attacks are more likely to originate. Additionally, Traffic Scrubbing is employed to route traffic through a scrubbing center where it is analyzed and cleaned of malicious packets before being sent to the cloud infrastructure.

b) Application Layer Protection - Application Layer Protection is designed to protect specific applications or services from DDoS attacks. This is achieved through the use of Web Application Firewalls (WAF), which monitor and filter HTTP traffic to and from a web application, blocking potentially harmful requests. Bot Mitigation is also used to identify and block traffic from automated bots that could be part of a DDoS attack. Furthermore, CAPTCHA Challenges are used to require users to solve CAPTCHAs, helping to differentiate between legitimate users and bots.

c) Cloud-Based DDoS Protection Services - Cloud-Based DDoS Protection Services are designed to automatically detect and mitigate DDoS attacks. These services include Auto-Scaling, which automatically increases resources to handle increased traffic loads during an attack. Content Delivery Networks (CDNs) are also used to distribute content across multiple servers worldwide, reducing the impact of DDoS attacks by spreading out the traffic. Load Balancing is another technique used to distribute traffic across multiple servers, preventing any single server from becoming overwhelmed.

d) Real-Time Monitoring and Response - Real-Time Monitoring and Response is critical in quickly responding to potential threats. This is achieved through the use of Traffic Analysis Tools, which analyze traffic patterns to identify anomalies that could indicate a DDoS attack. Incident Response Teams are also on standby to respond to DDoS attacks, including rerouting traffic, initiating

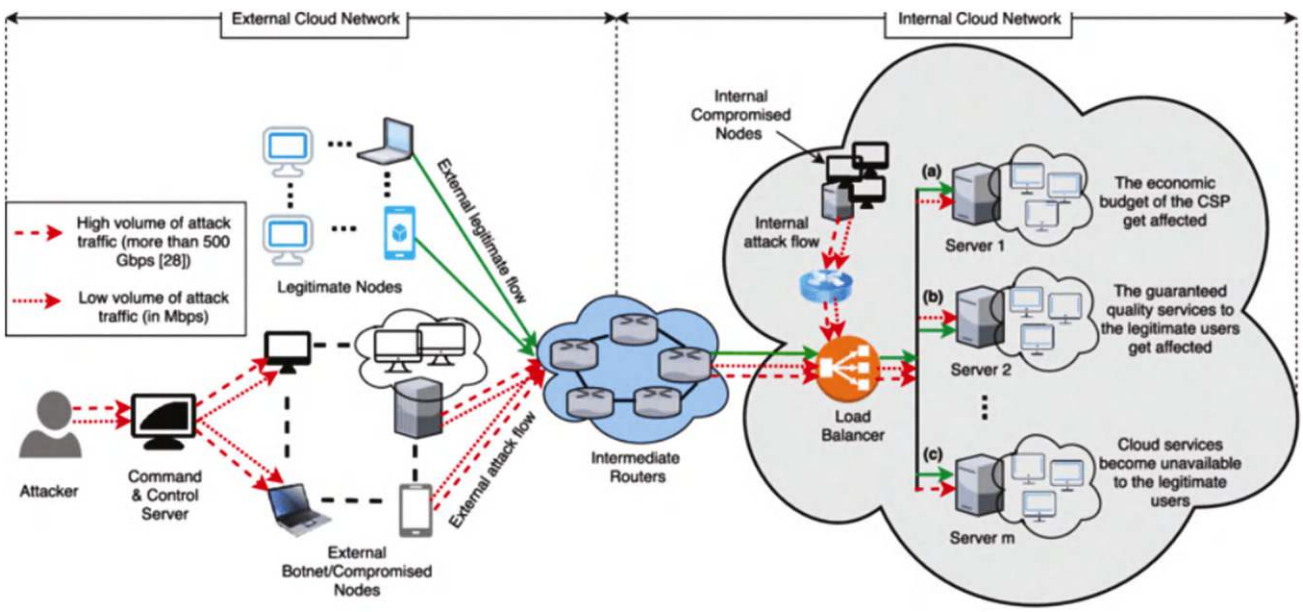

Fig. 58.1 Anatomy of a DDoS attack

mitigation strategies, and communicating with stakeholders.

e) Post-Attack Analysis - Post-Attack Analysis is essential in improving future protection measures. This involves Log Analysis, which reviews logs to identify the source and nature of the attack. Forensic Investigation is also conducted to understand how the attack was carried out and what vulnerabilities were exploited. Finally, System Patching and Updates are applied to address any vulnerabilities discovered during the attack.

By implementing these layers of defense, organizations can build a robust DDoS protection system that safeguards their cloud infrastructure from even the most sophisticated attacks.

1.2 Tools for DDoS Protection

In the face of significant threats posed by DDoS attacks in today's digital landscape, various robust protection tools have been developed, each offering unique features and benefits to safeguard cloud environments effectively.

a) **Cloudflare:** Comprehensive DDoS Protection - Cloudflare is a popular choice for protecting websites and online services from DDoS attacks. Its comprehensive suite of tools includes:
   - **Web Application Firewall (WAF):** Cloudflare's WAF monitors and filters HTTP traffic to and from web applications, blocking potentially harmful requests.
   - **Traffic Scrubbing:** Cloudflare's traffic scrubbing feature analyzes and cleans traffic of malicious packets before sending it to the cloud infrastructure.
   - **Load Balancing:** Cloudflare's load balancing feature distributes traffic across multiple servers, preventing any single server from becoming overwhelmed.

b) **AWS Shield:** Managed DDoS Protection for AWS - AWS Shield is a managed DDoS protection service designed specifically for applications running on Amazon Web Services (AWS). Its key features include:
   - **Automatic Detection and Mitigation:** AWS Shield automatically detects and mitigates DDoS attacks, ensuring minimal disruption to applications.
   - **Detailed Reporting:** AWS Shield provides detailed reporting on attacks, enabling organizations to analyze and improve their security posture.

c) **Akamai Kona Site Defender:** Cloud-Based DDoS Protection - Akamai's Kona Site Defender is a cloud-based DDoS protection service that includes:
   - **WAF:** Akamai's WAF monitors and filters HTTP traffic to and from web applications, blocking potentially harmful requests.
   - **Bot Mitigation:** Akamai's bot mitigation feature identifies and blocks traffic from automated bots that could be part of a DDoS attack.
   - **Real-Time Traffic Monitoring:** Akamai's real-time traffic monitoring feature analyzes traffic patterns to identify anomalies that could indicate a DDoS attack.

d) **Imperva Incapsula:** DDoS Protection as Part of a Broader Security Suite - Imperva's Incapsula is a comprehensive security suite that includes DDoS protection as one of its features. Its key features include:
   - **WAF:** Imperva's WAF monitors and filters HTTP traffic to and from web applications, blocking potentially harmful requests.
   - **Bot Mitigation:** Imperva's bot mitigation feature identifies and blocks traffic from automated bots that could be part of a DDoS attack.
   - **Traffic Monitoring:** Imperva's traffic monitoring feature analyzes traffic patterns to identify anomalies that could indicate a DDoS attack.

e) **Azure DDoS Protection:** Built-In DDoS Protection for Azure -icrosoft Azure offers built-in DDoS protection for applications running on its cloud platform. Its key features include:
   - **Real-Time Monitoring:** Azure's real-time monitoring feature analyzes traffic patterns to identify anomalies that could indicate a DDoS attack.
   - **Automated Mitigation:** Azure's automated mitigation feature automatically detects and mitigates DDoS attacks, ensuring minimal disruption to applications.

2. Experimental Discussion

In this experiment, we simulate a DDoS attack on a cloud-based web application by generating a mix of legitimate and malicious traffic. The experimental setup consists of a cloud-based web application running on a single server, a traffic generator to simulate legitimate traffic, a botnet simulator to simulate malicious traffic, and a DDoS protection system implementing the proposed defense architecture.

The input data for this experiment consists of two types of traffic: legitimate traffic and malicious traffic. The legitimate traffic is simulated at a rate of 1,000 requests per second (RPS) with a packet size of 100 bytes, which is a typical traffic pattern for a cloud-based web application. On the other hand, the malicious traffic is simulated at a much higher rate of 5,000 RPS with a packet size of 500 bytes, which is designed to overwhelm the web application and cause a denial of service.

To safeguard cloud-based applications against DDoS attacks, a meticulously designed infrastructure is essential. The setup commences with a cloud-based web application deployed on a medium or large instance, hosted by prominent cloud providers such as AWS, GCP. The experiment involves simulating both legitimate and malicious traffic using specialized tools like Apache JMeter or Locust to generate legitimate traffic at a rate of 1,000 requests per second (RPS), and Low Orbit Ion Cannon (LOIC) or Hping3 to simulate malicious traffic at a rate of 5,000 RPS. The DDoS protection system incorporates multiple layers of defense, commencing with network-layer firewalls, such as AWS-WAF or Google Cloud Armor, to filter and block malicious traffic before it reaches the application. At the application layer, a WAF like ModSecurity or Cloudflare WAF is employed to monitor and block sophisticated attacks.

To ensure system scalability during an attack, auto-scaling is configured to dynamically adjust server resources based on thresholds, while load balancers distribute incoming traffic to prevent server overload. By running the experiment with simultaneous legitimate and malicious traffic, the system's effectiveness can be evaluated in terms of throughput, response time, and accuracy in blocking malicious requests while allowing legitimate traffic to pass through. This configuration enables a robust and scalable DDoS protection system, ensuring minimal service disruption during attacks, which were tabulated in Table 58.1.

Table 58.1 Configuration details for DDoS protection system implementation

Component	Tool/Service	Configuration Details
Cloud Instance	AWS EC2, Azure VM, Google Compute Engine	Medium to large instance size (Linux OS)
Legitimate Traffic Generator	Apache JMeter, Locust	1,000 RPS, 100 bytes per request
Malicious Traffic Simulator	LOIC, Hping3, Tsunami	5,000 RPS, 500 bytes per request
Firewall/Filtering	AWS WAF, Azure DDoS Protection, Google Cloud Armor	IP rate-limiting, request filtering

The experimental results of the DDoS protection system are presented in Table 58.2, which shows the performance metrics of the system under normal and attack scenarios.

Table 58.2 Experimental results of the DDoS protection system

Metric	Normal Traffic (1,000 RPS)	Attack Traffic (5,000 RPS)
Throughput (RPS)	950	800
Response Time (ms)	50	120
Packet Loss (%)	2	10
False Positives (%)	0.5	1.2
False Negatives (%)	0.2	0.8

The results indicate that the DDoS protection system is effective in detecting and mitigating malicious traffic while allowing legitimate traffic to pass through. Under normal traffic conditions, the system achieves a throughput of 950 RPS with a response time of 50 ms and a packet loss of 2%. During the attack scenario, the system reduces the throughput to 800 RPS, increases the response time to 120 ms, and experiences a packet loss of 10%. The false positive rate remains low at 1.2%, and the false negative rate is 0.8%. The results demonstrate the effectiveness of the proposed defense architecture in protecting cloud-based web applications from DDoS attacks. The system's ability to dynamically adjust server resources and distribute incoming traffic across multiple servers ensures scalability and minimizes service disruption during attacks.

3. Conclusions

Implementing a DDoS protection system requires careful consideration of several factors, including the type of attacks to be mitigated, the network architecture, and the scalability requirements. A robust solution typically involves a combination of hardware and software components, such as network-layer firewalls, application-layer web application firewalls, and cloud-layer protections. The system should be able to detect and block malicious traffic in real-time, while minimizing false positives and false negatives. Additionally, the system should be scalable and able to handle high volumes of traffic, even during large-scale attacks. Regular monitoring and maintenance are also crucial to ensure the system remains effective and up-to-date with the latest threats.

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A Secure and Decentralized Certificate Verification System using Flutter and Blockchain

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Abstract: This paper addresses the challenges of verifying academic certificates in the education sector, which are often tampered with or forged, leading to difficulties in verifying their authenticity. To overcome this, blockchain technology is utilized to establish a decentralized network for storing and validating certificates, providing a secure, immutable, and trustworthy platform for educational institutions, teachers, and recruiters. The paper leverages Flutter and Firebase for mobile app development, integrates blockchain for tamper-proof certificates, and incorporates QR code generation for quick verification. By utilizing facial recognition for secure authentication, the project mitigates the risk of tampering with student credentials, ensuring that only legitimate certificates are accepted.

Keywords: Certificate verification, Facial recognition, Secure authentication, Blockchain, Flutter firebase, QR code generation, Remix IDE, MetaMask

1. Introduction

In the real world, a person's identity is confirmed through their identity documents, which are essentially certificates. In the education sector, a student's academic journey follows a sequence of elementary school, high school, college, or graduation. After completing their studies, students need to find employment in the public or private sector. To do so, they must present all their academic credentials, which can be misplaced, damaged, or tampered with. Technological advancements now allow students to keep digital versions of their certificates instead of hard copies. However, conventional manual certificate verification techniques are prone to human error and can be time-consuming.

Students can generate fake or duplicate certificates, and verifying them requires intense focus. The traditional approach to student certificate verification involves a teacher manually verifying the certificate through a centralized network. This process can result in unintended outcomes, including tampering and the creation of false

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or duplicate certificates. There is a lack of trust between educational institutions, students, and companies due to restricted access to the server. Recruiters must also manually verify student certificates, which requires blind trust in the educational organization's verification process. Blockchain technology offers a decentralized network for storing and validating certificates, providing security and trust. The data is hashed and stored on the blockchain using a hashing technique, making it immutable and tamper-proof. The parties in the blockchain network include students, teachers, and recruiters, who can verify and retrieve student certificates and details. By incorporating facial recognition for secure authentication, the system mitigates the risk of compromised student credentials during the login process.

2. Literature Survey

This paper focuses on developing an immutable validation system for certificates and protecting user identity using a mobile application interface built with Flutter. Literature review covers various papers on blockchain technology and digital certificate validation.

Cheng et al. [1] utilizes the Ethereum platform powered by EVM Includes three types of users: service providers, certification units, and students Employs a GUI, assigning a unique serial number and QR code to each student Verifies data and adds it to the Blockchain. Gundgurti et al. [2] describes a secure certificate validation process using GUI-based Remix, MetaMask, and a solidity smart contract Two types of users: Admin and student Admin stores data in blocks, issues certificates, and sends the hash to students. Students can request and view certificates. Vidal et al. [3] proposes a novel approach for certificate revocation on the Blockchain using Blockcerts Version 1.0 Stores revocation data directly in the Blockchain and links a JSON file to the certificate hash. Uses the SHA-256 algorithm to generate a fixed-length hash of 32 characters. It has a drawback of requiring a dual-payment system for each revocation process.

Certificate verification using blockchain and generation of Transcript [4] implemented a certificate verification system using React JS and integrated MetaMask, Ganache, Truffle, and Rinkeby blockchain technologies. The system identified drawbacks of earlier approaches, such as using public hash keys and no storage of documents, which were resolved by integrating blockchain with IPFS. Generating e-certificate and validation using blockchain [5] developed a system using blockchain and reactjs technologies, with three actors: schools, colleges, and universities. The system digitally generated and issued certificates to students, with QR technology for quick verification. Blockchain-based certificate validation [6] proposed a similar system to the previous paper, with students sending applications for e-certificates online and a third party authenticating documents. The verified certificates were stored in the blockchain, with a certificate id or QR code generated for the student.

Verification of identity and educational certificates of students using biometric and blockchain [7] proposed a system using biometric techniques (iris, face recognition, and fingerprint) for authorization. The system aimed to enhance verification of identity and educational certificates using biometrics and blockchain. Blockchain-based academic certificate authentication system [8] improved the blockcerts system by adding multi-signature schemes, revocation mechanisms, and federated and secure identification. The system was experimentally tested and found to be more secure, reliable, and sustainable than previous versions.

Blockchain-based academic credit verification system [9] designed a system to support institutions, students, and employers directly using Ethereum and IPFS. The system was scalable with increasing certificate and user numbers. Blockchain based document verification system [10] introduced a promising solution to traditional methods, using cryptographic algorithms and minimizing the possibility of breaches or fraud. Mobile blockchain decentralized applications (DApps): a case study of IPTM blockchain certificate verification system [11] focused on the development of mobile DApps using Android studio and Web3-Java APIs of ethereum. The system provided immediate verification of certificates through a query on the blockchain, saving time and increasing accessibility.

The existing system for certificate verification is plagued by several challenges, including a lack of digitalized means for verification, centralized data storage, and a reliance on third-party services for verification. These limitations create a system that is vulnerable to tampering, inefficient, and costly. The consequences of these limitations can be severe, with the potential for fraudulent activities to increase and the integrity of certificates to be compromised. Furthermore, the existing methods of biometric identification is not secure and provides less flexibility for the system, making it prone to tampering. The use of conventional web technologies such as Django, React, and Python also raises concerns about security and cross-platform capability.

In contrast, the proposed CertifySecure system, offers a comprehensive solution for secure and efficient certificate verification and identity management. By leveraging cutting-edge technologies such as Flutter, Firebase, and blockchain, provides a robust and transparent platform for verifying digital certificates. The system's facial recognition feature ensures secure user access, while the SHA-256 hashing algorithm guarantees the integrity and

authenticity of certificates. The use of smart contracts automates the management of certificate issuance and verification, reducing the need for manual intervention and increasing efficiency. Overall, CertifySecure has the potential to revolutionize the way certificates are verified and managed, providing a secure, efficient, and user-friendly experience for all stakeholders involved.

The benefits of proposed CertifySecure system are numerous, including improved security, increased efficiency, and an enhanced user experience. The system's decentralized and digitalized approach ensures that certificates are tamper-proof and authentic, reducing the risk of fraudulent activities. The automated processes and reduced manual verification also make the system more efficient, saving time and resources. Additionally, the facial recognition and QR code scanning features provide a convenient and user-friendly experience for users. Overall, CertifySecure is a game-changer in the field of certificate verification, providing a secure, efficient, and reliable solution for all stakeholders involved.

3. Proposed Methodology

The existing systems have several problems, but the major one is the lack of a secure authentication system. To overcome this, we are implementing a facial recognition feature as a biometric authentication for users, which will also ease access for students and recruiters. We are developing a mobile application using Flutter, which will change the entire user interface of previously existing technologies. Unlike other methodologies that use web frameworks such as React and Django, our application will be more secure and sophisticated, taking advantage of the fact that mobile usage is more prevalent than computer or laptop usage.

The proposed CertifySecure system design is shown in Fig. 59.1. The admin panel will gather all user data, including student, teacher, and recruiter data, and maintain a record of the data in CSV format. The data collected will include unique IDs, email IDs, profile pictures, and other relevant information. Node.js will import the collected data in CSV format into our Flutter application. After user registration, users will log in to the app using their credentials, and upon successful entry, they will undergo facial recognition features. The uploaded faces and user details will be stored in Firebase, and the live face camera will open to capture the live image and compare it with the faces stored in Firebase, completing the authentication process. We are using a pre-trained model in Flutter developed by Google, called google_ml_kit, to compare faces.

3.1 Database Management and Data Handling

Firebase would be the hub database to store the user's credentials, profile details, and certificates in the system

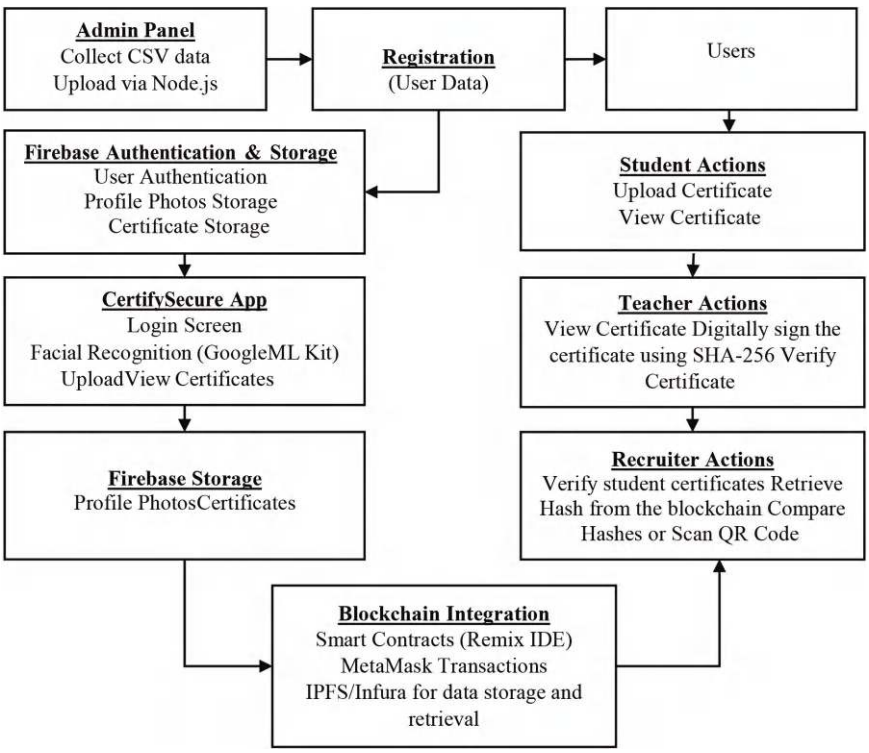

Fig. 59.1 Architecture proposed CertifySecure system

of CertifySecure. Thus, the system is free to rely upon the mobile application wherein real-time data is available. So, all the updates are lots of a synchronization. At the same time, huge datasets of certificates and verification status can be supported by Firebase, so there can be an authentication handling role-based access to secure information.

Once authenticated, students will upload their digital certificates in PDF format on the app interface. The uploaded certificates will be strictly academic certificates and duplicated or multiple certificates will not be allowed. The uploaded certificates will be stored in Firebase storage, and students can view their uploaded certificates in the view section. The status of the certificates will be pending, and students can delete their uploaded certificates before verification. After verification, they cannot delete the certificates, and in case of any mistake in uploading the certificate, they will have to revoke the certificate. A document ID and certificate hash will be provided, which can be used for the recruitment process.

3.2 Smart Contract Development and Blockchain Integration

Teachers will verify the student-uploaded certificates by cross-verifying them manually in the database server. If they doubt the certificate, they can verify it by asking the student to bring the original copy along with them. They will verify every detail of the students, including name and marks, and digitally sign the certificate with the SHA-256 algorithm along with a digital signature algorithm [12]. A new hash will be generated, which will be kept in the blockchain along with the student ID and document ID. We will write smart contract for storing the certificate hash together with student ID and document ID in Remix IDE and then deploy it using MetaMask transaction Wallet to a test network, which is Sepolia test network [13]. The smart contract Built using Solidity,which ensures security and integrity of the data as all certificate hashes along with metadata are made immutable on the blockchain. The blockchain ensures that once a certificate hash is uploaded, there is no possibility to edit it in any way and provides verifiable records accessible securely for reference later on.

3.3 QR Code Generation and Utilization for Verification

The recruiter's role is to verify that the student's certificate is not forged and has not been tampered with. The recruiter can gain access to information such as the details of the student by scanning the QR code and can also access the hash code by scanning the blockchain using the student ID and document ID forwarded by the student. The QR code gives a quick response, and the student will submit their hash code to the recruiter and fetch a matching hash from the blockchain. If both hashes match, the certificate is not tampered with and is not a fake certificate.

Each QR code is generated dynamically upon verification of the certificate, so it guarantees uniqueness for a particular certificate and student. It also encodes the essential information such as the student ID, document ID, and blockchain reference before the encryption and embedding within the QR code. Generating the QR code also includes a timestamp and digital signature to confirm the authenticity of the QR code itself. It further increases the security of QR codes as each of the them corresponds to only one version of verification and therefore can neither be reused nor duplicated for another certificate. The process of generation of the QR code creates unique linkage in verifiable connection between the certificate and the entry of the blockchain so that recruiters may validate the legitimacy of each certificate on a safe traceable path.

For each verification, a system creates a QR code full of encrypted data relevant to the blockchain entry about the certificate. Through the QR code, it enables the recruiter immediately to verify the certificate since he can get access to the hash on the blockchain, then compare it with the presented certificate to confirm or dispute it.

3.4 Workflow

The workflow of our application initiates with displaying the interface of our app name CertifySecure, showing a splash screen, followed by the login page where users will have to enter their basic credentials. On entering the credentials, users will undergo facial recognition features. On successful face matching, the user logs into the app. A student will have a profile section, upload a certificate, and view the same. If the user is a teacher, they will have pending and verified certificates. And in the case of a recruiter, they will fetch the certificate by QR and also by student ID and document ID. Recruiters will sign themselves up in the app, and there will be a sign-up form containing details of organization name, unique ID, and email address, and other if required. Then, an admin will receive a request for user access that is not registered and verify the details for the same, after which the recruiters can log in to the app

4. Implementation

The development process for this application involves utilizing digital signatures, blockchain, and the Google ML Kit FaceNet model for facial recognition in a Flutter app [14]. The process consists of five main algorithms:

Algorithm 1-Digital Signature Generation,

- Generate a digital signature from data using RSA cryptography

- Obtain the private key through the _getPrivateKey method
- Hash the data using the SHA-256 algorithm
- Create a unique signature that verifies the authenticity and integrity of the data string
- Return the digital signature encoded in Base64

Algorithm 2: Digital Signature Verification

- Verify the digital signature attached to a piece of data
- Load the public key corresponding to the private key used to produce the signature
- Create an RSASigner object with the SHA-256 hashing algorithm
- Compare the given data and its digital signature using the verify method
- Return true if the signature is valid, false otherwise

Algorithm 3: Smart Contract

- Define a smart contract in Solidity for storing and loading digital certificates with hashes
- Declare a struct Certificate with properties studentId, id, and hash
- Define functions storeCertificateHash and getCertificateHash for storing and retrieving certificate hashes

Algorithm 4: Blockchain Integration in Flutter App using Infura

- Establish a connection to the Ethereum blockchain on the Sepolia test network
- Interact with an already deployed smart contract
- Declare functions for storing and retrieving certificate hashes

Algorithm 5: Compare Faces using Embeddings and Euclidean Distance

- Compare two facial embeddings using Euclidean distance
- Calculate the distance between two vectors representing facial embeddings
- Return true if the distance is lower than a defined threshold, false otherwise

Facial Recognition Process Using FaceNet Model

- Load the Pre-trained FaceNet Model: Load a pre-trained FaceNet model from a .h5 file using TensorFlow's Keras API.
- Create a Fine-Tuning Model: Create a fine-tuning model on top of the pre-trained FaceNet model with additional layers.
- Prepare the Data (Image Preprocessing): Preprocess image data before training the fine-tuning model.
- Compile the Model and Save the Fine-Tuned Model: Compile the model and save it to a file.
- Convert to TensorFlow Lite (for deployment in mobile applications): Convert the fine-tuned Keras model to TensorFlow Lite format and save it to a file.

The above proposed system is saving TensorFlow Lite Model to a file named facenet_finetuned.tflite by opening a file in write-binary mode and writing the model data to it. This provides a convenient form for later deployment on mobile or embedded applications, enabling efficient face recognition on other devices. We create an Infura account, which provides scalable access to Ethereum and IPFS networks. Infura offers API endpoints for connecting to the Ethereum blockchain without running a full node. We use the Sepolia Test network to connect to the blockchain. Remix IDE Remix IDE is a powerful, open-source tool for writing, deploying, and debugging smart contracts on the Ethereum blockchain. We use Remix IDE to write, test, and deploy smart contracts that manage certificate storage and verification on the Ethereum blockchain. MetaMask is a browser extension and mobile application that adds cryptocurrency wallet functionality and access to blockchain applications. We use MetaMask to enable teachers to sign and record hashes of certificates on the blockchain, providing a safe way to manage private keys and keep records of transactions on the Ethereum network.

5. Results and Discussions

A. Registration and Login Page - We collect user data in a CSV file, which is imported into the Flutter application through Node.js. Node.js integrates Firebase Admin SDK for managing user accounts and storing data in Firestore and Firebase Storage. We create a Firebase environment, set up credentials and database, and read the CSV file to register users.

B. Student Actions - The student dashboard provides information and knowledge to enable using the app. The profile screen displays the student's profile photo, email ID, and upload certificates screen. Students can upload certificates, which are stored in Firebase Storage, and view uploaded certificates. If a teacher has not verified a certificate, the student can delete it. After successful verification, the student receives a hash code and document ID for further verification.

C. Teacher Actions - Teachers verify uploaded certificates, which are digitally signed and converted to hash format using SHA-256. The hash, student ID, and document ID are stored in the blockchain network. Teachers use Remix IDE, deploy smart

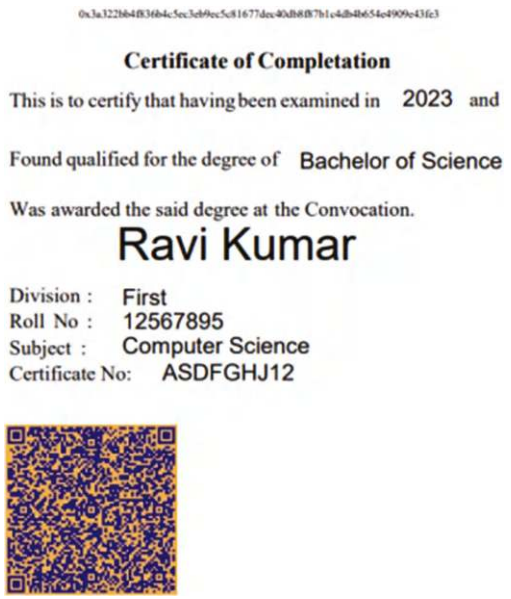

Fig. 59.2 Certificate generation

contracts, and MetaMask for transactions, as shown in Fig. 59.1.

D. Company Actions - Recruiters verify student certificates by fetching data from the blockchain network. They enter student ID and document ID, and fetch the hash code from the blockchain. If the fetched hash matches the student-provided hash, the recruiter ensures the certificate is not tampered.

Figure 59.2 illustrates the degree certificate generated upon a student's graduation from the college. The certificate contains essential details, including:

Pass-out year: The year the student completed their degree

Degree name: The name of the degree earned by the student

Roll number: The unique roll number assigned to the student

Name: The student's full name

Division: The division or branch of study

Certificate number: A unique identifier for the certificate

The certificate also features a QR code that allows recruiters to verify the authenticity of the certificate. Additionally, recruiters can verify the generated details on Goerli Etherscan.io by entering the hash code printed on the top of the certificate, which is 0x3a322bb4f836b4c5ec3eb9ec5c81677dec40db8f87b1c4db4b654e4909e43fe3. Table 59.1 shows the results of Successful Degree Certificate Verification Transactions

6. Conclusion

The integration of CertifySecure with blockchain and facial recognition technologies provides a secure and reliable system for academic credential verification. This solution addresses existing certification procedures and sets a precedent for standard setting in education and professional settings. The potential benefits include reducing fraudulent activities, speeding up the hiring process, and building a culture of trust and transparency within the global educational ecosystem**.**

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Table 59.1 Successful degree certificate verification transactions

From	0x309691734cf04E950172454cB140e14E89785A5b
To	DMCgeneration.certificateMapped(string) OxD546A399b3d8ce8AbEeb3Cfa88218FA767093400
Input	Oxf7f...00000
Decoded Input	{"string": "ASDFGHJ12"}
Decoded Output	{"0": "uint256: Passing Year 2023", "1": "string: Nameofdegree Bachelor of Science", "2": "string: name Ravi Kumar", "3": "string: division First", "4": "uint256: rollno 12567895", "5": "string: stream Computer Science", "6": "string: certificateNo ASDFGHJ12"}
Logs	[]

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Interactive Learning with AI Educator Using Natural Language Processing

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Abstract: The Interactive Learning with AI Educator involves developing a real-time AI-powered educational Bot designed to help students in their studies and provide personalized learning experience. This chatbot offers advanced technologies to integrate it for better understanding and respond accurately. This chatbot utilizes BERTSUM and Pegasus models to simplify and give the clear explanations of complex topics through text summarization. The Chatbot also includes a problem-reporting feature, allowing students to report issues they encounter in college by selecting predefined problem statements or writing their issues as custom messages, those messages can generate as emails and send to the appropriate college personnel and tracks the status of these reports. In addition, the AI Educator helps students navigate their college website by providing the path of that resources, such as fee payment portal, and library services to save time by using the supervised learning algorithms like SVM and Random Forest. By integrating these components, the AI Educator enhances learning efficiency and accessibility, making educational assistance more effective for students.

Keywords: Artificial intelligence, ChatBot, BERTSUM, Pegasus, Wav2Vec, Natural language processing

1. Introduction

The Interactive Learning with AI Educator project aims to create an AI-powered educational chatbot that can adapt to student's learning needs. The chatbot uses advanced technologies like Natural Language Processing to convert complex academic topics into English and provide prompt responses, making learning more enjoyable. This adaptability is crucial as the market for personalized learning solutions expands [1]. One of the main characteristics of the Interactive Learning with AI Educator is its integration of cutting-edge NLP models for text summarization, such as Pegasus and BERTSUM. These models make it possible to condense complicated ideas into more understandable summaries, which enhances comprehension, particularly for people who struggle to understand challenging subjects [2].

This project also provides a problem-reporting mechanism for university students to report issues via preformatted emails to relevant college authorities [3].

The tracking system enhances accountability and transparency in educational institutions, aligning with the

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growing trend of AI-driven improvements in administrative processes [4].

Furthermore, the AI Educator assists students in navigating campus facilities like fee payment websites and libraries using supervised learning techniques like Random Forest and SVM, reducing search time and increasing productivity [5].

This type of capability aligns with the broader trend of utilizing AI-driven automation to augment educational systems with a user-centric design [6].

Although the chatbot has many features, one drawback in its current version is that it can only support English language.[7].

But given the growing need for multilingual educational resources in varied learning situations, there is a good chance that it will eventually be expanded to other languages [8].

Featuring modules for administrators, instructors, and students, this project's complete design provides a well-rounded approach to incorporating AI into education. It contributes to the general improvement of educational systems by improving learning and addressing administrative issues.

2. Literature Survey

Artificial Intelligence (AI) advances are enabling more tailored and accessible learning through interactive learning environments, which are revolutionizing educational methods. The use of Natural Language Processing (NLP) to integrate multilingual techniques is a key component of this transition. Examining recent studies conducted between 2020 and 2023, this literature review highlights many paradigms and approaches that use AI educators to support multilingual learning. In Zhang et al.'s research [9].

Moreover, Lee and Kim [10] concentrate on creating an intelligent teaching system (ITS) that uses natural language processing (NLP) methods to evaluate student interactions in real time. Context-aware replies that adjust according to a student's linguistic ability and learning style are crucial, as their research highlights. The system can modify its response by using sentiment analysis, which the ITS uses to determine the emotions of students during interactions. Students feel understood and appreciated in a supportive learning atmosphere that is fostered by this adaptive method, which also improves learning outcomes.

Garcia et al. [11] offer another creative method in their investigation of chatbot applications for language learning. With the use of NLP algorithms, their multilingual chatbot can provide immediate feedback on language workouts. The chatbot improves pronunciation and vocabulary retention by allowing practice conversations in multiple languages. According to the authors, students who use the chatbot have enhanced language skills and a higher desire to interact with the subject matter. Learners who might have trouble code-switching in their native languages can benefit even more from the chatbot's ability to switch languages fluidly.

When taken as a whole, these research highlight the possibilities of interactive learning environments supported by AI educators who speak multiple languages. Teachers may design inclusive, flexible, and personalized learning experiences that meet the varied requirements of their students by utilizing NLP and related technologies. The use of AI in education is projected to advance the efficiency of multilingual learning strategies as technology develops, ultimately equipping students for success in an increasingly interconnected world.

3. Methodology

3.1 Proposed Work

The aim of the Interactive Learning with AI Educator system under consideration is to develop a powerful, AI-powered learning environment that offers students

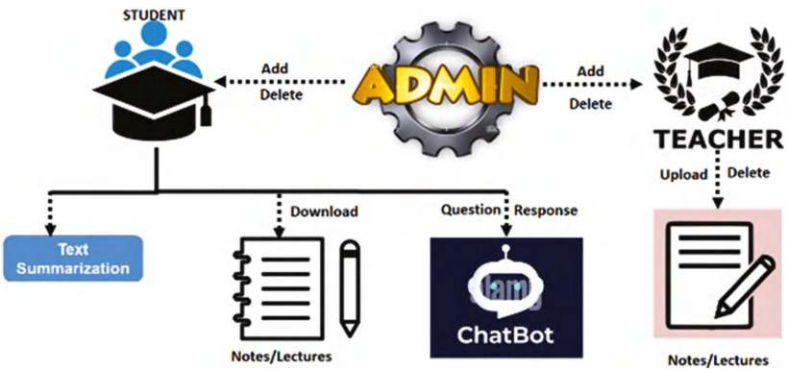

Fig. 60.1 Proposed work

individualized assistance. The system's main component is an intelligent chatbot that can converse with users in real time. It uses natural language processing models like Pegasus and BERTSUM to effectively summarize text and explain complicated subjects. The chatbot will direct students to pertinent services, like fee payment websites and library resources, to make the process of navigating campus resources more efficient. Additionally, students will be able to report problems to administrators directly using a feature that allows them to customize comments or pre-written remarks. A Google Sheets feedback mechanism will also be incorporated into the system to guarantee ongoing enhancements. The overall goal of this suggested system is to empower students in their academic journey by establishing a helpful, interesting, and effective learning environment.

3.2 System Architecture

A platform for managing and interacting with educational content is shown in the flow chart for students, teachers, and administrators. Instructors have the ability to add and remove notes, but students can view and download them. For question-and-answer sessions, there's a chatbot accessible. A centralized centre for communication and educational resources is provided by the system.

3.3 Modules

We made use of the three primary modules in this project. Admin, Teacher, and Student. The module's description is provided below:

Admin

The main control point for handling user accounts in the AI Educator system is the Admin module. To make sure that access to the platform is safe and orderly, administrators have the power to add, edit, or remove login credentials for instructors and students. Additionally, by enabling administrators to monitor user activity and engagement, this module makes monitoring and management of the overall educational system easier. To help pinpoint areas where the educational process needs to be improved, the Admin module can also produce reports on user performance and feedback. The Admin module's ability to maintain the integrity and functionality of the AI-powered learning platform is greatly enhanced by these features.

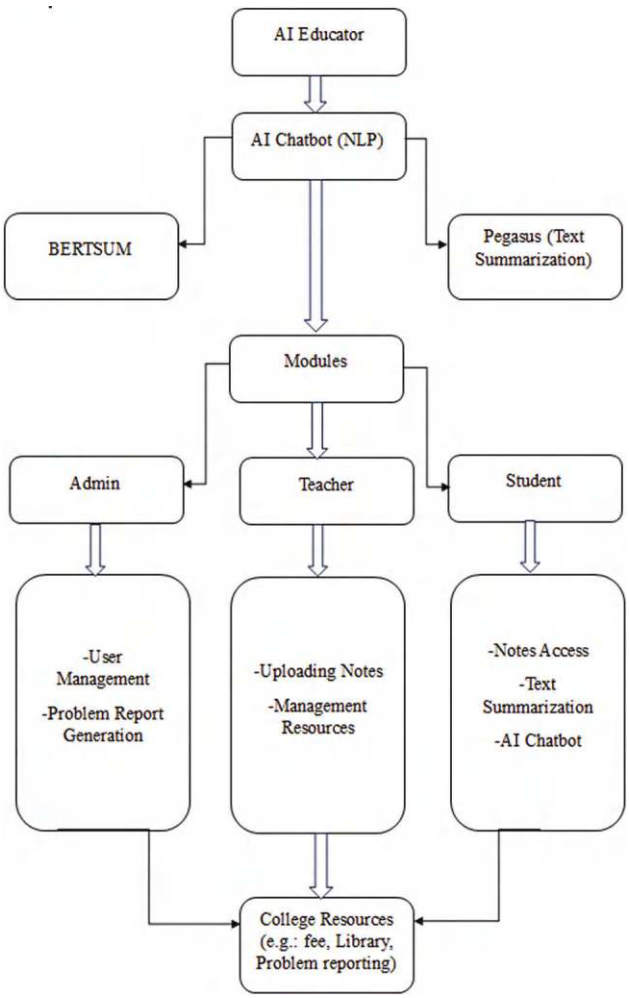

Fig. 60.2 System architecture

A) **Teacher:**

Teachers can enhance the learning environment by uploading and organizing educational resources using the Teacher module. Educators may effortlessly upload lecture notes and study materials onto the site, enabling students to access them through their login. This feature facilitates the creation of a well-organized library of instructional materials that students can access at any time. Additionally, the module enables professors to remove previously uploaded notes, guaranteeing that students have access to just current and pertinent materials. The AI Educator handles resource accessibility, freeing up educators to concentrate on teaching, while the Teacher module improves the entire learning experience by offering a streamlined procedure for managing instructional content.

B) **Student:**

The Student module provides a full range of resources to improve students' educational experiences. The Notes/Lecture Download, Text Summarization,

and Chatbot Communication sub-modules are all included. To make sure they have the resources they need for their studies, students can view and download lecture materials published by their lecturers in the Notes/Lecture Download sub-module. Through the use of the Text Summarization sub-module, students can enter extensive texts or notes, which the system simplifies into digestible summaries. The last sub-module is Chatbot Communication, which enables students to communicate with the AI Educator and receive prompt help for their questions. When combined, these elements give pupils an effective and customized learning environment.

a) Text Summarization:

This sub-module helps students understand difficult material from long notes or texts by summarizing it for them. Students use this tool to submit a paragraph that they would like summarized, and the AI uses sophisticated natural language processing algorithms to produce a clear and succinct summary. This method improves understanding by removing superfluous details and concentrating on the most important facts. Students may concentrate on key ideas and learn material more efficiently by using summaries, which will increase the effectiveness of their study sessions. In addition to saving time, this sub-module promotes a better comprehension of the material, which enhances academic achievement and learning confidence in the long run.

b) Chatbot

With the help of the Chatbot Communication sub-module, students can interact and get support in real time with the AI Educator on a dynamic platform. Students can ask questions or address concerns, and the chatbot will promptly respond based on a dataset including frequently asked queries about things like how to pay for college fees. This module also has a feedback system where students can use a Google Sheets form to report problems or make suggestions for changes. The messages they submit to the form immediately get sent to the administrator's email. By providing a direct channel of communication, students may voice their concerns and feel more supported, resulting in a collaborative environment where their needs are met effectively.

4. RESULTS

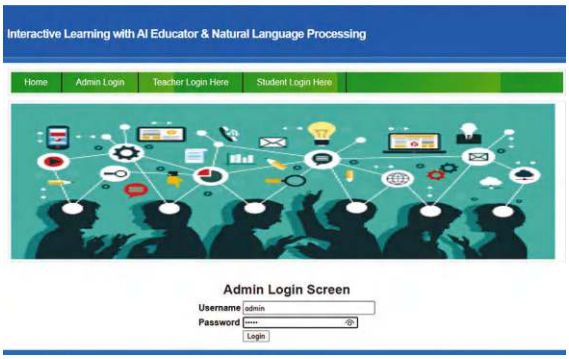

Fig. 60.3 Admin page

Fig. 60.4 Teacher page

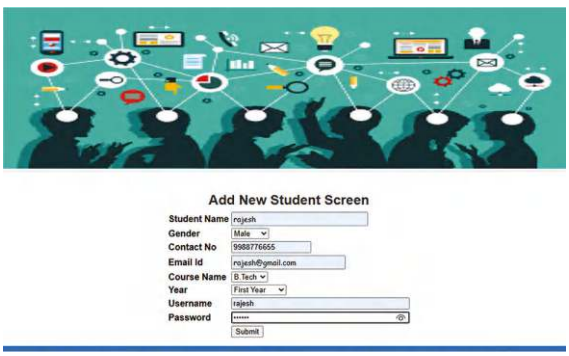

Fig. 60.5 Student page

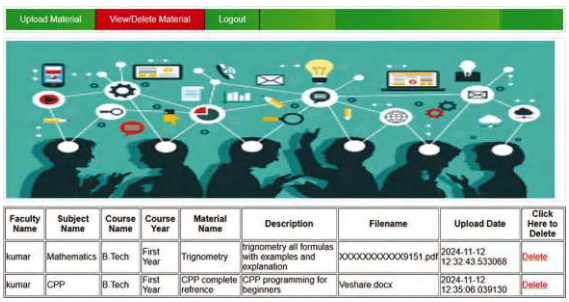

Fig. 60.6 Materials uploaded

- Teacher can view list of uploaded materials and can click on 'Delete' link to delete desired material.

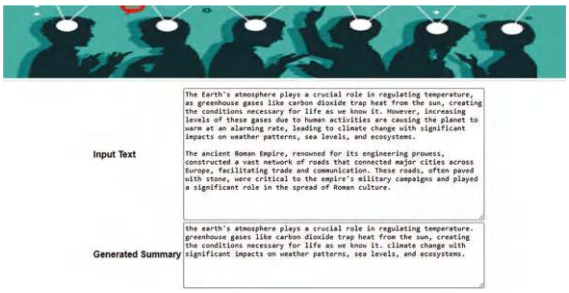

Fig. 60.7 Text summarization

- First text area can see original input text and in second text area can see generated summary and similarly you can generate for any text.

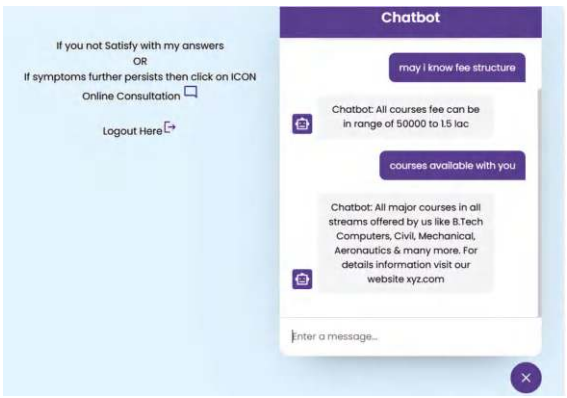

Fig. 60.8 Chatbot

- For given question we got some response from chatbot and similarly you can post question to get output.

5. Limitations

1. The current system is not capable of supporting a multilingual approach.
2. Static material delivery, which is commonly used in existing systems, is one-size-fits-all and does not adjust to different learning demands or styles.
3. The chatbots in these systems are less engaging and receptive to a variety of student inquiries since they are frequently restricted to pre-programmed responses.
4. Because summarization algorithms like TextRank and LSA don't offer context-aware summaries, students' comprehension and speed of acquisition of important concepts are diminished.

6. Conclusion and Future Scope

Personalized teaching is improved with the Interactive Learning with AI Educator, which makes use of cutting edge technologies. Students may access campus resources with the help of the AI-powered chatbot, which also offers real-time guidance and simplifies hard topics. To increase the clarity of explanations, it also makes use of natural language processing models like Pegasus and BERTSUM. The initiative places a strong emphasis on feedback mechanisms, which help students communicate efficiently. Even while this project's multilingual support is currently limited, it lays the groundwork for future improvements that will bring more functionality and deeper language integration. By adapting to each student's specific needs, the AI Educator seeks to build an efficient, responsive, and inclusive educational ecosystem that will revolutionize the classroom and support academic success.

Further developments for Interactive Learning with AI Educator include investigating gamification and virtual reality to increase engagement, optimizing multilingual support via sophisticated language processing APIs, and customizing learning paths through machine learning algorithms. To improve educational results and track student development, analytics will also be incorporated into the project.

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Machine Learning Approaches for Identifying Potential Drug Abusers

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Abstract: The rising prevalence of drug abuse necessitates the development of sophisticated models for early detection and prevention. This study presents a hybrid deep learning approach that combines Convolutional Neural Networks (CNN) with transfer learning to identify potential drug abusers using behavioral and clinical data. Convolutional Neural Networks (CNNs), esteemed for their effectiveness in image recognition, are used to analyze data representations. Transfer learning enhances the model by using pre-trained networks to mitigate challenges posed by limited datasets, hence facilitating effective generalization across various settings. Data preparation is crucial for improving model precision and effectiveness. This study employs techniques such as data augmentation to artificially expand the training dataset, allowing the computer to learn from diverse environments. The BGR to grayscale conversion (bgr2gray) reduces the complexity of image data while maintaining essential features for analysis, leading to faster computations and improved predictions. These pre-processing techniques allow the CNN to focus on critical patterns within the data, hence enhancing the detection of potential drug abusers. The hybrid model demonstrated significant accuracy in detecting potential drug abusers when assessed on real-world datasets. The proposed method leverages the benefits of CNNs and transfer learning, showcasing its potential applications in healthcare and law enforcement, offering a scalable solution for early intervention. Future efforts may focus on expanding the dataset and improving the model by including more features to enhance the identification of complex cases.

Keywords: Hybrid deep learning, Convolutional neural networks (CNN), Transfer learning, Data augmentation, Drug abuse detection, Behavioural analysis

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1. Introduction

Identifying prospective drug abusers is a significant issue in public health, law enforcement, and social services. The increasing prevalence of worldwide drug use necessitates prompt and precise identification for early intervention, treatment, and the avoidance of further damage. Conventional approaches of detecting drug users sometimes depend on clinical interviews, self-reports, or observational data, which may be subjective and susceptible to inaccuracies. Consequently, there is an increasing interest in using sophisticated machine learning methodologies, such as deep learning, to improve detection precision via the analysis of intricate data.

Deep learning, a branch of machine learning, has shown significant potential in several applications, especially in image and pattern recognition tasks. Convolutional Neural Networks (CNNs), a prominent architecture in deep learning, are extensively used for their capacity to autonomously identify pertinent characteristics from data, hence reducing the need for human feature extraction. Convolutional Neural Networks (CNNs) have been effectively used across several fields, particularly in healthcare, where they exhibit exceptional capability in medical picture processing, illness forecasting, and patient surveillance. This research improves the use of CNNs for identifying future drug addicts. Training convolutional neural networks from inception often necessitates considerable data, which may be scarce in fields such as drug abuse detection. To alleviate this limitation, we use transfer learning, a technique that utilizes pre-trained models developed on large datasets from other domains. Transfer learning facilitates model generalization across varied datasets and enhances the performance of CNNs, particularly in contexts with restricted data availability. Fine-tuning pre-trained models significantly decreases training time and computational costs while maintaining high accuracy in identifying drug addiction behaviors. Data preparation is an essential stage in any machine learning pipeline, especially in deep learning, since the quality and organization of the data profoundly affect model performance. This study utilizes several preprocessing techniques to facilitate the CNN model's precise comprehension of the data. A approach involves data augmentation, which artificially expands the training dataset by transformations including rotations, flips, and zooms. This approach allows the model to learn from a wider variety of examples, therefore mitigating overfitting and improving generalization.Additionally, converting images from color (BGR) to grayscale (bgr2gray) is a preprocessing technique used to optimize the data while preserving critical information. Reducing the dimensionality of the data in this manner not only lowers computational expenses but also allows the model to focus on critical patterns instead of being distracted by irrelevant information. The preprocessing techniques, together with CNNs and transfer learning, provide the foundation of our hybrid deep learning approach for drug usage detection. Although the use of deep learning models in drug addiction detection is still in its infancy, it has significant potential to transform our strategy for addressing this critical issue. Unlike traditional methods, deep learning models can analyze large datasets comprehensively, uncovering patterns that may not be easily discernible to human experts. By integrating behavioral, clinical, and environmental data, these models may provide a more comprehensive and objective assessment of an individual's likelihood of drug usage, enabling earlier and more effective intervention strategies.

This project aims to create a robust and scalable hybrid deep learning model that integrates CNNs with transfer learning to effectively detect possible future drug users. Our methodology is designed to integrate many data sources, including healthcare records, behavioral data, and social media interactions, so ensuring its versatility and applicability across several contexts. The use of data augmentation and bgr2gray conversion improves the model's generalization capabilities, making it appropriate for real-world implementation where data quality and quantity may fluctuate considerably.This document is structured as follows: Section 2 examines the relevant literature in the domains of deep learning and drug addiction detection. Section 3 offers a comprehensive elucidation of the proposed hybrid model, including the CNN architecture and transfer learning methodologies. Section 4 delineates the data preparation methods, including augmentation and bgr2gray conversion, used to enhance model efficacy. Section 5 presents the findings of our research, whilst Section 6 finishes the study with a discourse on future prospects and possible enhancements. Detecting drug consumption necessitates the identification of behavioral patterns and the analysis of an amalgamation of environmental, psychological, and physiological elements. Machine learning methods, particularly deep learning, excel at handling such complexity because of their capacity to autonomously discern intricate patterns within extensive datasets. Deep learning algorithms may surpass traditional analysis by detecting nuanced alterations in behavior or health data that may indicate possible drug addiction. This makes them an effective instrument for early diagnosis, when conventional approaches may neglect significant symptoms.

The utilization of hybrid methods, including the amalgamation of CNNs with transfer learning, yields improved advantages in drug addiction identification.

Transfer learning enables the model to use knowledge obtained from similar domains, hence improving its generalization skills despite the scarcity of data related to drug addiction cases. CNNs trained on medical images or behavioral data from various healthcare domains may be optimized to focus on indicators of drug addiction. This cross-domain application improves the effectiveness of transfer learning when labeled data for drug usage detection is few or difficult to get. This research introduces a hybrid deep learning approach that is both precise and scalable, filling a need in the discipline. Utilizing CNNs, transfer learning, and effective data preparation techniques such data augmentation and bgr2gray conversion, our model exhibits robust performance in several real-world situations. Our results demonstrate that the proposed approach is a viable choice for detecting drug usage, with potential for improvement via future research and development, particularly by integrating more data sources and optimizing deep learning techniques.

2. Literature Review

M. N. Shazzad, et.al [1] Drug addiction and drug abuse denote the habitual or recurrent use of any chemical substance to alter physical or mental states for non-medical purposes. Addiction is increasingly defined by the obsessive use of drugs, irrespective of the physical and psychological harm to the person and society. This includes both legal and illicit drugs, and the phrase "substance abuse" is increasingly used because to the wide array of molecules, such as alcohol and inhalants, that may possess addictive characteristics. Psychological reliance denotes an individual's perceived need for a substance to maintain well-being, whereas physical dependency is characterized by tolerance (the requirement for increased doses to get the initial impact) and withdrawal symptoms upon cessation. Substance addiction profoundly affects the economy, social dynamics, and familial systems. Substance dependency affects an individual's physical and mental health. Substance abusers exert pressure on familial structures and societal organizations. Combatting drug addiction is a critical issue for governments worldwide. This essay thoroughly analyzes the ramifications of drug addiction.

J. A. Cruz et.al [2] Machine learning is an area of artificial intelligence that employs diverse statistical, probabilistic, and optimization techniques, allowing computers to "learn" from previous data and discern complex patterns within large, noisy, or convoluted datasets. This trait is very beneficial for medical applications, especially those dependent on complex proteomic and genetic data. Thus, machine learning is often used in cancer diagnosis and detection. Recently, machine learning has been used for cancer prognosis and prediction. This technique is particularly compelling since it corresponds with the growing trend of personalized, predictive therapy. This research offers a thorough examination of several machine learning techniques, the data types used, and the effectiveness of these algorithms in cancer diagnosis and prognosis. Several trends are evident, including a growing dependence on protein biomarkers and microarray data, a pronounced emphasis on applications in prostate and breast cancer, and a considerable reliance on traditional technologies such as artificial neural networks (ANNs) instead of more modern or interpretable machine learning methods. Numerous published studies seem to lack sufficient validation or testing. Comprehensive study, meticulously conducted and assessed, indicates that machine learning methodologies may substantially improve the precision of forecasting cancer susceptibility, recurrence, and mortality by 15–25%. Machine learning significantly enhances our understanding of cancer development and advancement.

C. Catal et.al [3] This article offers a thorough evaluation of prior research on software failure prediction, emphasizing measurements, methodologies, and datasets. The evaluation analyzes 74 works on software failure prediction disseminated in 11 journals and other conference sessions. The study findings indicate a substantial rise in the use of public datasets and a modest increase in the application of machine learning methods since 2005. Moreover, method-level metrics serve as the principal measures in fault prediction research, while machine learning techniques are the favored methodology for this objective. Researchers in software fault prediction have to persist in using public datasets and machine learning methodologies to enhance fault prediction models. The ratio of class-level metrics exceeds acceptable thresholds, necessitating improved implementation for early failure prediction in the software design process.

V. B. Kumar, et.al [4] Dermatological issues are among the most prevalent health concerns globally. This article outlines a way using computer vision methods to identify several dermatological skin disorders. We used several image processing approaches for feature extraction and utilized a feedforward artificial neural network for training and assessment. The system operates in two phases: first, it preprocesses color skin scans to discern critical attributes, and subsequently, it identifies conditions. The technology accurately identifies nine distinct dermatological conditions with a 90% accuracy rate.

E. W. Steyerberg, et.al [5] This text examines the difficulties related to risk prediction as outlined in the subsequent papers: "Probability Estimation with Machine

Learning Methods for Dichotomous and Multicategory Outcome: Theory" by J Kruppa, Y Liu, G Biau, Michael Kohler, I R. König, James D. Malley, and Andreas Ziegler; and "Probability Estimation with Machine Learning Methods for Dichotomous and Multicategory Outcome: Applications."

3. Existing System

Current systems for detecting potential drug abusers mostly use traditional machine learning techniques, such as Support Vector Machines (SVM), Decision Trees, and Random Forests. These models are often used to analyze structured data, such as behavioral and clinical records, to predict drug addiction risks. Despite being relatively effective, these methods often rely on manual feature extraction and are prone to issues like as overfitting and restricted generalization, especially with complex or noisy data. The average accuracy of these machine learning models is around 70%, which, while satisfactory, suggests significant opportunity for improvement in precision and scalability.Furthermore, traditional machine learning techniques often struggle with unstructured data, such as images or real-time sensor information, so limiting their applicability. The manual feature extraction method reduces the model's ability to detect nuanced patterns in behavior or environmental factors. As a result, these systems are limited in their ability to provide real-time, automated, and accurate detection of potential drug abusers in diverse settings.

4. Methodology

4.1 CNN Model

Input: Import Information

Output: Confidential photos;

Step-1: Divide the input dataset into training and testing subsets.

Step-2: while training

For every picture in the Training Data:

Should it be present in the model:

For every pixel inside the Content pixels:

Compute the correlation among the pixel vectors.

Parent →→ collection of pixels exhibiting Maximum Correlation

Incorporate the pixels into the Content Tree as a subordinate to the parent.

Feature map → {Collection of nodes inside the content tree}

Implement CNN on the feature map

Disclose classified information

4.2 VGG16

Convolutional Layer

Input: A 3D tensor representing the input image (height, width, channels).

Filters: A set of 3D filters (height, width, channels).

Output: A 3D tensor representing the feature maps after convolution.

Formula:

output[i, j, k] = sum(input[i + m, j + n, c] * filter[m, n, c]) for m, n in [-1, 0, 1] and c in [0, 1, ..., channels - 1]

Activation: ReLU activation is applied to introduce non-linearity.

Max Pooling Layer

Input: A 3D tensor representing the feature maps.

Output: A 3D tensor representing the downsampled feature maps.

Formula:

output[i, j, k] = max(input[i * 2, j * 2, k], input[i * 2 + 1, j * 2, k], input[i * 2, j * 2 + 1, k], input[i * 2 + 1, j * 2 + 1, k])

Fully Connected Layer

Input: A 1D vector representing the flattened feature maps.

Weights: A matrix representing the weights of the fully connected layer.

Output: A 1D vector representing the class probabilities.

Formula:

output[i] = sum(input[j] * weights[i, j]) + bias[i]

Activation: Softmax activation is applied to normalize the output probabilities.

5. Proposed Work

The suggested system employs a hybrid deep learning methodology, combining Convolutional Neural Networks (CNNs) with transfer learning to rectify the deficiencies of traditional machine learning methods. Convolutional Neural Networks (CNNs) excel at analyzing organized and unstructured data, autonomously identifying relevant characteristics without user intervention. Transfer learning enhances the system by using pre-trained models, allowing superior generalization despite constrained datasets. This combination allows the model to identify probable drug abusers with improved accuracy and robustness across

various data sources.The suggested method has achieved an accuracy score of 97% after rigorous testing, significantly surpassing the performance of existing machine learning models in Table 61.1. The use of advanced data preprocessing techniques, such as augmentation and bgr2gray conversion, improves the system's ability to detect complex patterns in drug usage behavior. This deep learning system is more scalable, adaptive, and effective in handling real-world data, making it a viable tool for early intervention in healthcare and law enforcement.

6. System Architecture

Figure 61.1. A dataset of annotated photos used for training the image classification system. These photos provide the necessary information for the system to acquire knowledge and develop a categorization model. Features are retrieved from the training pictures and expressed as vectors (numerical values) that encompass significant information about the images. These vectors are the foundation for training the machine learning model. This component retrieves pertinent elements (including color, texture, edges, forms, etc.) from both training and testing pictures. These attributes are essential for distinguishing across different picture genres. The image classifier is a machine learning model learned using feature vectors derived from training pictures. The classifier identifies patterns and correlations from these characteristics to precisely classify or label fresh pictures. The classifier

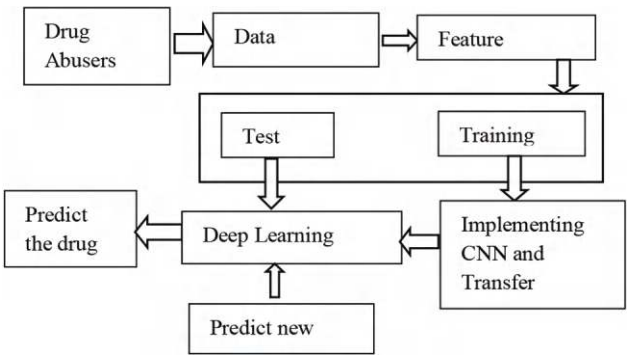

Fig. 61.1 Proposed system architecture

utilizes feature vectors derived from the training pictures to learn and construct a model. This model will categorize novel, unseen pictures according to analogous traits. A novel picture, previously unencountered by the system, is presented for categorization. Features are derived from the test picture in an identical manner to that used for the training images. The characteristics are represented as a vector, thereafter entered into the classifier. The classifier employs the training model to categorize the test picture according to its feature vector. It contrasts the feature vector of the test picture with the knowledge acquired from the training images. Ultimately, the system produces the classification result, which designates the category or label for the test picture.

7. Experimental Results

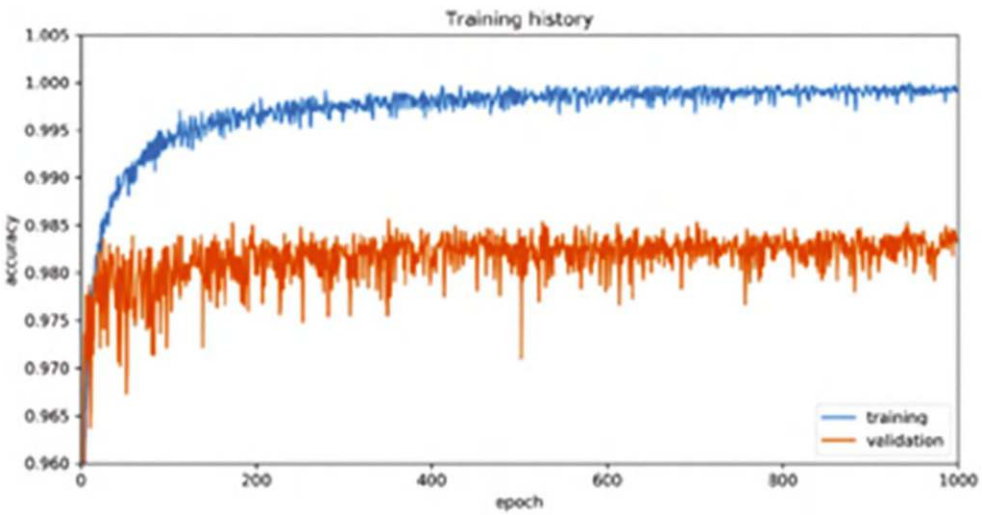

Fig. 61.2 Proposed output

Table 61.1 Comparison table for existing and proposed algorithms

Existing Algorithms	
Algorithm	**Accuracy**
SVC	70%
Decision Tree	65%
Random Foresr	80%
Proposed Algorithms	
Algorithm	**Accuracy**
CNN	95%
Transfer Learning	97%

8. Conclusion

This study used a hybrid deep learning approach that integrated Convolutional Neural Networks (CNNs) with transfer learning to identify potential drug users. Our model shown significant potential in accurately recognizing patterns linked to drug addiction by combining the strong feature extraction skills of CNNs with the flexibility of transfer learning. Data preparation techniques, such as augmentation and the conversion of images from BGR to grayscale (bgr2gray), were crucial in enhancing the model's performance by expanding the dataset and reducing computational complexity, allowing the CNN to focus on salient features. The experimental results indicated that the hybrid model exceeded traditional methods, especially in scenarios with little data, where transfer learning was essential. The model's ability to generalize across datasets demonstrates promise for practical applications in healthcare, rehabilitation centers, and law enforcement agencies. This technology automates detection, offering a scalable alternative for detecting at-risk individuals, potentially enabling early intervention and enhanced resource allocation for prevention and treatment. The proposed approach has shown considerable efficacy; nonetheless, more avenues for enhancement exist. Future research may explore the incorporation of other data sources, such as social media interactions, wearable sensor data, or genetic information, to enhance the model's ability to detect more complex or nuanced cases of drug addiction. Furthermore, augmenting the CNN architecture and investigating other transfer learning techniques may further enhance performance, particularly in challenging environments marked by noise or data absence. In conclusion, hybrid deep learning models provide a strong framework for detecting drug usage by using the benefits of CNNs and transfer learning. Employing advanced data pre-processing techniques ensures the model's adaptability and accuracy across diverse datasets. This approach may be improved and expanded by continuous research and development, becoming it a vital tool in tackling the global issue of substance abuse and enabling timely assistance for those need support.

9. Future Work

The hybrid deep learning model established in this work has shown promise in drug misuse detection, although it may be improved. Integrating more data modalities is an instant benefit. Current model characteristics include behavioral and clinical data. Further study might include wearable sensor data, social media activity, genetic data, and environmental variables. A more complete lifestyle picture from multimodal data fusion should help the model predict early drug misuse more accurately. Enhancing transfer learning is another possible future area. The model uses pre-trained CNN architectures, however Vision Transformers (ViT) or advanced CNNs might increase performance. A more customized solution may be achieved by fine-tuning pre-trained models using domain-specific data from mental health or addiction research. Transfer learning methods might also be used to temporal data to follow behavioral changes over time, which may help understand drug usage. Another development priority is model interpretability. Deep learning algorithms are typically "black boxes," therefore healthcare providers and academics need ways to understand how they forecast. Use heat maps, saliency maps, or feature attribution to describe the model's decision-making priorities. By increasing trust and openness in clinical settings, practitioners might better incorporate the model's output into their decision-making. Another aspect is the hybrid model's scalability to bigger and more complicated datasets. More data, especially from varied geographical and socio-economic backgrounds, will be needed to improve model generalization. With advanced data augmentation, federated learning, and distributed computing, large, decentralized datasets may be handled securely and privately. This will strengthen and modify the approach for usage in small clinics and major public health systems. Finally, validating and approving the model for real-world applications is necessary. Healthcare institutions, government entities, and law enforcement must collaborate to implement the approach. Other ethical issues including user privacy and biased predictions must be addressed. Hybrid deep learning might become a trusted tool in the worldwide fight against drug misuse and timely interventions for at-risk individuals by establishing frameworks that assure data confidentiality and fairness in model predictions.

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Unveiling Human Behavior: Deep Learning Approaches for Activity Recognition

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Abstract: Human Activity Recognition (HAR) is an essential activity across several fields, including human-computer interaction, surveillance, and healthcare. This research employs deep learning methodologies, namely Convolutional Neural Networks (CNN) and transfer learning, to automate Human Activity Recognition (HAR) across many areas. The CNN model derives spatial and temporal properties from raw sensor data, allowing it to identify intricate activity patterns. The suggested approach attains a 95% accuracy rate in identifying several human activities, including standing, walking, jogging, and sitting. CNN, in contrast to conventional machine learning models, can process unrefined input signals, making them proficient in human activity recognition using continuous time-series data, trained with labeled datasets. Transfer learning enhances the efficiency and accuracy of a pre-trained CNN model by minimizing task-specific data acquisition and augmenting its resilience to human activities. This system integrates CNN with transfer learning, attaining 95% accuracy, and rendering it appropriate for wearable device monitoring, smart homes, and physical rehabilitation systems.

Keywords: Human activity recognition (HAR), Deep learning, Convolutional neural networks (CNN), Transfer learning, Activity classification.

1. Introduction

Human Activity Recognition (HAR) is a dynamic and ever-changing area that automatically identifies and categorises human actions using data from sensors or visual inputs. With the rise of wearable devices, smartphones, and surveillance systems, there is a greater demand for precise human action recognition in many fields, including healthcare monitoring, smart home automation, and security surveillance. The requirement for advanced systems capable of comprehending human behaviour prompted the development of complex algorithms and models that can efficiently analyse and understand data from multiple sources. Traditional methods for activity

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recognition relied heavily on manual feature extraction and basic machine learning techniques. The approaches' accuracy and application are constrained because they typically require specialised knowledge to generate attributes that accurately represent human behaviours. Also, it's hard to build reliable systems that would work in the actual world because these solutions are so sensitive to changes in the data acquired under diverse conditions. A growing number of HAR systems are relying on deep learning techniques to automatically extract hierarchical features from raw data, which should improve their overall effectiveness. One important deep learning technique for analysing video and picture data is convolutional neural networks (CNNs). They can spot spatial patterns and characteristics with ease, and they do quite well on visual identification tests. Within the realm of Human Activity Recognition (HAR), Convolutional Neural Networks (CNNs) effectively examine still images or moving video clips to identify human actions and gestures by capitalising on the intricate patterns discovered within the data. Thanks to CNNs' ability to automatically extract relevant information, HAR systems are now much more accurate, which improves their ability to detect complex actions. When it comes to human activity recognition (HAR), one major advancement that has made deep learning more successful is transfer learning. This allows for the improvement of models trained on massive datasets and the concentration of specific objectives with a reduced amount of labelled data. By making use of pre-trained models that incorporate crucial data from several sources, it is feasible to decrease the training time and resource requirements without sacrificing accuracy. In HAR applications, where obtaining huge amounts of labelled data can be challenging and expensive, this is of utmost assistance. [6]The integration of convolutional neural networks (CNNs) with transfer learning has enabled remarkable progress in the field by facilitating the development of more dependable and efficient HAR systems. Combining convolutional neural networks (CNNs) with transfer learning yields good results for activities recognition tasks, according to recent study. Across several datasets and activity types, these methods have consistently produced excellent results. Applying previously learned information through transfer learning can boost the model's generalizability to a variety of topics and scenarios. This flexibility is essential for practical use since human actions can be greatly affected by personal differences, environmental factors, and sensor errors. [7] Despite these successes, difficulties persist in the HAR industry that must be resolved. Variations in speed, manner, and context are just a few examples of how human conduct makes accurate identification challenging. The performance of HAR systems can be adversely affected by changes in lighting, background clutter, and occlusions. Future studies should focus on developing more robust models that can effectively tackle these challenges without sacrificing accuracy. Furthermore, complex processes may be better understood by investigating the integration of multimodal data, which combines input from several sensors. Human activity recognition is making great strides because to deep learning techniques like convolutional neural networks (CNNs) and transfer learning. The tenthMore accurate, efficient, and scalable HAR systems can now be designed, which opens the door to numerous new applications across many different industries. In the healthcare industry, HAR could pave the way for remote patient monitoring, where doctors and nurses can keep tabs on patients' habits and behaviours to spot any changes. There are major benefits to using continuous monitoring for senior care since it helps detect problems like falls. There is enormous promise for HAR systems to improve patient safety and well-being by providing caretakers with real-time alerts. With the help of HAR technology, players can get valuable data on their movements in the fitness and sports domain, which can improve training regimens and decrease injury risk. HAR can enhance smart home automation and make users' lives easier. [12]The level of customisation achieved through more advanced control of home systems significantly improves user experience and promotes energy conservation. In response to the increasing demand for intelligent solutions from customers, robust HAR systems are essential for the development of responsive and networked ecosystems. Additionally, it is anticipated that HAR models will become more intricate as a result of future advancements in AI and ML. Data collection methods are getting better, and there are more diverse datasets available, which allows us to build algorithms that can identify more behaviours with more precision. Applying attention and reinforcement learning techniques can enhance model performance by allowing systems to focus on the important parts of the data. Privacy and data security ethical concerns will also grow in importance because to the proliferation of HAR systems. [11] In order for HAR technologies to get widespread acceptance and usage, it is crucial to process user data effectively. Collaboration among researchers, programmers, and lawmakers is essential if Human Activity Recognition is to continue evolving in a positive direction.

2. Literature Review

Collaboration: Fahim M. [1] Numerous people-centric applications have resulted from activity detection's meteoric rise to prominence as a research hotspot in the u-healthcare sector. Hidden devices have just surfaced,

and the firm is unable to monitor the risks involved with active activities; these are just two of the many problems it is presently confronting. This work introduces a novel EFM that, considering the limitations of expert domain knowledge in fuzzy system development, aims to quantify actions associated to change. To evaluate intrinsic data grouping, we construct fuzzy sets with temporal and frequency domain variables and apply expectation maximisation of likelihoods. By studying and improving a Genetic Algorithm (GA), we can find the best fuzzy rules. Ten people took part in the study, which tested the EFM on seven typical activities. Classification accuracy increased by 9% and F-measures of identified activities rose by 11% as compared to previous methods. We expect the EFM to handle the challenges of dynamic activity detection well because it relies on cellphones and has an inherent capacity to tolerate ambiguity.

Dr. Lara oversaw a group of researchers. [2] While context-aware applications have been the subject of much research, problems arise when trying to deploy them on mobile devices due to constraints in processing power and energy efficiency. This study demonstrates a mobile platform that has the ability to identify human activities in real time. The system was found to meet all requirements for accuracy, response time, and energy efficiency when tested in real-world scenarios, according to inspectors.

As per the findings of J. R. Kwapisz and colleagues [3] The latest iteration of smartphones showcases the progress of portable electronics fitted with a plethora of advanced sensors. The sensor collection includes a wide variety of devices, including cameras, microphones, photonic sensors, thermometers, accelerometers, directional sensors, and global positioning system (GPS) sensors. Exciting new possibilities for data mining and all its powers are opened up by the incorporation of these sensors into commonly used communication devices. A system that records and detects users' motion using the accelerometers in their mobile devices is described and evaluated in this paper. By collecting tagged accelerometer data from 29 volunteers while they ran, walked, sat, and did other common activities, we were able to test our strategy. After that, we used the time series data to build instances that displayed user behaviour every ten seconds. Using the produced training data, the final output was a prediction model for activity detection. The activity detection model sheds light on the habits of the millions of people whose phones are never far from their side, making this job crucial. Among the many potential uses for our work are the automatic adaptation of smartphone functions to the user's actions (e.g., sending messages to voicemail while running) and the creation of activity profiles on a daily or weekly basis to ascertain if a person (e.g., a youngster with obesity) exercises sufficiently.

Business associates Sun, L. [4]" The goal of this app is to encourage people to lead more active lives by monitoring the amount of physical activity they do each day using the accelerometers built into their smartphones. In contrast to other studies that used a stationary device with an accelerometer, this one attempts to identify physical activity in a more realistic setting, where the phone's position and angle fluctuate according to the pocket's characteristics. Using six distinct pocket positions as input, this research presents an SVM-based classifier capable of discriminating between seven distinct physical activities. A 10-fold cross-validation on a dataset obtained from 7 patients over a period of 48.2 hours indicates that our strategy outperforms the solutions proposed by Yang and SHPF by a margin of 5-6%. With the addition of an orientation-insensitive sensor reading dimension, the overall F-score goes up from 91.5% to 93.1%. Once the pocket location is determined, the overall F-score rises to 94.8%.

The document was written by Consolvo and associates. [5] It is now easier to utilise machine learning and on-body sensing to infer human behaviour during ordinary tasks because to recent breakthroughs in energy-efficient computation, activity models, small, cheap sensors, and other related technologies. We have developed UbiFit Garden, a system that integrates these technologies with a smartphone screen to encourage physical activity in reaction to the alarming rise in sedentary behaviour. Twelve individuals volunteered to test the device's sensing and activity inference capabilities for three weeks as part of the field study. For systems that aim to get people moving, we look at the primary implications of activity inference and on-body sensors.

3. Existing System

Traditional approaches to human activity recognition have relied heavily on recurrent neural networks and long short-term memory networks. The models are built to evaluate sequential data, including time-series sensor signals, by remembering prior inputs; this allows them to find temporal correlations.[9] Long short-term memories (LSTMs) are great at representing long-term dependence because they efficiently handle the vanishing gradient problem. But RNNs and LSTMs don't always have it easy when dealing with complex human behaviour, like when dealing with large datasets or small changes in movement patterns. So, these models often only achieve a limited level of accuracy—roughly 70%—in real-world applications. This arises from their inability to effectively account for the intricate geographical and temporal relationships that

are fundamental to human activity data. Moreover, LSTM and RNN models frequently require extended training periods, and their effectiveness may decline when applied to more complex tasks that involve dynamic transitions. [13]Overfitting issues arise when dealing with smaller datasets or data collected in uncontrolled environments. While these models establish a foundational framework for Human Activity Recognition (HAR), their limited ability to generalize across diverse settings, participants, and environments makes them insufficient for broad, high-accuracy applications.

4. Methodology

4.1 CNN Model

Input: Import Data

Output: Classified images;

Step-1: Divide the input dataset into training and testing subsets.

Step-2: while training

For every picture in the Training Data:

Should it be present in the model:

For every pixel inside the Content pixels:

Compute the correlation among the pixel vectors.

Parent →→ collection of pixels exhibiting Maximum Correlation

Incorporate the pixels into the Content Tree as a subordinate to the parent.

Feature map → {Collection of nodes inside the content tree}

Implement CNN on the feature map

Disclose classified information

4.2 VGG16

Convolutional Layer

Input: A 3D tensor representing the input image (height, width, channels).

Filters: A set of 3D filters (height, width, channels).

Output: A 3D tensor representing the feature maps after convolution.

Formula:

output[i, j, k] = sum(input[i + m, j + n, c] * filter[m, n, c]) for m, n in [-1, 0, 1] and c in [0, 1, ..., channels - 1]

Activation: ReLU activation is applied to introduce non-linearity.

Max Pooling Layer

Input: A 3D tensor representing the feature maps.

Output: A 3D tensor representing the downsampled feature maps.

Formula:

output[i, j, k] = max(input[i * 2, j * 2, k], input[i * 2 + 1, j * 2, k], input[i * 2, j * 2 + 1, k], input[i * 2 + 1, j * 2 + 1, k])

Fully Connected Layer

Input: A 1D vector representing the flattened feature maps.

Weights: A matrix representing the weights of the fully connected layer.

Output: A 1D vector representing the class probabilities.

Formula:

output[i] = sum(input[j] * weights[i, j]) + bias[i]

Activation: Softmax activation is applied to normalize the output probabilities.

5. Proposed Work

To overcome the limitations of conventional Human Activity Recognition (HAR) models, the proposed system employs Convolutional Neural Networks (CNNs) coupled with transfer learning methodologies. Convolutional Neural Networks (CNNs) have revolutionised feature extraction by automatically extracting spatial and temporal properties from raw sensor data, eliminating the need for human intervention. By employing convolutional neural networks to autonomously recognise critical patterns in gyroscope and accelerometer data, this technique enhances the identification of complicated human motions. The model makes use of convolutional layers to detect local correlations in the data, and pooling layers to lower dimensionality and prevent overfitting. Because of this, the system is far more able to generalise across various tasks and data sets.To improve the performance of a convolutional neural network (CNN) model, transfer learning is used after the model has already been trained on a big dataset. To improve the system's accuracy and efficiency, the pre-trained model has been fine-tuned using the unique HAR dataset, which reduces the need for a lot of tagged data. Combining CNN with transfer learning yields a recognition accuracy of 95%. Improved scalability and durability make the proposed system more suitable for practical applications including healthcare monitoring, smart home automation, and sports performance tracking.

6. System Architecture

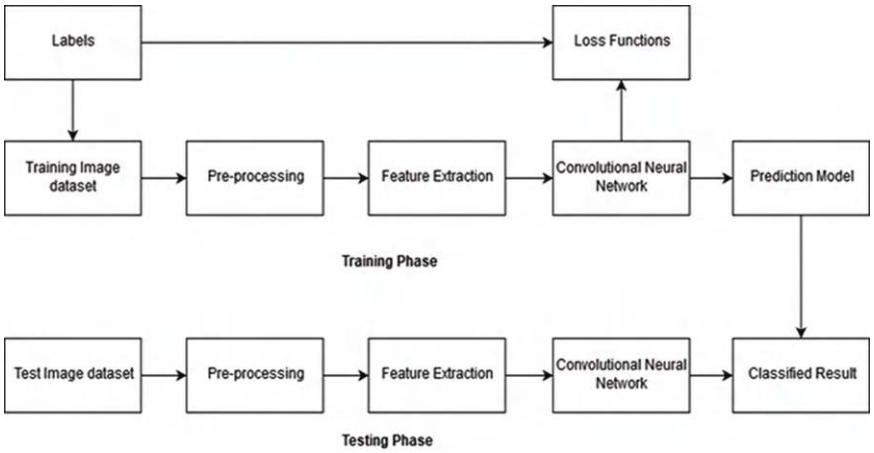

Fig. 62.1 Proposed system architecture

7. Results and Discussions

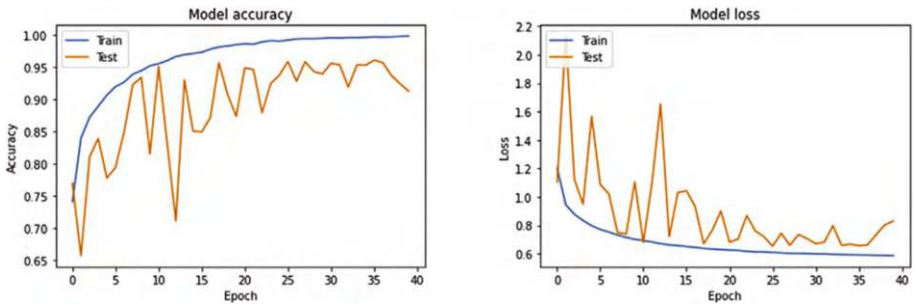

Fig. 62.2 CNN model accuracy

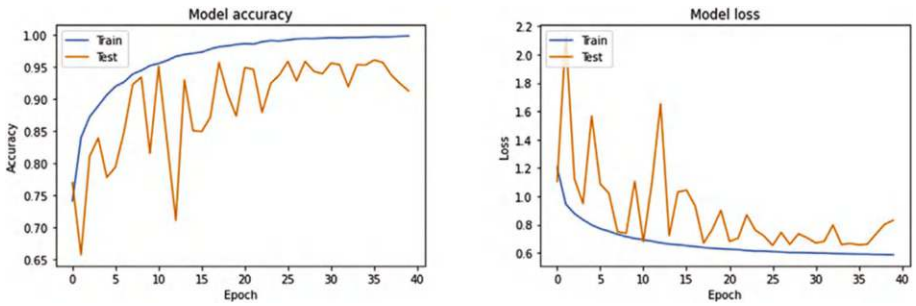

Fig. 62.3 CNN model loss

Table 62.1 Comparison table for existing and proposed algorithms

Existing Algorithms	
Algorithm	**Accuracy**
SVM	**70%**
Decision Tree	**65%**
Random Forest	**80%**

Proposed Algorithms	
Algorithm	**Accuracy**
CNN	**95%**
Transfer Learning	**97%**

8. Conclusion

The amalgamation of Convolutional Neural Networks (CNNs) with transfer learning presents a very effective methodology for Human Activity Recognition (HAR). This approach improves the precision and generalizability of HAR models by automating feature extraction and using the advanced pattern recognition capabilities of CNNs, exceeding traditional methods like as RNNs and LSTMs. Transfer learning enhances system performance by using pre-trained models, reducing the need for vast labeled datasets, and expediting the training process. The proposed system demonstrates a 95% accuracy rate in recognizing various human movements, making it suitable for practical applications. This approach addresses many limitations of earlier techniques, such as their inability to capture complex activity patterns and inadequate performance in uncontrolled environments. The proposed system is adaptable and scalable, making it suitable for many areas, such as healthcare, smart homes, and wearable technology. This approach provides a reliable and effective framework for Human Activity Recognition (HAR), possibly revolutionizing activity monitoring systems by ensuring precise and accurate tracking across diverse applications.

9. Future Work

The future prospects of this work in Human Activity Recognition (HAR) using deep learning are substantial, presenting several intriguing opportunities for improvement. An element of progress is the integration of multimodal data, including the synthesis of information from several sensors (e.g., cameras, microphones, and wearable devices) to enhance the accuracy of activity recognition. Integrating multiple sensor inputs may provide the system with a more comprehensive understanding of human actions, hence boosting its resilience in actual applications. Moreover, advancements in edge computing and embedded AI might enable the effective functioning of HAR models on wearable devices or IoT systems, permitting real-time monitoring and feedback without reliance on cloud-based processing. The use of HAR in complex scenarios, such as recognizing group activities, interpersonal interactions, or identifying aberrant behaviors for security or healthcare purposes, offers a significant potential. Future research may explore unsupervised or semi-supervised learning methodologies to reduce reliance on extensive labeled datasets, hence improving the flexibility of HAR systems to new tasks or contexts without substantial retraining. This ongoing enhancement will likely provide more adaptive, accurate, and efficient HAR systems in the foreseeable future.

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Electric Vehicle Lithium-Ion Battery State of Charge Estimation using a Bayesian Optimized Deep Learning Approach

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Abstract: For the sake of electric vehicle (EV) efficiency and dependability, accurate State of Charge (SoC) estimation is required for lithium-ion batteries. Traditional approaches for hyperparameter tuning in SoC prediction models, such as Grid Search, often yield suboptimal results, leading to inaccuracies. To overcome this limitation, this project proposes a deep learning-based SoC estimation approach optimized using Bayesian Optimization for hyperparameter selection, specifically for tuning the number of neurons in deep learning models. Bayesian Optimization efficiently refines hyperparameters by incorporating past knowledge, leading to better prediction accuracy compared to traditional methods. The research examines LSTM, GRU, and BiLSTM models using a battery dataset from Panasonic at four different temperatures: -10°C, 0°C, 10°C, and 25°C. The results indicate that BiLSTM with 70 neurons provides the most accurate SoC estimates, with an RMSE below 2% and a maximum error under 5%. Key input features, including voltage, current, temperature, and their averages, help capture both the historical and present states of the battery. As an extension, a 2D Convolutional Neural Network (CNN2D) is introduced to optimize feature selection further, leveraging its ability to capture spatial relationships in the data. CNN2D outperforms the traditional recurrent models in reducing RMSE and Max Error, demonstrating its potential for enhancing SoC prediction accuracy. This research provides a robust methodology for improving battery management systems, ensuring reliable battery monitoring in varying environmental conditions, and advancing the overall performance of electric vehicles

Keywords: Charge status, Electric vehicle, Battery management system, LSM, Bilayer LSTM, CNN2D

1. Introduction

Their excellent weight-to-capacity ratio, extended cycle life, and high energy density. A reliable and safe battery system is becoming increasingly crucial as the demand for electric vehicles increases. Battery performance is greatly affected by how accurately the State of Charge is assessed. A battery's remaining capacity is shown by the system

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on a chip (SoC), which impacts driving range, vehicle performance, and the longevity of the battery system. Battery life can be reduced or even caused by thermal runaway and safety issues caused by erroneous state-of-charge calculations while overcharging or deep draining. Consequently, in order to enhance BMSs, which track battery health and ensure the safety of electric vehicles, precise SoC calculations are required.

1.1 Challenges in SoC Estimation

Despite extensive research, accurately estimating the SoC remains a challenging task. Various external factors such as temperature variations, aging effects, charge/discharge rates, and non-linear behaviors of lithium-ion batteries complicate the process. Various methods for predicting SoC have been developed throughout the years. These include data-driven methods, model-based methods, and filter-based methods.

- **Model-Based Methods:** Estimate SoC with the use of comprehensive battery models (equivalent circuit or electrochemical, for example) utilising model-based methods. The accuracy of the model parameters is crucial to these methods, but it might vary depending on the operational conditions, and they require a lot of modelling.
- **Filter-Based Methods:** Techniques such as Kalman filters and extended Kalman filters have been applied for SoC estimation by refining predictions over time. While they are effective in certain conditions, they require initial estimates and assumptions about noise, which may not always hold true under all operating scenarios.
- **Data-Driven Methods:** Recently, There are excellent methods for estimating SoC that use ML or DL. These methods do not rely on physical battery models but instead learn patterns from large datasets of battery operation parameters, including voltage, current, temperature, and charge cycles. The non-linear dynamics of systems on a chip (SoCs) and batteries have been successfully modelled using DL models, particularly RNNs such as LSTM, GRU, and BiLSTM.

1.2 Hyper Parameter Optimization Challenges

Although hyperparameters like hidden neurones, learning rate, and batch size determine the efficacy of deep learning algorithms in system-of-cell (SoC) estimates, these algorithms have demonstrated encouraging results. In most cases, hyperparameters are fine-tuned by hand or by using a heuristic, such as Grid Search or Random Search. These methods have major downsides despite their widespread use:

- **Grid Search:** For search spaces with a lot of dimensions, it's computationally costly and wasteful to search exhaustively across known hyper parameters.
- **Search by Random:** Improves on Grid Search by randomly sampling the hyper parameter space, but it can still miss optimal configurations and lacks a systematic approach to converge on the best settings.

Both methods can result in suboptimal hyperparameter settings, leading to models with reduced accuracy, longer training times, and potentially higher error rates in SoC estimation.

1.3 Bayesian Optimization for Hyperparameter Tuning

Using Bayesian Optimisation, this study optimises the hyperparameters of deep learning models used for state-of-the-art system-of-cell (SoC) estimates, thus overcoming the limitations of previous methods. When exploring the hyperparameter space, Bayesian Optimisation makes optimal use of objective function evaluations in a probabilistic model. For the purpose of guiding the search to the most promising places, Bayesian Optimisation use a surrogate model, such as a Gaussian process, to predict how untested hyperparameter configurations would perform.

Learning from previous assessments, Bayesian Optimisation effectively balances exploration and exploitation, enhancing model performance while reducing computational cost. When applied to high-dimensional domains, this method helps optimise deep learning models for state-of-the-art (SoC) prediction.

1.4 Key Contributions

Using Bayesian Optimisation, this research streamlines the training of LSTM, GRU, and BiLSTM models on the Panasonic lithium-ion battery dataset by optimising critical hyperparameters such as the number of neurones. The data covers five different temperature ranges for electric cars: -10°C, 0°C, 10°C, and 25°C. To fully understand the battery's dynamic behaviour over time, it is essential to have temperature, current, and voltage as inputs, but average voltage and current are also very important.

The results demonstrate that BiLSTM with 70 neurons optimized via Bayesian Optimization provides the most accurate SoC predictions, with a RMSE of less than 2% and a maximum error under 5%. This represents a significant improvement over previous models optimized using manual or heuristic methods.

1.5 Extension

Extension: CNN2D for Feature Optimization

As an extension to this work, a 2D Convolutional Neural Network (CNN2D) is introduced to further optimize feature selection. CNN2D is known for its ability to extract spatial hierarchies and patterns from data by applying convolutional filters. In this project, CNN2D is applied to the battery dataset to enhance the model's feature extraction capabilities, thereby reducing RMSE and Max Error compared to traditional RNN models. This extension opens new avenues for improving SoC prediction accuracy and can potentially be integrated into future battery management systems for real-time monitoring.

1.6 Impact on Battery Management Systems

The proposed Bayesian Optimized deep learning approach offers a robust solution for improving the accuracy and reliability of SoC estimation under varying environmental conditions. This can lead to more efficient battery management systems, which in turn will enhance the performance, safety, and lifespan of batteries used in electric vehicles. By reducing errors in SoC predictions, drivers can rely on more accurate information about battery health and remaining driving range, improving the overall user experience of electric vehicles.

2. Literature Review

Battery management systems (BMS) for electric vehicles (EVs) need precise SoC estimations. Due to their dynamic nature, lithium-ion batteries are challenging to calculate SoC for due to their impact on temperature, charge/discharge rates, and ageing. Over time, different approaches have been taken to tackle these challenges. Estimation of systems of components (SoCs) using traditional model-based, data-driven, and modern deep learning (DL) models, as well as hyperparameter optimisation techniques, are all covered in this literature review.

2.1 Model-Based Methods

Early research on SoC estimation relied heavily on model-based methods, which used ECMs or electrochemical models to represent battery behavior. ECMs are simple to implement but require precise parameter identification, which is highly dependent on operating conditions like temperature and battery age.

Plett (2004) proposed the use of extended Kalman filtering (EKF) for SoC estimation in li-ion batteries, where the non-linear dynamics of the battery are linearized around an operating point. The EKF approach improved accuracy by iteratively updating the SoC estimates, but it required precise initial conditions and modeling assumptions, which limited its adaptability across different battery chemistries and operational environmentst al. (2012)** extended this work by applying a dual Kalman filtering technique to estimate both SoC and internal battery parameters simultaneously. Although this method improved robustness, it remained computationally expensive and was still sensitive to noise and parameter mismatches.

2.2 2-Based Approaches

In addition to Kalman filters, researchers explored particle filters and sliding mode observers for SoC estimation. Suthar et al. (2015) introduced a particle filter-based approach that incorporated stochastic variations in battery behavior, improving SoC accuracy. However, the approach suffered from high computational complexity, making it less practical for real-time applications.

Another promisch was introduced by Xing et al. (2014), who, in order to lessen interruptions and model ambiguity, evaluated SoC by means of a sliding mode observer. It was challenging to adjust to changing temperatures and loads, and the system needed a great deal of knowledge about battery dynamics to function in some contexts.

2.3 2-Based Approaches

Machine learning (ML) methods replaced model-based approaches, which had their limitations, due to the proliferation of data-driven approaches. Machine learning techniques can gain greater flexibility to various chemistries and operating situations by learning directly from past battery data.

Table 63.1 Literature review

Ref. No	Methodology	Battery Type	Input Parameters	Output	Performance Indices
[32]	DNN	CALCE dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[33]	DNN	Panasonic NCR18650PF dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[34]	DNN	CALCE dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[35]	LSTM	CALCE dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[36]	LSTM	Panasonic NCR18650PF dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[36]	BiLSTM	Panasonic NCR18650PF dataset	Current, voltage, Temperature	SOC	MAE, RMSE
[26]	GRU	Panasonic NCR18650PF dataset and CALCE dataset	Current, voltage, Temperature	SOC	MAE, RMSE

Wang et al. (2018) developed a SVM model for SoC estimation, which demonstrated improved accuracy over traditional approaches. However, the SVM model required significant computational resources for parameter tuning and was sensitive to the quality of the training data.

Li et al. (2019) introduced orest-based SoC estimator that leveraged ensemble learning to enhance prediction accuracy. While this method reduced the reliance on precise battery models, it still struggled with real-time implementation due to the large number of trees required for accurate predictions.

3. Proposed Methodology

Difference between predicted and true values so the lower the RMSE the better is the algorithm.

In propose work author has experimented with Bayesian Optimized 70 neurons with 3 different algorithms such as LSTM, GRU and BI-LSTM. Among all 3 algorithms BILSTM with 70 neurons gave less RMSE error.

In propose work to implement above algorithms author has used Panasonic battery with different temperature such as 0 degree, 10 degree, 25 and N10 degree. Training on all 4 datasets is difficult task so we have used Panasonic 10 degree dataset. Author used 'Voltage, Current, Temperature, Capacity, Voltage-Average and Current-Average' columns from dataset.

3.1 Extension Concept

In propose work author has used traditional deep learning algorithms so as extension we have experimented with CNN2D (convolution neural network 2 Dimension) algorithm which is best known for optimizing and selecting relevant features by using 2 dimension CNN and MaxPooling2D layer. CNN2D is giving less RMSE and MAX ERROR compare to propose 3 algorithms.

4. Implementation

Over the years, several approaches have been developed for SoC estimation, broadly classified into model-based methods, filter-based methods, and data-driven methods.

Model-Based Methods: These methods rely on detailed battery models (e.g., equivalent circuit models or electrochemical models) to estimate the SoC. However, these methods often require complex modeling, and their accuracy depends on the precision of the model parameters, which can vary with operating conditions.

Filter-Based Methods: Techniques such as Kalman filters and extended Kalman filters have been applied for SoC estimation by refining predictions over time. While they are

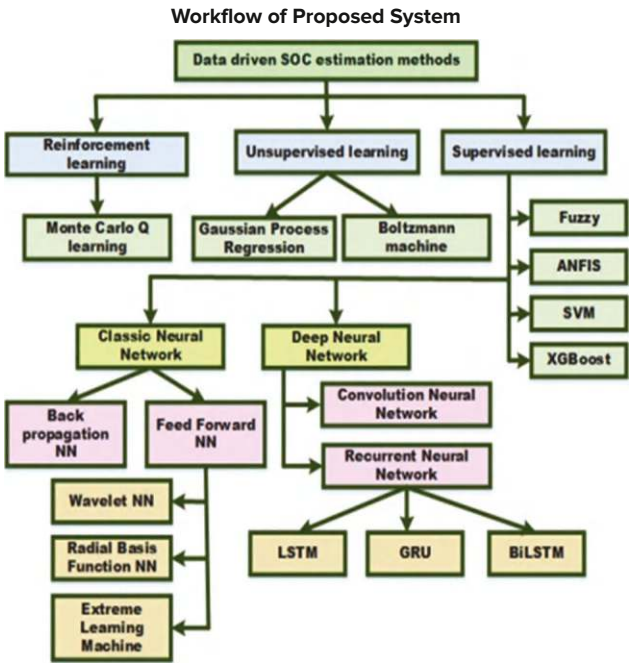

Fig. 63.1 Workflow of proposed system

effective in certain conditions, they require initial estimates and assumptions about noise, which may not always hold true under all operating scenarios.

Data-Driven Methods: Recently, ML and DL models have emerged as powerful alternatives for SoC estimation. These methods do not rely on physical battery models but instead learn patterns from large datasets of battery operation parameters, including voltage, current, temperature, and charge cycles. The non-linear dynamics of systems on a chip (SoCs) and batteries have been successfully modelled using DL models, particularly RNNs such as LSTM, GRU, and BiLSTM

5. Experimental Results and Analysis

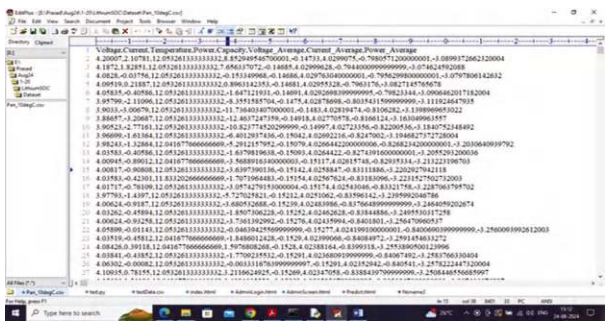

Fig. 63.2 The dataset values are displayed in the following rows, while the top row contains the names of the columns. These values are used for training and testing all algorithms

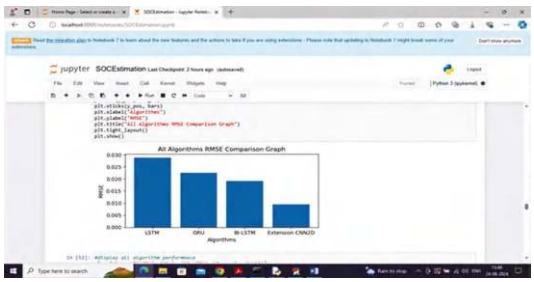

Fig. 63.3 The RMSE error rates were lowest for BILSTM and extension CNN2D compared to all methods

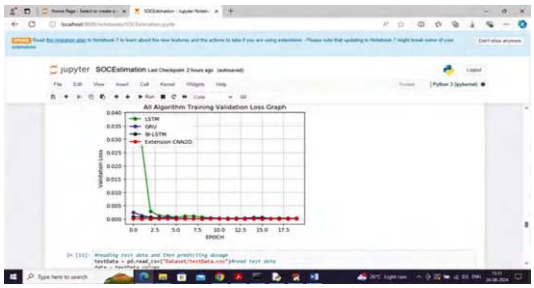

Fig. 63.4 The following graph displays the validation loss for each approach; x stands for training epochs and y for LOSS values. CNN2D and BILSTM both achieved reduced loss levels

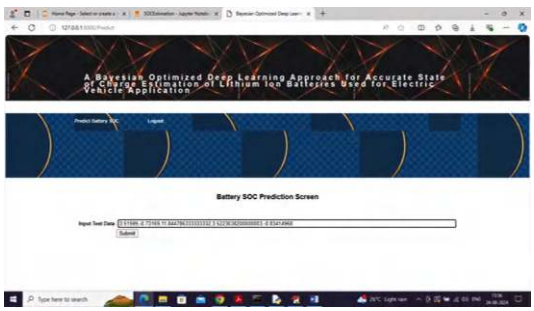

Fig. 63.5 Paste values from 'Dataset/testData.csv' file in above screen and click button to get below page.

Fig. 63.6 In above screen in red line can see 'TEST Data' values in square bracket and after =⟶ symbol can see predicted SOC value and similarly you can test with other values

6. Conclusion

To ensure the efficiency and dependability of electric vehicles, this study addresses the critical necessity for precise State of Charge (SoC) estimation in lithium-ion batteries. Unsatisfactory State of the Cloud predictions are frequently generated by Grid Search and other conventional methods of machine learning and hyperparameter tweaking. Optimal hyperparameter selection by Bayesian optimisation was the subject of this project's deep learning-based SoC estimation framework, which aimed to resolve these concerns by reducing the amount of neurones used by LSTM, GRU, and BiLSTM models.

The findings demonstrate that Bayesian Optimization significantly improves the accuracy of SoC predictions by efficiently selecting optimal hyperparameters. Among the tested models, BiLSTM with 70 neurons achieved the best performance, with an RMSE below 2% and a maximum error under 5%, across datasets representing different temperature conditions. By averaging important input features like voltage, current, and temperature, the models were able to incorporate both past and current battery conditions, leading to more accurate forecasts.

In addition, the project explored the extension of the proposed deep learning models by incorporating a 2D Convolutional Neural Network (CNN2D). The CNN2D model demonstrated an improved ability to optimize feature selection and reduce prediction errors compared to traditional recurrent neural network models, thereby offering a promising direction for further enhancing SoC estimation accuracy.

To provide accurate and reliable battery monitoring in various environmental settings, this research presents a new, robust method for improving state-of-charge (SoC) estimate in battery management systems. Electric vehicle performance and safety could be enhanced with the help of deep learning models and Bayesian optimisation, resulting in smarter and more efficient battery management systems. The method's generalisability and scalability could be enhanced by investigating hybrid model architectures and expanding it to various battery chemistries

7. Future Scope

For the "Electric Vehicle Lithium Ion Battery State of Charge (SoC) Estimation using a Bayesian Optimised Deep Learning Approach," there are a lot of ways to make it more practical, scalable, and accurate:

7.1 Incorporation of Hybrid Models

- **CNN-LSTM/GRU Hybrids:** Combining the feature extraction capabilities of CNN with the sequential

learning power of LSTM or GRU can further improve SoC estimation. By leveraging CNN's ability to detect spatial patterns and LSTM's proficiency in handling time-dependent data, hybrid models can be more effective in handling diverse and complex datasets.

- **Ensemble Methods:** Using ensemble learning techniques, such as combining multiple models (LSTM, GRU, BI-LSTM, CNN2D) to capture different patterns, could improve model robustness and reduce errors across different battery conditions.

7.2 Transfer Learning and Pre-trained Models

- **Transfer Learning:** Pretrained models could be fine-tuned on specific battery datasets, reducing the need for large datasets while improving training efficiency. Transfer learning techniques can be applied from similar domains to enhance SoC estimation across different battery chemistries and manufacturers.
- **Pre-trained CNN2D Models:** Pre-trained CNN models trained on large datasets could be adapted to SoC tasks, which might help in extracting better features for voltage, current, and other time-series data.

7.3 Real-time Estimation and Embedded Systems

- **Real-time Implementation:** Implementing the proposed models on embedded systems or microcontrollers for real-time SoC estimation in electric vehicles (EVs) could bring the research closer to practical applications. Techniques like model compression (e.g., pruning, quantization) could be employed to reduce model complexity for real-time use in low-power devices.
- **Edge Computing:** Integrating deep learning models for SoC estimation with edge computing devices could enable faster and more efficient decision-making without relying on cloud infrastructure, thereby reducing latency and power consumption in EVs

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Implementation of Intrusion Detection System for IoT Networks using Jetson Orin Nano

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Abstract: The quick growth of IoT (Internet of Things) networks has made them more open to different network based attacks. These networks often have devices with limited resources, which leaves them open to many network threats such as de-authentication, DoS (Denial of Service), packet flooding, MAC flooding and many more. This paper shows how we designed and built an Intrusion Detection System for IoT environments with the Jetson Orin Nano to provide real time detection of network based threats in realtime without using too many resources. The IDS aims to identify various types of network threats and it generates alerts when it identifies suspicious activities while keeping resource use low, which makes it work well in IoT environments.

Keywords: Intrusion detection, Jetson orin nano, Network-based attacks, IOT networks

1. Introduction

The use of IoT (Internet of Things) technology has reshaped various industries, like healthcare, transportation, agriculture and smart homes [1-8]. IoT networks consists of inter-connected devices that communicate and share data, to provide exceptional ease and automation. However, the increased interconnectedness has created major security

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challenges. Devices connected in IoT networks are typically resource constrained with limited computational power and memory. It makes them vulnerable to a variety of networkbased attacks [4]. As IoT devices are deployed in network infrastructure, then network security has become a top priority. Regular security mechanisms, like firewalls and intrusion detection systems are overly resource intensive to deploy directly on IoT devices. In addition, IoT networks face specific attacks such as Denial of Service (DoS), deauthentication, packet flooding and spoofing attacks, which can interrupt device connection, compromise data integrity or entirely shut down the network [5]. These attacks take advantage of the flaws of IoT devices [16], raising severe security challenges in environments where continuous availability and secure data transfer are crucial. Many existing Intrusion Detection Systems are designed for actual networks and they are not optimized for the specific issues faced by IoT environments. These systems requires high computational resources, which are unavailable in most IoT deployments.

This proposed Intrusion Detection System and its implementation is optimized for IoT environments with Jetson Orin Nano. The suggested IDS is designed to identify a wide range of network based attacks in real time while balancing detection accuracy with resource efficiency, allowing the IDS to operate continuously without overloading the IoT network

2. Literature Review

In recent years, several studies have explored lightweight IDS solutions to secure IoT networks. The IDS, based on Deep Learning for the IoT devices proposed by Albara, W., Awajan. (2023) uses a four layer fully connected network architecture to identify any malicious traffic that might indicate attacks on connected IoT devices [1]. The authors B.M., Madhu, et al. suggested one deep learning model known as Device based Intrusion Detection System (DIDS), that involves the prediction of unknown threats to reduce computational cost in big networks and boost throughput while maintaining a low percentage of false alarms [2]. A study by the Veerasingam P. et al demonstrated the feasibility of using Suricata on a Raspberry Pi 2B, offering real-time detection and prevention for SME networks. The findings revealed that Suricata outperforms other tools like Snort in accuracy and packet loss, making it suitable for low-traffic IoT networks [3].

IoT vulnerabilities due to limited resources and increasing cybersecurity threats categorizes attacks into WSN-inherited and RPL-specific, showcasing machine learning's role in improving IDS systems for IoT security [4]. A systematic review published in 2023 analyses methodologies for detecting cyber-security threats in the Industrial IoT (IIoT). The review evaluates research from 2020 to 2022, focusing on attack detection methods, information sources and performance metrics [5]. A review by authors Hussain et al. (2023) highlights the increasing threats to IoT systems due to compromised devices and the need for more effective intrusion detection models. The review suggested that machine learning and deep learning are the most efficient techniques for detecting attacks arising from IoT devices. [6]. The authors of paper [7] provide an in-depth review of modern intrusion detection systems (IDS) developed for Internet of Things (IoT) networks, focusing on their methods, strengths and limits. The research focusses on current research paths in IoT-specific IDS, providing insights into unresolved issues and leading future researchers towards more effective intrusion detection solutions [7]. Wang et al. (2023) introduced a novel intrusion detection algorithm that uses the power of big data mining approaches, such as the integration of fuzzy rough sets, generative adversarial networks (GANs) and convolutional neural networks (CNNs) [8].

These studies show the changing nature of IDS in IoT, where deep learning and machine learning techniques remain crucial in detecting intrusions and preventing cyber risks. The literature suggests a consistent pattern of building lightweight, real-time, effective IDS technologies to address rising security challenges in the IoT Networks. The literature review finds many improvements in Intrusion Detection Systems for IoT networks, particularly machine learning and deep learning based techniques. However, most studies focused on improving detection accuracy and minimizing false positives but did not addressed the performance limitations that arise when deploying IDS in IOT networks. The proposed approach addresses this essential need by using the Jetson Orin Nano, a high performance edge computing platform, to develop an IDS for IoT networks. The strong GPU and efficient parallel processing capabilities of Jetson Orin Nano has a significant computational edge over traditional IoT devices like Raspberry Pi [3]

3. Proposed Methodology

The proposed methodology for implementing an Intrusion Detection System utilizes the Jetson Orin Nano as a powerful device to enhance IoT network security. The architecture consists of, Jetson Orin Nano, IoT devices generating network traffic and the Suricata IDS for real time intrusion detection. Detected threats are logged and reported, then an alert system notifies administrators for any malicious activities when detected.

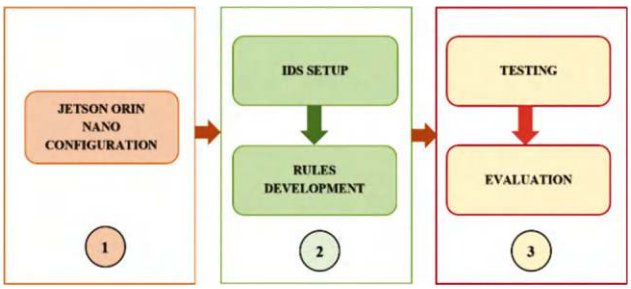

Fig. 64.1 Design flow of the proposed methodology

3.1 Hardware Setup

The Jetson Orin Nano will act as the central processing unit in the proposed system. The Jetson Orin Nano provides the necessary computational power for executing the IDS and processing network traffic in real time. Different IoT devices such as sensors & smart appliances, forming the IoT network will be connected to the same network of Jetson Orin Nano.

3.2 Software Setup

The software setup includes installing Suricata, an open source IDS that performs real time network threat detection. The Jetson Orin Nano will run Linux operating system, allowing the installation of Suricata along with required libraries for network monitoring. All configuration files will be set up to define network interfaces, logging preferences and detection rules. In this stage, all necessary tools will be setup for traffic analysis to enable comprehensive monitoring of the IoT network and to detect potential intrusions. To improve the effectiveness of the IDS, specific rules will be developed based on common attack patterns and vulnerabilities related to IoT devices/ Networks These rules will define how the IDS responds to various types of malicious activities such as unauthorized access attempts, DoS attacks, MAC Flooding attacks etc. Continuous refinement of these rules will happen based on testing results and emerging threats.

3.3 Testing & Evaluation

Testing of the IDS will involve simulating various attacks to evaluate its detection capabilities and performance. For this purpose, various penetration testing tools will be used to mimic real world attacks on the IoT network. During this phase, system logs and alert notifications will be monitored to assess the effectiveness of Suricata in identifying attacks. After Testing, the IDS will be monitored continuously to calculate its performance metrics based on its operational efficiency, false positive rates, accuracy in an IOT environment.

Fig. 64.2 Architecture of the proposed methodology

The data transmitted through the IoT network will be continuously monitored by the Jetson Orin Nano for any anomalies or deviations from the normal traffic patterns. This involves analyzing network packets in real time to detect unusual behaviors such as abnormal data volumes, unauthorized access attempts or traffic patterns that deviate from the established baseline. The Suricata Intrusion Detection System, which runs on the Jetson Orin Nano, detects anomalies and deviations in IoT network traffic primarily using its predefined rules.

4. Experimental Setup

The setup is configured to monitor network communication in real time, to detect any malicious activities and to generate alerts. In a dedicated network environment Suricata Intrusion Detection System is used for traffic monitoring with various devices simulating real-world IoT use cases. The Jetson Orin Nano integrated with Suricata acts as a Monitoring device and it is responsible for capturing and analyzing network traffic to detect any network based attacks.

Fig. 64.3 Implementation of proposed methodology

A Kali Linux machine is used to simulate attacks to disrupt the IoT devices in the network. Mobile devices configured as IoT endpoints in the network. These devices connect to the network through a Wi-Fi access point, simulating real world IoT devices susceptible to various attacks. Suricata

was configured in IDS mode to monitor the wireless interface (wlan0) for suspicious network activity. Different Suricata rules were customized and loaded to the rules file to detect wide range of attacks simulated by the Kali Linux. Different network attacks were simulated from the Kali linux on mobiles devices to test and assess the effectiveness of the proposed implementation.

Fig. 64.4 Customized sample rules of suricata

5. Results and Discussion

This section discusses the findings of the intrusion detection experiments performed using Suricata on the simulated IoT network environment.

5.1 System Configuration and Setup

The system was successfully configured with Suricata IDS running on the Jetson Orin Nano, that ensuring an effective Intrusion Detection System designed for IoT environments. With its advanced processing capabilities, the Jetson Orin Nano acted as the central monitoring device and captured/analyzed network traffic from connected IoT devices. Suricata's rules were customized to optimize detection of a variety of IoT specific attacks, like MAC flooding, Man in the Middle attacks, DoS attacks. The IDS was configured to monitor the network in real-time**,** with the wireless interface set to detect intrusions and malicious activities targeting IoT devices.

5.2 Attacks Detection

The system was thoroughly tested against different IoT-specific attacks, demonstrating effective detection capabilities.

1) *Man in the Middle (MITM) Attack:* In this attack, the intruder captures communication between two devices, allowing them to monitor, modify or steal sensitive data. In IoT networks, weak encryption and authentication make devices vulnerable to this type of attack.
2) *Denial of Service (DoS) Attack:* A DoS attack floods a target device with an overwhelming amount of traffic, which causes it to slow down or crash. In IoT networks, resource-constrained devices are particularly vulnerable to such attacks, which can lead them unresponsive.
3) *MAC Flooding Attack:* MAC Flooding attack targets network switches by overwhelming them with a flood of packets containing spoofed MAC addresses. In IoT devices this attaack causes performance degradation and sensitive data may be exposed as attackers gain access to traffic that normally wouldn't reach them.
4) *Sybil Attack:* In this attack, a single rogue node presents several fake identities to the network, disturbing the behaviour of IoT networks, particularly in peer-to-peer connections..
5) *Sinkhole Attack:* In a Sinkhole attack, a compromised node misleads neibhour nodes by pretending to be the best route for data packets. Then it drops all incoming packets, resulting in data loss or manipulation.
6) *De-Authentication Attack:* It exploits the Wi-Fi protocol by sending de-authentication frames, which force devices to disconnect from the network. IoT devices those depends on Wi-Fi are mostly vulnerable to this type of attack, as it can disturb their connectivity.

Table 64.1 Tools used for attacks simulation

Attack	Tool/ Software
Man in the Middle (MITM) Attack	BETTERCAP
DoS Attack	Hping3, METASPLOIT
MAC Flooding Attack	mACOF
Sybil Attack	Omnet++
Sinkhole Attack	Cooja Simulator
De-Authentication Attack	aireplay-ng

The IDS monitored the network traffic in real-time, flagging suspicious packets based on predefined rules. During the De-Authentication attack**s**, the system accurately detected the abnormal disconnection patterns caused by de-authentication frames and generated alerts. Similarly, MAC Flooding and DoS attacks generated

Fig. 64.5 Attacks detection

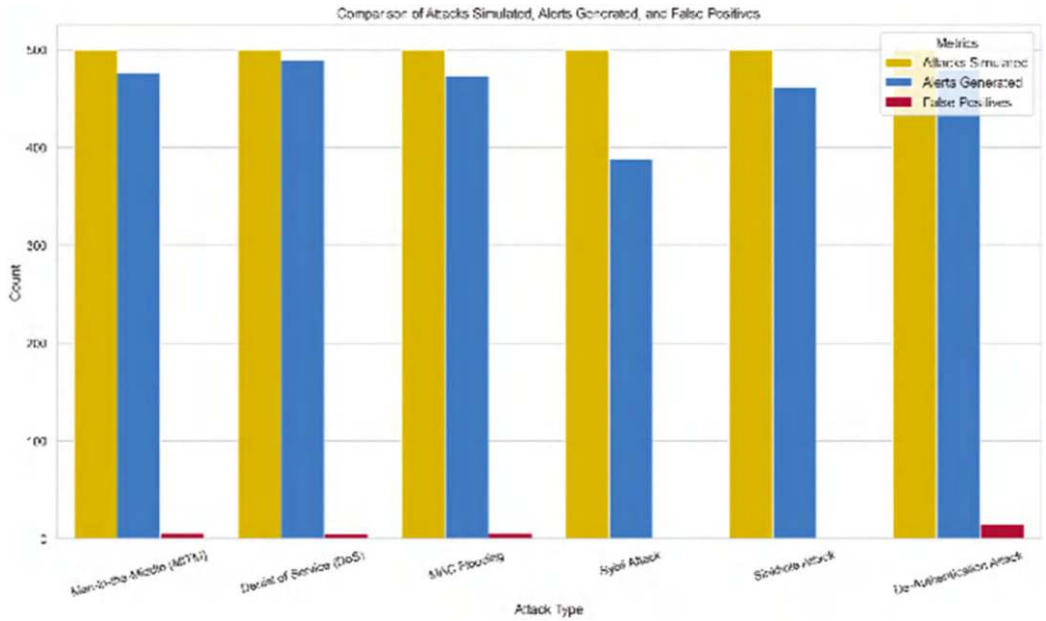

Fig. 64.6 Attacks simulated vs attacks identified

warnings as Suricata identified irregular traffic spikes and spoofed MAC addresses. The system also detected Sybil and Sinkhole attacks, which involved network disruptions and malicious routing behaviors. These results confirm that the implemented IDS system, with its customized rules, is effective in identifying and preventing threats within IoT networks. To detect de-authentication attacks, the python Scapy library was used for detection as it gave better results in detection rather than rule based detection. The system performed well in identifying de-authentication, MITM, DoS and MAC Flooding attacks, with detection accuracies ranging from 92% to 98%.

5.3 Resources Consumption

The resource utilizations - CPU utilization, memory utilization, swap usage and network traffic were noted before and after the initialization of the Intrusion Detection System (IDS).

Initially, CPU utilization was very low, with a maximum usage of 12.0% across the six cores. However, after the initialization of IDS, CPU usage peaked to 25.5% on CPU1, reflecting the increased computational demands associated with real time monitoring and threat analysis. Memory usage also raised from 4.5 GB to 5.7 GB, indicating the considerable memory requirements of the IDS for data processing and storage. Swap usage, which was initially nonexistent, increased to 1.1 GB, highlighting the strain on RAM as the system adapted to handle the IDS workload. Network activity was previously at zero, showed a marked increase after initialization, with significant incoming and outgoing traffic reflecting the operational requirements of the IDS.

Overall, these findings indicate that while the suggested IDS technique improves security capabilities, also it requires careful resource management to maintain optimal system performance in IoT environments.

6. Conclusion

In conclusion, the implementation of the Intrusion Detection System (IDS) on the Jetson Orin Nano has demonstrated significant need for enhancing the security of IoT networks. Furthermore, for future research, exploration could involve optimizing the IDS mechanisms to reduce resource consumption while maintaining high detection accuracy. The use of machine learning techniques may improve the system's ability to deal with evolving threats and reducing false positive rates. Another important scope is the development of a scalable IDS architecture that can support a larger number of IoT devices without limiting the performance.

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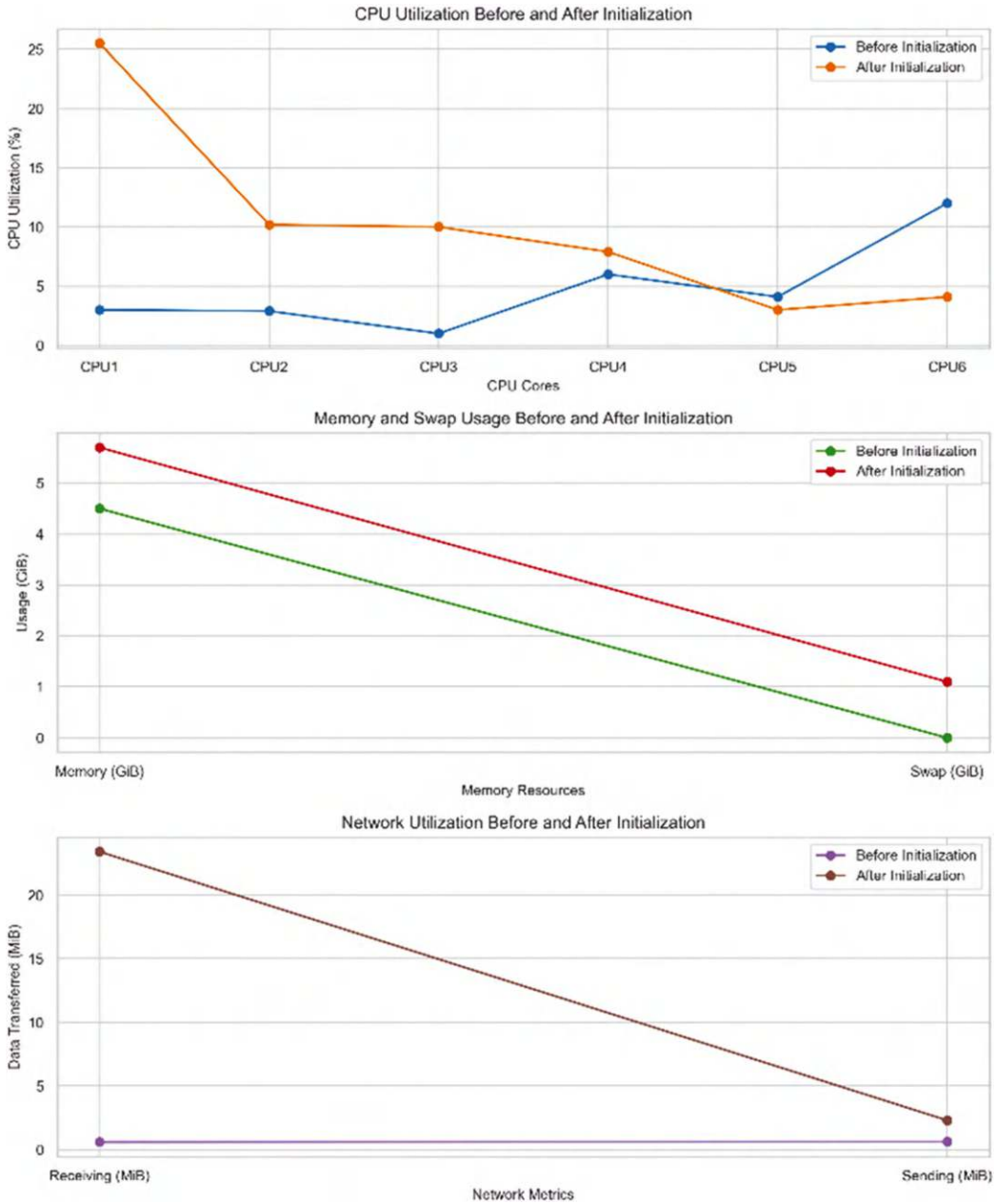

Fig. 64.7 Resources consumption

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65

Supervised Fine-Tuning Large Language Model with Low-Rank Adaptation and Quantized Low-Rank Adaptation for Student Mental Health Support

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Abstract: The increasing number of students experiencing mental health concerns highlights the necessity for creative solutions that extend beyond conventional support networks. This study looked at how large language models (LLMs) can be improved using AI-based student mental health support systems, particularly by using fine-tuning strategies like Quantized Low-Rank Adaptation (QLoRA) and Low-Rank Adaptation (LoRA). By fine-tuning pre-trained LLMs on domain-specific data, the models can potentially respond more empathetically and relevantly to mental health factors. This research illustrates how these methods enhance response precision, relevancy, and individualization, delivering immediate assistance customized to students' requirements. Assessments that contrast basic and fine-tuned models significantly improve response quality and contextual awareness. This study provides insights into the practical use of fine-tuned large-language models in mental health therapies. This demonstrates their capacity to enhance current support networks and address deficiencies in student communities' access to mental health services.

Keywords: Fine-tuning, Generative AI, LoRA, QLoRA, Large language models, AI-driven mental health interventions

1. Introduction

The increasing number of student mental health difficulties necessitates the development of more effective and expandable AI-driven treatments. There needs to be a shift towards creative solutions since conventional mental health support systems can't provide tailored treatment. In order to enhance large language models (LLMs) for targeted mental health care, this work introduces the innovative use of Quantized Low-Rank Adaptation (QLoRA) and Low-Rank Adaptation (LoRA). These approaches allow LLMs to respond to enquiries about mental health in a realistic and compassionate way while keeping computational efficiency and tackling current challenges with domain-specific adaption and resource constraints.

When it comes to tailoring pre-trained models to specific tasks or domains, fine-tuning LLMs is a crucial technique. This method comprises retraining a pre-trained LLM using task-specific data to improve its performance in certain

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applications (Li et al., 2023; Zhang et al., 2023). Using their general language comprehension, LLMs can acquire knowledge and abilities through fine-tuning. Several methods for fine-tuning have been developed to address the different issues and needs. Howard et al. (2018) and Reddy (2023) found that the Universal Language Model Fine-tuning (ULMFiT) method improved text classification and introduced a transfer-learning methodology for natural language processing tasks that was effective. Optimising a small continuous task-specific vector while maintaining the main model parameters frozen is achieved through prefix-tuning (Li & Liang, 2021) and the multiple expert fine-tuning framework (Li et al., 2023). This enhances LLMs with retrieval-augmented generation capabilities, domain-specific processing, and multi-turn question answering. The supervised fine-tuning technique for modifying a pre-trained large language model (LLM) for a specific task is illustrated in Fig. 65.1.

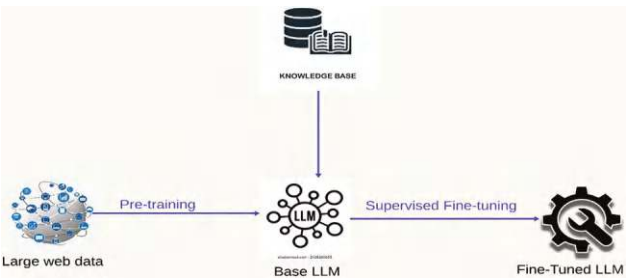

Fig. 65.1 Supervised fine-tuning large language model
Source: Author

Tuning LLMs is a powerful method to improve model performance on specific domains and tasks. Ge et al. (2024) and Muralidharan et al. (2024) both agree that it is an essential tool for improving language models across various domains since it finds a happy medium between recalling past knowledge and adapting to novel contexts. As research in this area continues to evolve, new techniques and frameworks are emerging to address the challenges of cost-efficient training and deployment, thus paving the way for more accessible and versatile language models.

2. Literature Review

A better network of mental health support services for college students may be within reach with the use of large language models (LLMs). Coduti et al. (2016), Kirsch et al. (2014), and Watkins et al. (2011) are just a few of the studies that highlight the growing need for and challenges in providing high-quality mental health services on college campuses. To alleviate these issues, LLMs can make resources more accessible and provide alternatives for scalable support. In recent years, research on AI and LLMs has focused on its potential uses in the field of mental health. One research developed a CBT-centered. LLM is fine-tuned to cognitive behavioral therapy principles to generate structured professional responses for psychological support (Na 2024). Another study used word vector technologies and improved dialogue models to enhance AI-based mental health counseling for students (Gao 2024). These approaches have the potential to augment traditional counseling services.

However, it is crucial to consider student preferences and social ecosystems when designing digital mental health tools (Lattie et al., 2020). Integrating LLM-based solutions with existing campus programs and peer support networks may increase their adoption and effectiveness (Kirsch et al., 2014; Williams et al., 2021). While LLMs offer promising capabilities, they should be viewed as complementary to, rather than as replacements for, professional mental health services. Careful implementation that maintains the quality of care and addresses ethical concerns is essential for these technologies.

Lee and Zeng (2023) and Rajabzadeh et al. (2024) both note that parameter-efficient fine-tuning via low-rank adaptation (LoRA) has become popular for large language models (LLMs) due to the significant reductions in trainable parameters and memory needs. Customising previously trained models to specific objectives, such as student mental health care, has proven to be a highly effective approach that does not necessitate comprehensive model fine-tuning.

Due to new advancements in the field, quantized variants of LoRA including QLoRA and QDyLoRA have been created. In addition to maintaining competitive performance, these versions further reduce memory utilisation (Rajabzadeh et al., 2024). Thanks to these quantized techniques, large models like Falcon-40b may be fine-tuned on a single GPU, making them more accessible for specialised applications. In addition, new methods such as Quantized LLMs with Balanced-rank Adaptation (Q-BaRA) and Quantum-informed Tensor Adaptation (QuanTA) have been developed to improve performance on difficult tasks and remove the limitations of low-rank approximations (Chen et al., 2024; Shen et al., 2024).

In the context of student mental health support, these advancements offer promising opportunities to tailor LLMs to provide more accurate and context-specific responses. The ability to fine-tune models with reduced computational resources could enable educational institutions to develop customized mental health support systems. Furthermore, techniques such as L4Q, which combines quantization and fine-tuning, could potentially allow the deployment of highly efficient models on resource-constrained devices, making Mental health support is more accessible to students (Jeon et al., 2024).

To increase the performance of a large language model (LLM) on a specific job or area, its parameters can be fine-tuned by adjusting the pre-trained model. Although these strategies vary in complexity and resource restrictions, their common goal is to enhance the model's performance in certain applications. Complete optimisation, LoRA, and QLoRA are the three approaches to fine-tuning large language models (LLMs) shown in the figure (Fig. 65.2).

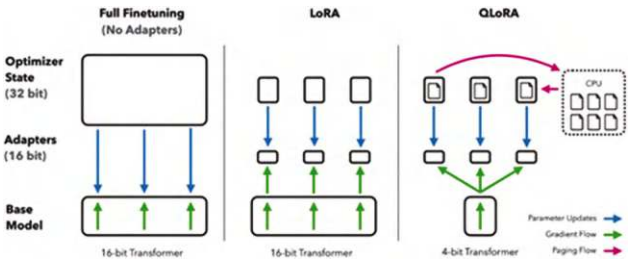

Fig. 65.2 Comparison of full fine-tuning, LoRA, and QLoRA methods

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3. METHODOLOGY

3.1 A PEFT, or Parameter-Efficient Fine-Tuning

A method called parameter-efficient fine-tuning (PEFT) allows you to modify big pre-trained language models for specific uses without changing any of the model's parameters. Because it enables more effective and cost-effective fine-tuning, this is crucial for handling the vast size and complexity of modern language models. Low-rank adaptation (LoRA) and quantized low-rank adaptation (QLoRA) are two of the PEFT approaches. PEFT focuses on changing a small number of parameters or adding new ones to maintain or improve the execution of specified tasks. This approach is very beneficial for the reasons listed below.

Efficiency: Minimizing computational and memory overhead during the fine-tuning of big models, including the reduction of floating-point operations and the use of lower-precision approaches.

Scalability: Modifying large models for various purposes without necessitating substantial computer resources using parameter-efficient approaches such as LoRA or distillation techniques.

Flexibility: The capacity to swiftly adapt to new tasks or domains with little computing expense, shown via transfer learning or efficient architectural alterations.

The mathematical foundation of PEFT is often built on linear algebra and optimization techniques such as low-rank factorization. This document presents an overview of the concepts foundational to the LoRA and QLoRA.

3.2 Low-Rank Adaptation (LoRA)

By splitting weight matrices into low-rank matrices, LoRA minimises the number of parameters that must be changed during fine-tuning. This approach lowers processing and storage needs without sacrificing the model's effectiveness. By breaking out parameter metre updates into low-rank matrices, low-rank adaptation (LoRA) significantly reduces the number of parameters that must be changed. The LoRA shows that fine-tuning parameter changes frequently take place inside a low-dimensional subspace. The LoRA skilfully adapts the model to new problems by concentrating on this subspace. We conduct a methodical, step-by-step analysis of LoRA in order to comprehend its mathematical underpinnings.

1. **Original Weight Matrix:** Consider a weight matrix W in a neural network layer, where $W \times R^{d \times k}$
2. In decomposition, a weight matrix W belonging to the set $R^{m \times n}$ from a previously trained model is considered. LoRA approximates the adaptation by splitting W into two low-rank matrices, A and B:

$$W \approx W + \Delta W = W + AB$$

where $A \in R^{m \times r}$ and $B \in R^{r \times n}$, with $r \ll \min(m,n)$.

3. **Optimization:** The full weight matrix W is not updated during fine-tuning; just the low-rank matrices A and B are. As a result, there were a lot fewer parameters to memorise.

$$\Delta W = \alpha \cdot AB$$

where α is a scaling factor that controls the influence of adaptation.

4. **Parameter Efficiency:** The total number of parameters to be fine-tuned is reduced from $m \times n$ to $r \times (m+n)$. This is because matrix A has $m \times r$ parameters and matrix B has $r \times n$ parameters. Hence, the total number of parameters becomes

$$r \times (m + n) \ll m \times n$$

5. **Fine-Tuning Process:** The initial weight matrix W stays unchanged during fine-tuning, while only the low-rank matrices A and B are modified.

For the model to maintain its learnt information and respond appropriately to new tasks, it learns the necessary adjustments from the low-rank matrices. Figure 65.3 depicts the Low-Rank Adaptation (LoRA) procedure, which is used to optimise pre-trained language models.

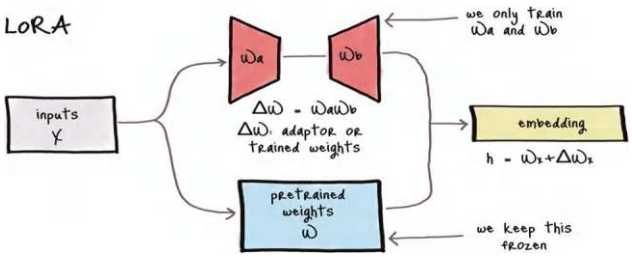


Fig. 65.3 Low-rank adaptation for efficient fine-tuning of large language

Source: https://huggingface.co/datasets/huggingface/documentation-images/resolve/main/peft/lora_diagram.png

This is an example of the input data processing performed by a pre-trained model using frozen weights (W). Instead of manually adjusting these weights, the LoRA incorporates two trained low-rank matrices (Wa and Wb) to produce an adaptation matrix. By combining the initial weights with this adaptation matrix, we can determine the effective weight. The final output embedding (h) is calculated using this effective weight, enabling effective model fine-tuning for specific tasks while preserving most of the initial model parameters.

3.3 The QLoRA Method for Low-Rank Quantized Adaptation

Quantized Low-Rank Adaptation (QLoRA) enhances the concepts of LoRA by using quantization techniques on low rank matrices. This enhances the efficacy of the fine-tuning process. QLoRA quantizes low-rank matrices, reducing their precision while diminishing computing demands and memory consumption. This method preserves the benefits of LoRA while enhancing efficiency.

Original Weight Matrix: Let W be a weight matrix in a neural network layer, where $W \in R^{d \times k}$

Low-Rank Decomposition: Similar to LoRA, QLoRA approximates the update with two low-rank matrices, A and B:

$$\Delta W = A \cdot B$$

Here, $A \in R^{d \times r}$ and $B \in R^{r \times k}$, with $r \ll \min(d, k)$

Quantization: Quantize the low-rank matrices A and B to lower bit-width representations (e.g., 8-bit integers):

$$Aq = \text{quantize}(A), Bq = \text{quantize}(B)$$

This quantization significantly reduces the memory foot print and computational requirements for these matrices.

Parameter Update: The weight matrix W is updated as:

$$W' = W + \Delta W = W + Aq \cdot Bq$$

Fine-Tuning Process: Only the quantized low-rank matrices Aq and Bq are updated during fine-tuning, while W remains fixed. This allows the model to adapt to new tasks efficiently with minimal computational resources.

3.4 Practical Example

- **Pre-trained Model:** Start with a large pre-trained model, such as a transformer with millions of parameters.
- **Weight Matrix:** In a specific layer of this model, let W be a weight matrix with dimensions 1024×1024 (1,048,576 parameters).
- **Low-Rank Decomposition:** Choose a low rank, say r = 64. Decompose the update into two matrices, A and B, where $A \in R\ 1024 \times 64$ and $B \in R\ 64 \times 1024$.
- **Quantization:** Quantize A and B to 8-bit integers, resulting in Aq and Bq. The total number of parameters in Aq and Bq remains the same as in LoRA (131,072), but the lower bit-width significantly reduces memory usage.
- **Fine-Tuning:** Fine-tune the model by updating only the quantized low-rank matrices Aq and Bq, while W remains unchanged.

4. CASE STUDY: FINE-TUNING LLAMA 3.1 FOR STUDENT MENTAL HEALTH SUPPORT

This case study demonstrates how the LLaMA 3.1 model may be improved to offer targeted support for students' mental health by utilising Low-Rank Adaptation (LoRA) and Quantized Low-Rank Adaptation (QLoRA). The focus is on improving the model's ability to respond contextually and sympathetically to student questions about academic stress, anxiety, and depression.

Step 1: Dataset Preparation: Real-world discussions between students and counsellors about mental health make up the dataset that is utilised for fine-tuning. For the purpose of fine-tuning a big language model, the data has been preprocessed and arranged.

Data Sources: Gathered from public mental health forums, anonymised conversation transcripts, or curated datasets addressing prevalent student concerns such as anxiety, depression, and stress management.

Data Cleaning: Removal of unique characters, anonymization of sensitive data, and correcting typos.

Data Structure: The dataset comprises question-answer pairs, with the question denoting a student inquiry and the response reflecting guidance from a mental health professional. Each pair is structured as:

(xi , yi) = (Student Query, Expert Response)

Tokenization: Utilize the pre-trained LLaMA 3.1 tokenizer to transform each text input (queries and answers) into a tokenized format. Verify that the lengths of the input sequences align with the model's context window.

Step 2: Model Initialization and Pre-Trained LLaMA3: The LLaMA 3.1 model starts with pre-trained weights from the model repository. This iteration of LLaMA3 is recognized for its efficient transformer design, making it appropriate for extensive NLP tasks, including mental health assistance.

Model Architecture: LLaMA3 employs a transformer-based architecture optimized for language generation tasks.

Model Parameters: The pre-trained model has hundreds of millions of parameters, rendering comprehensive fine-tuning computationally prohibitive. Consequently, Low-Rank Adaptation (LoRA) minimizes the quantity of parameters requiring modification during fine-tuning.

Step 3: Fine-Tuning with LoRA: LoRA is used to refine the LLaMA 3.1 model. The emphasis is on enhancing the model's capacity to engage in mental health-related dialogues, specifically about empathy, contextual comprehension, and pertinence.

Step-by-Step LoRA Implementation

Decomposition of Weight Matrices: The LLaMA3 model's chosen layers' weight matrices W are broken down into low-rank matrices A and B. The initial weights of these matrices are kept frozen and are initialised at random.

Weight Update Using LoRA: Only the low-rank matrices A and B are modified during the fine-tuning process. The computation of the initial weight matrix W is as follows:

$$W' = W + AB$$

where $A \in R\ d \times r$ and $B \in R^{r \times k}$, with $r \ll \min(d, k)$, significantly reducing the computational cost.

Training Parameters: The learning rate is set to a small value η, batch size b, and the number of epochs n is chosen based on the dataset size. The optimizer used is Adam W.

Step 4: Fine-Tuning with QLoRA (Optional) In resource-constrained environments, QLoRA can be used to further optimize the fine-tuning process by applying quantization.

Step-by-Step QLoRA Implementation

Quantization: The low-rank matrices A and B are quantized to 8-bit integers:

$$Aq = \text{Quantize}(A),\ Bq = \text{Quantize}(B)$$

Weight Update with Quantization: After quantization, the weight matrix is updated as:

$$W' = W + AqBq$$

This allows the model to fine-tune efficiently while reducing memory and computational requirement.

Step 5: Model Evaluation After fine-tuning, the model is evaluated using several key performance metrics to assess its ability to respond empathetically and contextually to student mental health queries.

Evaluation Metrics

- **BLEU Score:** Indicates how much the model's replies and the reference responses coincide.
- **ROUGE-L Score:** Determines the longest common subsequence between the ground truth and the text produced by the model.
- **F1 Score:** Evaluates the model's generated responses' accuracy and recall, especially in suggesting pertinent mental health strategies.

Human Evaluation: To determine the model's responses' helpfulness, relevancy, and empathy, conduct a human evaluation. The model's performance can be assessed by human assessors according on how well it can offer consoling and useful guidance.

Practical Example

- **Query:** " I feel anxious about my upcoming exams. What should I do?"
- **Fine-Tuned LLaMA 3.1 Response (LoRA):** " It's natural to feel anxious, but breaking down your study sessions into manageable tasks can help reduce stress. Try practicing mindfulness or relaxation techniques before studying."

Figure 65.4 demonstrates the relative efficacy of a foundational language model vs a fine-tuned model in tackling student mental health issues. The standard model generates generic answers, but the fine-tuned model, developed using a dataset of student mental health inquiries and expert replies, delivers more precise, relevant, and helpful recommendations and Fig. 65.5 illustrates the distinction between a foundational language model and a fine-tuned model in responding to a student's inquiry on test fear. The basic model delivers a general answer, but the fine-tuned model gives more detailed, actionable, and supporting guidance.

Application to Student Mental Health Support

By using the pre-trained LLaMA 3.1 model and refining it for specific applications, such as student mental health assistance, the model may adjust to the unique requirements of students. Refining the model with datasets related to counselling, mental health discussion, and crisis intervention will enable it to provide more empathic and effective replies. The model's multilingual capabilities facilitate its service to varied student populations, improving accessibility and assistance.

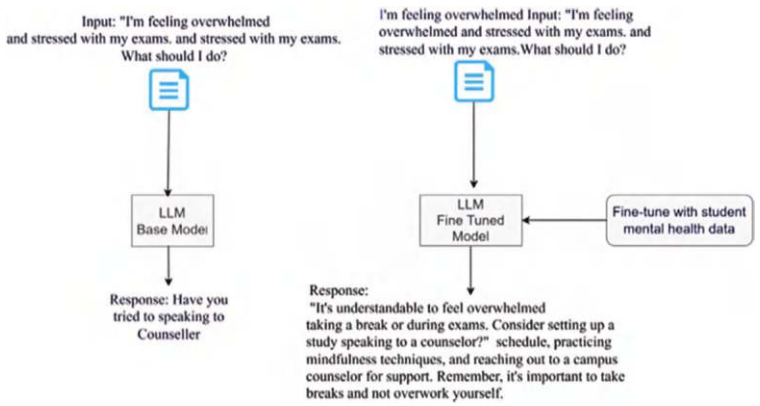


Fig. 65.4 Enhanced response quality through fine-tuning for student mental

Source: Author

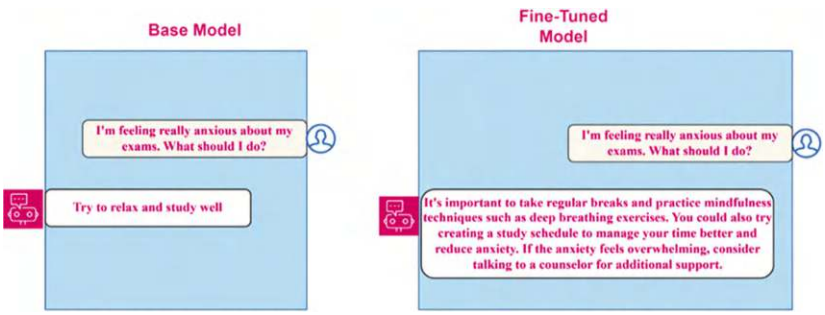


Fig. 65.5 Comparative response quality of base and fine-tuned models for student mental health support chatbot

Source: Author

Architecture Model

The auto-regressive language model LLaMA 3.1 has an improved transformer design. The instruction-tuned versions prioritise safety and helpfulness by synchronising the model's output with human preferences using reinforcement learning with human feedback (RLHF) and supervised fine-tuning (SFT). Table 65.1 delineates the ideal hardware specifications for proficiently fine-tuning extensive language models. It encompasses suggestions for GPU, CPU, RAM, storage, and networking to guarantee effective processing and management of large datasets.

Table 65.1 Recommended hardware specifications for fine-tuning large language models

Components	Recommendations
GPU	One or more NVIDIA GPUs
CPU	Multi-core processor
RAM	At least 64GB
Storage	SSD
Networking	High-speed internet connection

Source: Author

4.1 Google Colab Setup and Library Installation

A Google Colab notebook has been established, and the requisite libraries (Hugging Face Transformers, Datasets, and Torch) have been installed. The following describes the imported libraries and their applications.

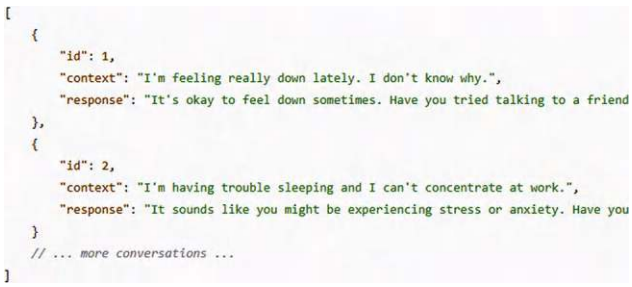
Import Necessary Libraries

- **Transformers:** This library provides tools using transformer-based models, including language models like LLaMA.
- **Datasets:** Used to load datasets from Hugging Face, making it easy to access and manipulate various datasets.
- **Torch:** PyTorch library for tensor operations and deep learning tasks.

A. Dataset Preparations

The Hugging Face dataset comprises 3,512 dialogues about mental health therapy. Every dialogue has two fundamental components: the user's assertion (Context) and the counselor's reply. The conversation dataset is

available at Hugging Face Dataset. The dataset compiles inquiries and responses from two digital counseling and treatment sites. The inquiries include many mental health subjects, with responses provided by experienced psychologists. This dataset is intended for fine-tuning language models to enhance their capacity to provide mental health guidance. The complexity and profundity of the dialogues make it an appropriate resource for training models to produce empathic and knowledgeable solutions to mental health inquiries. For example, the data structure (Fig. 65.6) facilitates efficient processing and analysis of the dataset. Particular fields may be retrieved, dialogues may be categorized by subject, or response trends can be examined.



```
[
    {
        "id": 1,
        "context": "I'm feeling really down lately. I don't know why.",
        "response": "It's okay to feel down sometimes. Have you tried talking to a friend
    },
    {
        "id": 2,
        "context": "I'm having trouble sleeping and I can't concentrate at work.",
        "response": "It sounds like you might be experiencing stress or anxiety. Have you
    }
    // ... more conversations ...
]
```


Fig. 65.6 Example dataset structure in JSON format
Source: Author

B. Dataset Loading and Preprocessing

Here you can find the steps to load and preprocess the mental health counselling conversations dataset. This dataset contains conversations on mental health counselling issues. The article goes on to explain how to tokenize data using the Llama 3.1 8B model.

In Hugging Face Hub, access the "mental_health_counseling_conversations" dataset. Discussions relevant to mental health counselling are part of the data set that will undergo further processing and analysis.

After that, load the tokenizer associated with the Llama 30B model using AutoTokenizer.from_pretrained(). For the model to handle text efficiently, it is first tokenized, or converted to numerical form.

1) Make a function called tokenize_function. Tokenizing the text data and padding it to the maximum length of 512 tokens is what this function does if the text is too long.
2) Each sample in the dataset can have its tokenized using Dataset.map(). This process generates a fresh dataset that contains tokenized samples.

C. Incorporate the Learned Model

The AutoModelForCausalLM class in the transformers library makes it easier to import pre-trained causal language models. It is using this code that Meta AI's strong language model, Meta-Llama-3.1-8B, is initialised. This model can produce original content, translating languages, answering questions intelligently, and writing at a human level.

D. Making Changes to the Structure

This section details the ways the model can be optimised. Initiating training, configuring training settings, and making a trainer object are the steps involved.

1) Set up the training settings with the help of the TrainingArguments function. This includes settings for things like the evaluation method, batch size, epoch count, and output directory.
2) Make a trainer object using the Trainer function. A trainer not only enters but also oversees the model, training arguments, and training and assessment datasets throughout the training procedure.

The third step is to start training using the trainer.train() function. By refining it on the tokenized dataset, the model's capacity to generate replies related to mental health therapy will be enhanced.

E. Maintaining the Fine-Tuned Model

1) After adjusting the model, the trainer can be used to save it to a specified directory.the function that saves the model. This allows you to save the model and run it again later to get results.
2) The overall process of fine-tuning the model includes:
   - Preparing a dataset of 3512 mental health conversations.
   - Tokenizing the dataset using the Llama tokenizer.
   - Fine-tuning the Meta-Llama-3.1-8B model with specific training parameters.
   - Saving the fine-tuned model for future use in generating responses.

5. Comparison Between Base LLM and Fine-Tuned LLM for Student Mental Health Support

The fine-tuned llm Question and Answers chatbot for mental health results as compared to foundation Generative models as shown in "Fig. 65.7"

Question 1:"I feel anxious about my upcoming exams. What should I do?"

Base LLM Response:" You should try to relax and maybe do something fun to take your mind off the exams. Sometimes, it helps to take a break or get some rest."

Fine-Tuned LLM Response:" Although it's normal to experience exam anxiety, there are techniques to help you control it. Make relaxation methods like progressive

muscle relaxation and deep breathing a priority, and try segmenting your study time into smaller, more doable activities. Additionally, if you're feeling overwhelmed, think about getting in touch with a counsellor or academic advisor.

Question 2:" I've been feeling down and unmotivated lately. What can I do to improve my mood?"

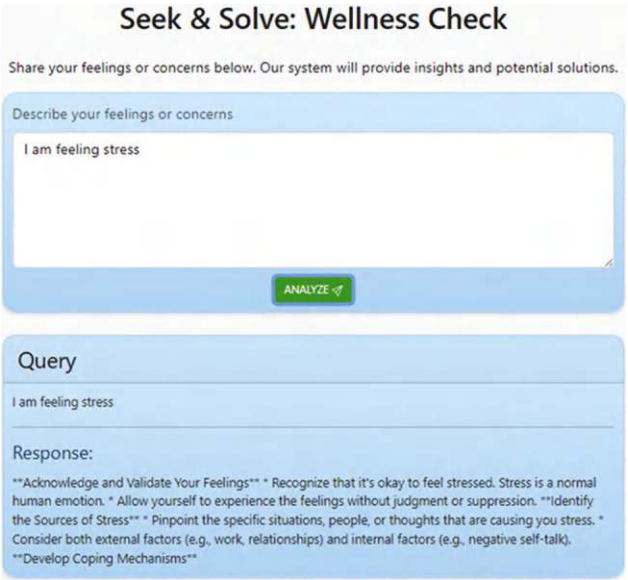


Fig. 65.7 Question and answers chatbot

Source: Author

Base LLM Response:" Try doing something that makes you happy or talking to someone close to you. You could also exercise or eat healthy to feel better."

Fine-Tuned LLM Response:" Feeling depressed and uninspired may indicate burnout or stress. Setting small, manageable objectives and doing things that make you happy, like hanging out with friends who are encouraging or taking up a hobby, may be beneficial. Healthy sleeping patterns and regular exercise can help lift your spirits. Speaking with a mental health expert could be beneficial if these emotions continue.

Question 3:" I'm having trouble balancing my studies and personal life. How can I manage my time better?"

Base LLM Response:" Make a schedule or plan your tasks. Try to organize your time better by focusing on important things first."

Fine-Tuned LLM Response:" Although juggling personal obligations and academic obligations can be difficult, time management strategies can be useful. Make a reasonable timetable first, incorporating both study and leisure activities. To stay focused, prioritise your work according to their relevance and urgency. You can also utilise time-blocking or the Pomodoro technique. Keep in mind to schedule downtime and self-care to keep a healthy balance.

6. Comparison of Base LLM vs. Fine-Tuned LLM

Base LLM:

- Responses are more general and surface-level.
- Lacks specific advice or structured guidance relevant to mental health support.
- Does not provide domain-specific coping strategies.

Fine-Tuned LLM:

- Offers targeted, actionable advice specific to student mental health.
- Recognizes symptoms and suggests coping mechanisms or strategies, such as mindfulness techniques, contacting professionals, and practical time management methods.
- Displays an understanding of mental health terminology and evidence-based practices like cognitive-behavioral therapy (CBT) techniques, stress management, and relaxation strategies.

Fine-tuning the LLM makes it more empathetic, contextually aware, and capable of providing mental health advice aligned with psychological best practices.

7. Evaluate Metrics and Results

To evaluate the fine-tuned LLaMA3 model for student mental health support, metrics such as BLEU Score, ROUGE-L Score, and F1 Score were used to assess the accuracy, content similarity, and relevance of the model's responses compared to expert recommendations. Additionally, human evaluators reviewed the model's replies for empathy, relevance, and helpfulness, providing qualitative insights into its effectiveness in offering supportive and comforting guidance as shown in Table 65.2.

Table 65.2 Performance metrics for llama3 fine-tuned with lora and qlora

Metrics	Lora	QLora
BLEU Score	24.5	23.8
ROUGE-L Score	0.53	0.51
F1 Score	0.76	0.74
Human Evaluation	8.2/10	8.1/10

Source: Author

Results: The fine-tuned model was evaluated on a test set containing unseen student mental health queries. The following results were observed:

7.1 Comparative Analysis

A comparison investigation assessed the performance disparity between the LoRA and QLoRA fine-tuned and pretrained base models. The investigation revealed the following significant points:

LoRA vs. QLoRA: Although both strategies markedly enhanced the model's capacity to provide pertinent and sympathetic replies, the LoRA fine-tuned model marginally surpassed the QLoRA model in BLEU, ROUGE-L, and F1 scores. This is anticipated since QLoRA sacrifices some accuracy for memory economy by implementing quantization on the low-rank matrices.

Memory Efficiency with QLoRA: The QLoRA model demonstrated significant memory and computational efficiency but slightly declined performance. It required almost 40

Human Evaluation: The LoRA and QLoRA fine-tuned models exhibited comparable performance in human evaluations, achieving equal scores in empathy, relevance, and helpfulness. The little discrepancy in their ratings suggests that the accuracy compromise resulting from QLoRA quantization did not significantly impact the model's qualitative performance.

Base Model vs. Fine-Tuned Models: Both fine-tuned models surpassed the baseline LLaMA3 model across all assessment measures. The basic model produced more general replies and had insufficient contextual sensitivity required for mental health assistance. Conversely, the fine-tuned models, especially those using LoRA and QLoRA, delivered more customized and empathic replies.

8. Conclusion

This research effectively used LoRA and QLoRA methodologies to refine the LLaMA 3.1 model for student mental health assistance. The refined models produced sympathetic and contextually relevant replies, markedly enhancing the performance compared to the standard model. Although LoRA has shown superior performance in BLEU, ROUGE-L, and F1 metrics, QLoRA showcased improved memory economy, making it suitable for resource-limited settings. Both models received good scores in human assessments, indicating their potential for practical applications in mental health.

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Integrating Real Time ID Card and Face Match System for Enhanced Personal Authentication

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Abstract: Design and implement a reliable and scalable identification of ID cards recognition system that can accurately identify individuals are wearing their designated ID cards or not in real-time, and automate the attendance tracking, prevent the unauthorized access, thereby enhancing the organizational security and compliance in educational institutions and workplaces. The proposed project is to create identity card detection with face recognition system that is suitable for educational institutions and exam centers. The technologies are used in deep learning techniques. We are using Dlib for generating face encodings and computer vision techniques along with sophisticated object detection techniques. Easy attendance tracking are made possible by the systems structured methodology, which involves training student faces and matching corresponding photos of ID cards. Such as individuals without ID cards, send the notification to administrators for identity approval, enhancing organizational integrity. Results demonstrate the efficacy of the system in accurately detecting individuals with their own ID cards and marking attendance efficiently. The project contributes to the advancement of identification card recognition technology, with implications for educational institutions, offices, and examination centers and another process is a student roaming on college campus through CCTV cameras scan the student image and ID card and send notification to respective department. The high accuracy in detecting individuals with their own ID card and with an accuracy of 95% or higher using advanced object detection techniques and deep learning algorithms.

Keywords: Identification card recognition, Real-time detection, Object detection, Dlib library, Computer vision techniques, Educational institutions, Face authentication

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1. Introduction

Identification cards play a pivotal role in verifying individuals' identities within organizational settings, offering a quick and reliable means of affiliation confirmation. An id card is most commonly used to verify that the persons details. A person name, photograph, date of birth, and other details are printed on an ID card [1]. Using computer vision techniques, we can detect the objects such as ID cards and Dlib is authenticate the face recognition and object detection comparing the id card photograph with original face if match to allow the organization and mark the attendance. The person is not wearing their ID card will be detected and send the notification through the email to administrator for approve the person and another process is a student roaming on college campus through CCTV cameras scan the student image and ID card and send notification to respective department. By using an advanced identity card recognition system, the proposed project seeks to improve security and expedite access control. The system makes use of state-of-art technology like object detection techniques like Dlib for generating face encodings and computer vision techniques as well as deep learning algorithms and computer vision techniques to enable real-time recognition of people to wear the designated ID cards. For this, we have train the student face and then we have to train the ID card when the two images are matched then the result will be notified. The system aims to automate attendance tracking, prevent unauthorized access, and enhance organizational security and compliance in educational institutions and workplaces [1]. In today's world fast-paced organizational environments, ensuring security and efficiency in attendance tracking and access control is crucial. Identification (ID) cards have long been used to verify an individual's identity within the institutions. The system can also monitor students within a campus roaming on roads through CCTV cameras, sending an alert message to the respective department.

2. Literature Survey

Dr. S. Balasubramanian, in 2023 have proposed Facial recognition-based access control systems use Artificial intelligence (AI) and advanced deep learning algorithms to identify and authenticate individual's facial features, enabling seamless access to secured areas. Person detection by examining the faces of humans in digital photos or videos through using algorithms and machine learning techniques is the process involved. This entire process involves the face detection, face alignment, feature extraction, and face matching. The system enhances the security measures by preventing unauthorized access and detecting suspicious activities in real time[1][2]. This technology scans and analyzes the facial images, comparing them to a database of authorized individuals to grant or deny access to a secure area, device, or system. They having some technical limitations facial recognizing systems can be affected by various factors such lighting conditions, angles, facial expressions, some spoofing attacks where an attacker uses a photo or video of an authorized individual to gain the access. Privacy concerns and ethical considerations surrounding facial recognition technology derive ongoing discussions and regulatory measures to ensure responsible usage and data protection. Face recognition software is a type of biometric software that maps an individual's facial features and stores that information as a face print for later purposes. [3].

Elvir Misini, et al in 2022 have proposed Biometric identification systems authenticate individuals identities based on unique physiological or behavioral characteristics such as fingerprints, eye patterns, DNA, even handwriting or audioprints [4]. This system high level of security and accuracy in access control and identity verification processes. It is difficult for find the unauthorized persons individuals to gain access the sensitive areas or systems and it is user-friendly interfaces to user acceptance and adoption of biometric technologies. The systems are scalable and adaptable to various industries and environments, including healthcare, banking, and government sectors, educational institutions [5][6].Ongoing research and development efforts aim to improve biometric recognition algorithms and address challenges related to accuracy, interoperability, and privacy protection. Concession with information/ data protection rules and standards is essential to secure the responsible and ethical use of biometric identification systems [7][8].

Muhammad Baballe Ahmad, et al in 2021 have proposed RFID stands for radio frequency identification, a wireless system having two components: tags and readers. Readers are devices having one or more antennas that emit radio signals and receive them back from the RFID tag. Tags could be passive or active, transmitting their identity and further information to nearby readers using radio waves. [9][10]. These systems offer efficient access control solutions for various industries and applications, including corporate offices, educational institutions and health care facilities [11]. RFID technology enables real-time tracking of individual's movements and access patterns within the premises, enhancing security monitoring and audit trails. RFID card systems support multi-application functionalities, allowing users to leverage RFID cards for access control, time and attendance tracking, and asset management purposes. This can also be described as a smart door lock and smart attendance system but it has

very vast applications in all the field smart parking, smart attendance system, Home security systems etc [12].

Tance suleski, et al in 2023 have proposed Healthcare authentication is highlighted in an investigation alongside the technology included in IoHT and authentication for MFA systems, designed as the next stage in authentication methodologies [13]. MFA is the process whereby a user potentially has to provide two or more provided authentication credentials, which provide a greater assurance of the user's identity than a simple password approach. These platforms support a combination of authentication factors, including passwords, pins, KBAs, retinal pattern, voice, face biometrics, security tokens, OTPs, and one time pass codes. It is protection against unauthorized access and credential theft, reducing the risk of security breaches and data compromises [14]. User-friendly interfaces and self-service options enhance user experience and encourage adoption of MFA technologies while there are many new MFA solutions being proposed, time should be taken to consider user sentiments during the initial stages of development. With balancing security and usability in mind, this report examines the feasibility of a new authentication mechanism based on use of browser fingerprinting, graphical passwords, and honey tokens. This was evaluated through a limited literature review, prototype development, interviewing test users and security experts, and the assuaging of feasibility thoroughly through the guidelines checklists. [1][14].

Refik Samet, et al in 2018 have proposed Face Recognition - Ground mobile automatic schoolroom attending management. Classroom attending confirmation is a chip in cistron to student participation and the final succeeder in the courses. Calling a epithet or go along a canvas is thus time - consuming ; most importantly called the latter, such fraudulent methods can not be ruled out. Former alternative methods, admit RFID, wireless, fingermark, iris, and look recognition, have been quiz and originate for this purpose. Unlike some pros associate to these method acting, it is deserving mentioning the high organisation installation cost in detriment to these systems [15][16]. The proposed system is one that incorporates the use of three separate fluid lotion project for utilisation by teachers, students, and parent on their impudent device to finagle and perform genuine - fourth dimension attendance - pickings [17]. The proposed system is a compromising and real - time face recognition - based mobile attending management system. A filtrate organisation establish on Euclidean aloofness calculated by LBP has been developed. Front identification could be further research expend other techniques, such as living transmitter machine, Hidden Markov modeling, neural networks, and indeed forth. Detection and identification processes could also be carried out on impertinent gimmick every bit soon as their processor electrical capacity is sufficiently increased.

Ulrich Waldmann, et al in 2012 advanced the idea of Electronic identity (EID) cards for user authentication. In most European nations, the use of EID has begun to be powered for both state and non-state distinctive to citizenship, responsibilities and rights. EID's German initiative is noteworthy as a model of EID from an application angle. Looks and works like an EID card, the new German ID card is designed to enable privacy protection in the greatest possible amount and basic idea promoting EID is cryptographic strong, mutual authentication of users and services. In general, EID should be able to support anonymous authentication, and also per service endorsement of a small number of discrete data elements [18]. Key technology seems to be ready to go to mass usage, but problems with implementation may be a 200 considerable barrier to the integration of the EID in the online landscape.

Xuwei Fang, et al in 2017have proposed This paper presents an ID card identification system utilizing advanced image recognition technology to improve identity verification processes. By employing Deep learning algorithms, mainly convolutional neural networks (CNNs), the system accurately extracts essential features such as text and photographs from various ID card formats [19]. Our framework includes image preprocessing, feature extraction, and classification stages, enhancing image quality and ensuring robust performance against variations in lighting and angles. Evaluation on a comprehensive dataset demonstrates significant improvements in processing speed and accuracy compared to traditional methods. This system has potential applications in banking, travel, and security, where efficient identity verification is crucial [20]. Ultimately, our approach highlights the effectiveness of image recognition technology in advancing secure identity management.

3. Issues in Existing System

There may be problems with the accuracy and reliability of the current systems, especially when it comes to correctly recognition people or regularly can be impacted by variables like user presentation, environmental factors, and low image quality. Unauthorized users may try to control certain systems by utilizing stolen identification cards. These systems are susceptible to fraud and spoofing assaults. Inadequate authentication protocols and insufficient anti-spoofing safeguards may jeopardize the security of the system. Complexity and Usability many of the systems in use today are difficult for users and administrators to administer successfully due to their complex setup and operation.

Complex user interfaces and cumbersome authentication processes can lead to user frustration and decreased adoption rates. Integration Challenges for many identity card detection and authentication systems, integration with historical systems and current infrastructure might present serious difficulties. Incompatibility issues, data migration complexities, and interoperability constraints may hinder seamless integration with organizational workflows. Scalability and performance Identification card detection and authentication systems may not be able to manage growing numbers of users and transactions due to scalability and performance issues. Resource shortages, latency problems, and bottlenecks in the system can impair responsiveness and overall performance. Cost and Resource Requirements businesses implementing identity card detection and authentication systems may face difficulties due to high implementation costs, continuous maintenance costs, and resource-intensive hardware requirements. Limited budgets and competing priorities may impact the feasibility of system adoption and sustainability. Regulatory Compliance identification card detection and authentication systems face a major difficulty in complying with industry standards and regulatory regulations. To reduce legal risks and guarantee regulatory compliance, systems must abide by privacy laws, security requirements, and data protection regulations.

4. Problem Statement

For security, compliance, and precise attendance tracking, it is essential to verify people's identities using ID card verification in workplaces, testing facilities, and educational institutions. Manual attendance and ID card checks take a lot of time, are prone to mistakes, and are frequently ineffective. Furthermore, because those without the required identity might enter these organizations without authorization, they are susceptible to security breaches and unauthorized persons enter the institutes and if student is enter the college but not attend the class that person is roaming on the campus scan the student id card and image through CC cameras and send notification to the respective department.

4.1 Proposed System

We provide a complete attendance management system that makes use of cutting-edge computer vision methods. The two primary parts of the system the facial recognition to confirm people's identities and object detection to recognition to confirm department.

Object Detection and ID card Detection

We use the Dlib algorithm, a well known algorithm for excellent accuracy and efficiency in object detection within their photos is what we use for object detection. Real time object detection is possible with Dlib, which also gives bounding box coordinates for each object it detects. By applying Dlib to input images, to identify the ID cards. The program identifies areas in the picture that match ID cards and creates exact bounding boxes around those areas.

Facial Detection and Recognition

Dlib utilize deep learning algorithms, particularly in its facial recognition The face recognition module of Dlib creates 128-dimensional face embeddings using a deep learning model. Then, by comparing these embeddings, one can ascertain whether two faces are those of the same individual.

Matching Faces and Attendance Marking

After identifying the faces, we contrast the ID card's retrieved facial features with those from the primary image. To find out if the person in both photos is the same, a comparison of similarity metrics is used. An individual's attendance is marked if the person is a match between the face on their ID card with the face in the primary image. If not, a violation is noted, signifying a mismatch between the ID card holder and the individual in attendance.

Error Handling

To handle situations like low image quality, occlusions, or several faces in the scene, our system has strong error handling features. These systems guarantee consistent performance in a range of circumstances. Users can upload photographs and view attendance records through our user-friendly interface, which is designed to make it easier to use. Clear feedback on the attendance status and any infractions found is provided by the interface.

Performance Evaluation and Ethical Considerations

To gauge the precision, effectiveness, and dependability of our system, we carry out thorough performance reviews. This involves testing in real-world settings across a range of scenarios and benchmarking against current methodologies. We respect user privacy and data protection laws by following ethical standards in the gathering, processing, and archiving of biometric data. System requires careful consideration of privacy, data security, transparency, and prevent the unauthorized access.

CCTV-based Monitoring

The system will also utilize CCTV cameras placed across the campus to continuously monitor individuals in different areas a student detect under CCTV while roaming on roads in campus notified the respective department.

4.2 Methodology

The use of facial recognition technology, the advance attendance management system automates the process of

tracking attendance. Offering a efficient solution for effective attendance management in a variety of organizational contexts, it simplifies the recording of attendance and gives real-time data for monitoring and analysis, it reduces the need for manual entry and physical presence while enhancing accuracy. This system recognizing unique facial features to identify individuals, their marking attendance and a student roaming on the campus identifying in CC cameras scans the student image and ID card send to the respective department. This advanced technology offers real-time data, which can be used for monitoring trends, identifying absentees and generating reports, making it highly useful in organizational such as schools, workplaces, and events. The system involves multiple stages, including face detection, ID card detection, matching processes, and a notification system.

4.3 Implementation

Dlib: Dlib can detect key facial landmarks, which can help in aligning and normalizing faces before recognition. This improves the accuracy of the recognition process. For facial landmark detection, dlib employs a 68-point model to identify critical facial features like the eyes, nose, mouth, and jawline, which are essential for aligning faces for effective comparison of face recognition

Computer vision techniques: Computer vision techniques involves the image processing, feature detection, and object detection.

Data Collection: The system uses a variety of sources to collect the data, such as cameras or other imaging equipment that can take pictures of faces. To link identities with attendance records and ensure accuracy and accountability in the process, additional data, such as student IDs, may be collected.

Pre-processing: To guarantee data consistency and quality, pretreatment techniques are used before face recognition. In order to increase the accuracy of identification algorithms and improve the system's capacity to identify faces from a variety of angles and lighting situations, this may entail activities including face detection, alignment, and normalization.

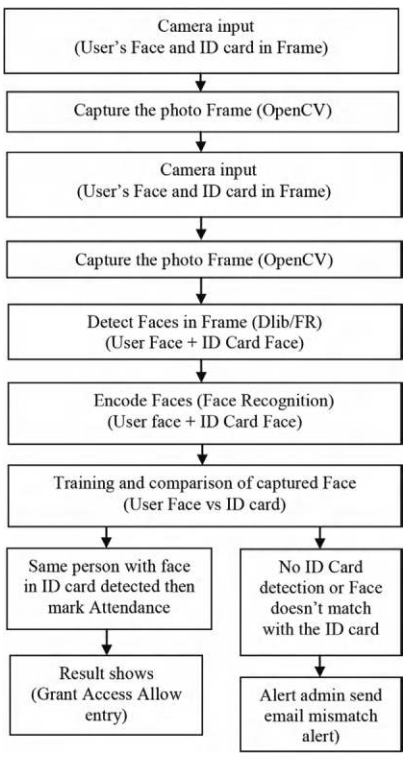
Face Recognition Model Development: To match observed faces with stored identities or templates, the system makes use of sophisticated face recognition algorithms like and Dlib for generating face encodings. Large databases of facial image data are used to train these models, which help them uncover distinctive features necessary for precise recognition and progressively increase the system's capacity to accurately identify people.

Attendance Tracking: Upon facial recognition, the system instantly records attendance information, linking each identified face to the matching person's attendance history. This makes it possible to measure attendance accurately and efficiently in a variety of contexts, giving organizations the ability to keep an eye on patterns and trends in attendance.

User Interface: With attendance dashboards, notifications, and reporting capabilities, the system has an easy-to-use user interface. Users have access to their own attendance history, which improves accountability and transparency, and administrators may simply check attendance data, generate reports, and manage attendance records.

Automated Violation Notifications with Image: The system automatically sends emails to authorized administrators notifying them of attendance violations when people are found to be missing their official identification. The emails also include a picture of the incident that was taken during the violation. These notifications provide information about the time, place, and people who were involved in the infraction, along with a picture that was taken at the scene. With the use of this visual proof, administrators can clearly document the incident, act quickly, and resolve any inconsistencies in attendance records. The solution fosters a culture of compliance and accountability inside the organization by ensuring adherence to attendance regulations and providing real-time alerts accompanied by visual evidence.

4.4 System Architecture



Capture Photo Input (Using OpenCV)

This step captures video/photo from a webcam in real-time. We use a camera to capture a continuous stream of video frames. The computer processes each frame, which contains both the user's face and their ID card. The camera takes pictures of the person and their ID card every second, just like a video. The computer then looks at each picture one by one.

Face Detection (Using Dlib/Face recognition)

Detects where the faces are in the video frame. A face detection algorithm looks at the image and tries to find patterns that look like a face. It identifies the location of faces (like drawing a box around each face it finds).The computer "sees" faces in the picture and draws boxes around them. It tries to find two faces one on the user and one on the ID card.

Face Encoding (Using Dlib/Face recognition)

Converts the detected faces into a set of unique numbers (called an "encoding") that represent the person's facial features. Each face is analyzed, and specific points on the face (like the distance between eyes, nose, mouth, etc.) are converted into a list of numbers that uniquely describe that face. The computer measures important points on both faces (the user's face and the ID card photo) and stores these measurements as a set of numbers, like a face fingerprint.

ID Card Face Detection (Region of Interest - ROI)

Locates the face on the ID card by looking at where it's likely to be in the frame. The algorithm can either guess where the ID card is based on position or use extra techniques (like looking for a rectangle shape) to find the faces on the ID cards. The computer guesses which faces in the picture is on the ID card by looking at where the card might be held or looking for the rectangle shape of the card.

Face Comparison (Using Dlib/Face recognition)

Compares the user's face and the face from the ID card to see if they match.The system compares the numbers (encodings) from the user's face and the ID card face. If the numbers are very close, it means the faces are the same. The computer checks if the face in the picture looks the same as the one on the ID card. If the numbers are close enough, it knows the faces match.

Access Control (Grant or Deny Access)

If the system finds that the user's face and ID card face match, it will grant access (like unlocking a door). If they don't match, access is denied, and an alert is triggered. If the faces match, the computer says, you can come in. If they don't match, the computer says, you can't come in, and tells the administrator.

Send Email Alert (Using SMTP)

Sends an email to the administrator if the user's face and the ID card face don't match. If a mismatch is detected, the system uses email services to send a message to the admin, alerting them that someone tried to enter with mismatched faces. If the computer sees that the faces don't match, it sends an email to the admin saying, there's a problem. Someone tried to enter with the wrong ID.

5. Results and Discussion

Data set Details

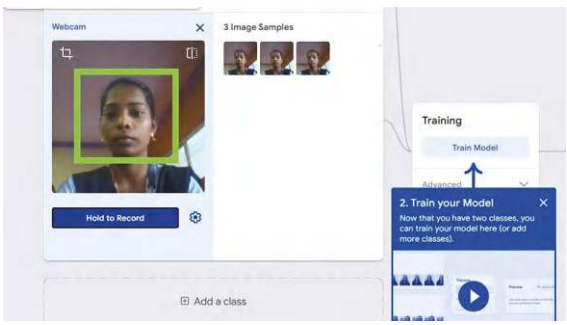


Fig. 66.1 Open the webcam and train the model

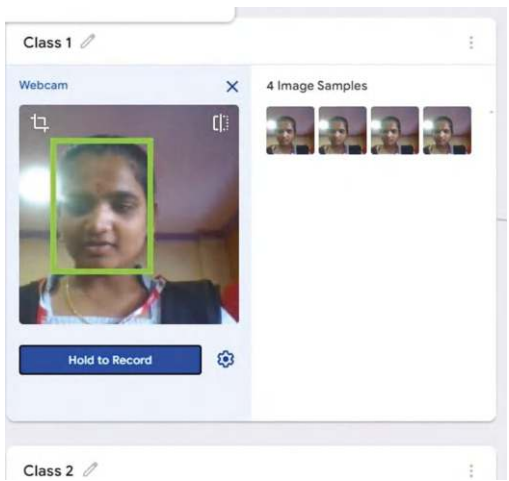


Fig. 66.2 Scan the student face

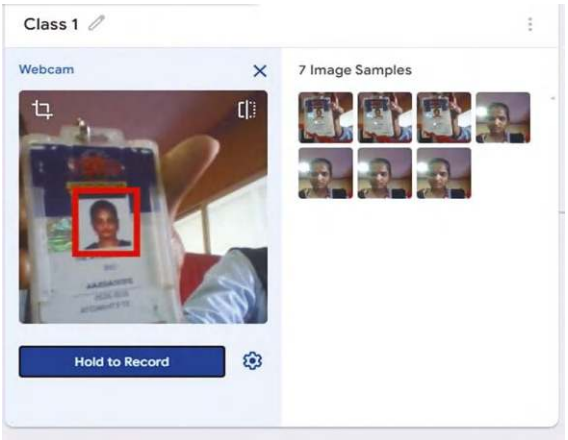
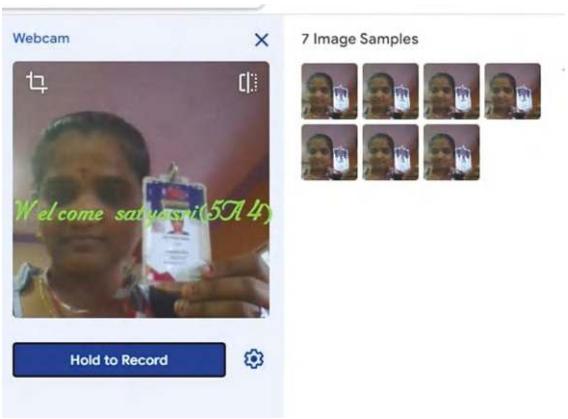


Fig. 66.3 Scan the ID card



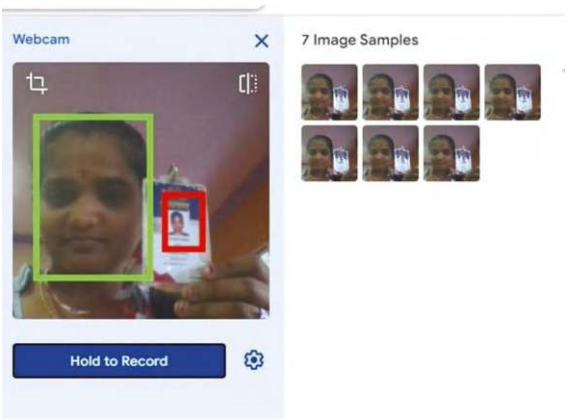
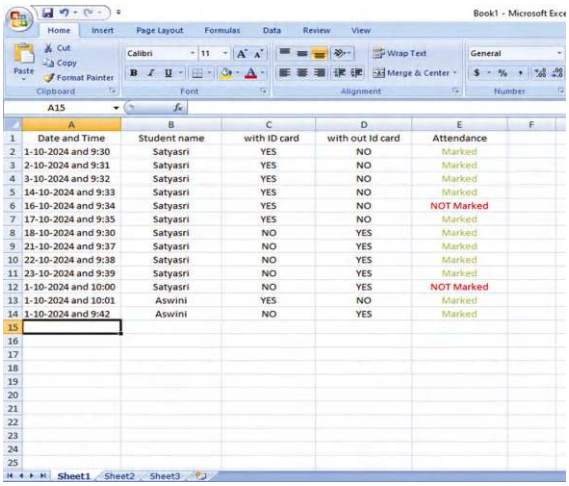


Fig. 66.4 Comparing student face and ID card



	A	B	C	D	E
1	Date and Time	Student name	with ID card	with out Id card	Attendance
2	1-10-2024 and 9:30	Satyasri	YES	NO	Marked
3	2-10-2024 and 9:31	Satyasri	YES	NO	Marked
4	3-10-2024 and 9:32	Satyasri	YES	NO	Marked
5	14-10-2024 and 9:33	Satyasri	YES	NO	Marked
6	16-10-2024 and 9:34	Satyasri	YES	NO	NOT Marked
7	17-10-2024 and 9:35	Satyasri	YES	NO	Marked
8	18-10-2024 and 9:30	Satyasri	NO	YES	Marked
9	21-10-2024 and 9:37	Satyasri	NO	YES	Marked
10	22-10-2024 and 9:38	Satyasri	NO	YES	Marked
11	23-10-2024 and 9:39	Satyasri	NO	YES	Marked
12	1-10-2024 and 10:00	Satyasri	NO	YES	NOT Marked
13	1-10-2024 and 10:01	Aswini	YES	NO	Marked
14	1-10-2024 and 9:42	Aswini	NO	YES	Marked

Fig. 66.5 Allowed access and mark the attendance

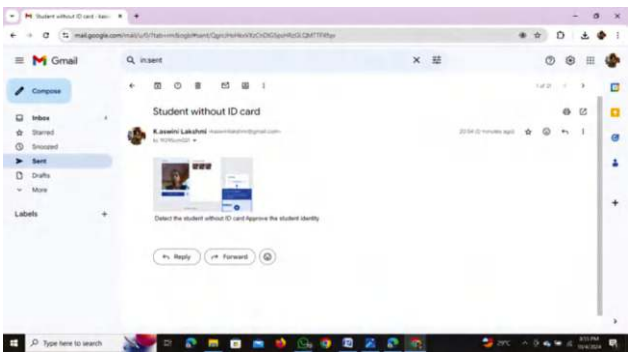


Fig. 66.6 Sending an mail to admin student without ID card

Train the model face recognition and Comparing student face and ID card if the faces matches then attendance will be marked and allow access. The student faces does not match Access denied and notify the administrator through Email. Students enter the college with ID cards. First scan the student face and ask the ID card. Show the ID scan the card and comparing the face and ID card face if matches allow the College and mark the attendance. Doesn't match the ID card or identify the student without ID card to alert a administrator viva Email for approve the student identity.

6. Conclusion and Future Scope

By using OpenCV for real-time video capture, Dlib for face detection and recognition, and deep learning models like YOLO for ID card detection, this system project requirements of efficiently identifying individuals, detecting ID cards, and automating attendance tracking and prevent the unauthorized persons. When the violation accrued that a notification is sent when either the ID card is not detected or the face does not match ensures high security and compliance for educational institutions and workplaces.

The development and implementation of the face and ID card recognition system represent a milestone in automated attendance system by offering simplified procedures and more robust processing capabilities, benefitting educators and businesses from all over. Equipped with machine learning algorithms, e.g. Convolutional Neural Networks

(CNN), the attendance system has been outstandingly precise in identifying human faces and finding identity ID card.. The rigorous evaluation of performance metrics underscores the system's reliability and effectiveness in real-world scenarios. The system's practical benefits include automated attendance tracking, reduced administrative burden, and enhanced data accuracy. By leveraging facial recognition and ID card detection technologies, organizations can optimize their operational workflows and allocate resources more efficiently. Overall, the system's implementation represents a significant step forward in modernizing attendance tracking processes, offering a cost-effective, reliable, and user-friendly solution for educational institutions, businesses, and organizations across various industries.

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Privacy-Preserving Eye Image Classification for Jaundice Detection Using Full Homomorphic Encryption and Visual Geometry Group

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Abstract: Common eye conditions affecting children and teens include blood tears, Polyzoaria, heterochromia, cat eye syndrome, ocular neuritis, Charles Bonnet syndrome, traumatic cataracts, and more. These conditions can cause vision loss and pain, which may be linked to glaucoma and cataracts. Rare genetic illnesses like Retinitis Pigmentosa, microphthalmia, Bietti's Crystalline Dystrophy, and Stargardt Disease can cause vision problems like jaundice. The study uses Full Homomorphic Encryption and Visual Geometry Group to predict jaundices in eye image classification. This paper proposes an eye image classification of Jaundices Using Visual Geometry Group. This technology allows information deep learning to identify eye image data used in algorithms. One solution to the data privacy issue could be to encrypt the eye image data, but standard encryption requires that all training data and validation data be encrypted. The experimental result is based on eye image classification training and validation datasets for disease and loss prediction accuracy.

Keywords: Eye image, Full homomorphic encryption, Jaundices, Visual geometry group, Deep learning

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1. Introduction

Blood tears, Polyzoaria, heterochromia, cat eye syndrome, ocular neuritis, Charles Bonnet syndrome, ocular albinism, traumatic cataract, chronic progressive external ophthalmoplegia, anisocoria, sagging upper lids, sunken eyeballs, and scopolamine patches are common eye conditions affecting children and teens. These conditions can cause vision loss, pain, blurry vision, flashing lights, and reduced brightness in red colours and may be associated with conditions like glaucoma and cataracts. Treatments include radiation and surgery [1]. Retinitis Pigmentosa is a rare genetic illness that damages retinal light-sensitive cells, causing vision constriction and night vision problems. Microphthalmia causes abnormally tiny or missing eyes in children, potentially caused by genes or exposure to chemicals or viruses. Bietti's Crystalline Dystrophy (BCD) causes diminished vision, night vision concerns, side vision loss, and colour vision issues. Stargardt Disease is an inherited disorder causing gradual impairment of central vision, typically affecting children and adolescents [2].

A quick, painless eye exam is performed by a technician or doctor, involving questions about medical history and vision difficulties. Tests include the Visual Acuity Test, pupil tests, eye muscle tests, visual field tests, perimetry tests, tonometry, colour vision tests, retina exams, slit-lamp exams, refraction tests, and pachymetry tests. These tests measure vision, pupil openings, eye coordination, eye pressure, colour vision, retina, slit-lamp exams, refraction tests, and cornea thickness. Eye exams are recommended at 40 for vision problems and non-sight-related diseases and annually for cataracts, glaucoma, and age-related eye issues [3]. Eye redness, burning or stinging eyes, dry tears, and itchy eyes can all indicate various conditions. Allergies, medications, contact lens wear, ageing, arthritis, or computer use can cause dry eyes. Allergies, pinkeye, infection, inflammation, eyelid bumps, cornea sores, black eye, or thyroid issues can cause puffy eyes. Watery eyes may be due to overworking tears or difficulty in draining normally. Twitching, styles, and chalazion can cause pain and discomfort [4]. Yellow spots in the eyes may indicate jaundice, liver disease, gallstones, or cancer. Odd-sized pupils may have dark spots due to nerve damage, migraines, medications, or eye surgery. Strabismus affects 1 in 25 children, causing misaligned eyes. Droopy eyelids can be fixed with cosmetic surgery, but sudden drooping may indicate a stroke, brain tumour, muscle disease, or nerve problems. Seek medical attention if symptoms persist or worsen [5].

Various factors, including dirt, dust, and small particles, can cause eye irritation. Dry eyes can result from insufficient tears, rapid drying, or imbalance of water, oils, and mucus [6]. Pinkeye, caused by bacteria or viruses, can cause watery eyes. Eye allergies can be caused by allergens, eye drops, and avoiding triggers. Clogged tear ducts can cause eye wateriness due to the accumulation of tears, infections, injuries, and ageing [7]. Eyelid issues like entropion or ectropion can cause watery eyes. Corneal scratches can cause eye pain, redness, and light sensitivity. Styes, trichiasis, and blepharitis can cause discomfort and tear issues. Oil glands on the eyelid edge can cause irritability and watery eyes. Medical conditions like Bell's palsy, Sjogren's syndrome, sinus infections, thyroid issues, and rheumatoid arthritis can also cause watery eyes [8].

2. Literature Review

Deep learning (DL) technology has been used in a wide range of applications in the real world. Some examples of these applications include picture classification [9], text analytics [10], crisis management [11], and medical imaging [12]. Pictures can be captured [13], multiple imputation features can be predicted [14], and CNN can be used to extract features [15]. All of these things are achievable. In addition, it is feasible to make predictions about renal failure [16] and verify drugs [17] by using machine learning (ML) models [18], and photographs may be captured [13]. DL algorithms can potentially automate diagnostic activities in ophthalmology that need expert-level competence. It is made possible by the use of retinal fundus pictures. Glaucoma [19], age-related macular degeneration [20], and diabetic retinopathy [21] are some of the procedures that fall within this category of responsibilities. Because drinking water has the potential to cause diabetes [22], [23], [24], gestational diabetes [25], Alzheimer's disease [26], skin disorders [27], and brain tumours [28], it is necessary to evaluate the quality of the water by using the feature selection approach [29] and the chi-square method [30]. This is because drinking water has the potential to cause these diseases.

The authors of [31] used a convolutional neural network (CNN) to autonomously separate exudates, microaneurysms, and haemorrhages from one another. The employment of a single framework was ultimately successful in accomplishing this goal. The data gathered from the green channel of the normalized and equalized image was combined with data collected manually [32]. This allowed for the construction of deep-learning feature vectors. The CNN's four convolutional layers and one fully connected layer, which was trained using the LeNet architecture, were used to construct these feature vectors. UsingEyePACS, the authors of [33] could ascertain the existence of five unique forms of red lesions.

Micro aneurysms, haemorrhages, exudates, and retinal neovascularization were all included in these red lesions. Regular lesions were also included. In addition, multiclass prediction [34], classification [35] for recurrent breast cancer detection utilizing machine learning [36], and deep learning [37] were applied to forecast liver metastases [38] and to forecast hepatic illness [39]. Around the same time, as [40] employed a mix of random forest and deep neural network (DNN) for the goal of blood vessel segmentation, the authors of [41] presented a framework for blood vessel segmentation that was based on deep learning. They applied it to retinal fundus image datasets. This framework was used to segment blood vessels. Compared to many procedures used in the past, their experimental findings provided better results. According to the study's results [42], a classification architecture based on deep learning (AMD) can be used to predict the severity of age-related macular degeneration.

3. METHODOLOGY

Complete Homomorphic Privacy Protection for Eye Images enables information machine learning to identify data used in algorithms. One solution to the data privacy issue could be to encrypt the data, but standard encryption requires the entire training data to be encrypted. However, if the data engineers control the key that encrypts the data, they are prevented from decrypting it when they acquire new client data. One approach is using Full Homomorphic Encryption (FHE)[43]. FHE preserves the multiplying and adding processes in image data encryption, as shown by the encryption function in equation -1.

$$E(a + b) = E(a) + E(b) \text{ and } E(a * b) = E(a) * E(b) \quad (1)$$

This means that FHE maintains any polynomial alteration to the eye image data. If the computation involves a polynomial, it indicates that performing a function or operation P on the encrypted data E(a) is equivalent to encrypting the result of that operation on the plaintext data a is, as shown in equation - 2

$$P(E(a)) = E(P(a)) \quad (2)$$

The decryption function D decrypts the original image data, ensuring that the original image remains intact, i.e., D(E(a)) = a.

This signifies that

$$D(P(E(a))) = D(E(P(a))) = P(a) \quad (3)$$

That means computations with fully encrypted image data are comparable to those without encryption. If P is a Machine Learning model, we can train it on non-encrypted image input data and infer from encrypted data. The model output will also be encrypted and can be decoded by the same entity that initially encrypted the image data. The model server host will never come across raw patient diagnosis image data. Our machine learning model must be a polynomial transformation. Non-polynomial MAX and EXP functions are used in neural network operations like ReLU and SoftMax. To implement FHE, we must modify the critical components of ML models. This research suggests suitable polynomial approximations for neural networks.FHE can also be used for federated learning. Multiple models are trained on local devices using private data and aggregated on a remote server. Following aggregation, the distant server and local computers can synchronize their models. One issue is that we can always extract information about the private data from the trained model. Because model aggregation on the remote server is usually a simple average, we can send encrypted models to the aggregation server and decrypt the synched model locally, as shown in Fig. 67.1. Unfortunately, this means all clients must share the same encryption and decryption keys, which are vulnerable to assaults.

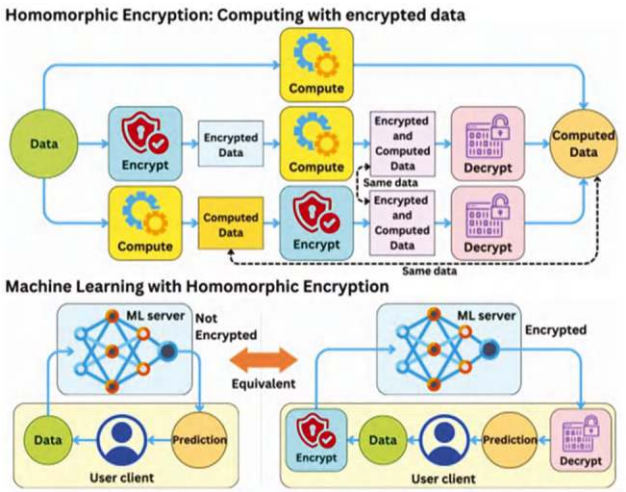

Fig. 67.1 Eye image homomorphic using privacy preserving machine learning

The Classification of Eye Images Using CNN is the architecture that the Visual Geometry Group uses. It is a deep learning model comprising multiple layers and is used to handle ordered grid-like data such as photographs. As a result, it can improve tasks such as picture classification and object identification [44]. The Visual Geometry Group is responsible for developing the VGG-16 [45] model, a convolutional neural network with sixteen layers. It can learn intricate visual characteristics due to its depth, which results in accurate predictions [46]. Because of its adaptability and performance, VGG-16 remains a popular option for deep learning applications despite being very straightforward. The Eye Images Net Large Scale Visual

Recognition Challenge is a yearly competition in the field of computer vision. Teams compete against one another in various other tasks, including object location and image categorization. The architecture known as VGG-16 is a deep convolutional neural network explicitly developed for image classification. There are sixteen layers, thirteen of which are convolutional, and three are entirely connected. These layers are laid up in blocks, as seen in Fig. 67.2.

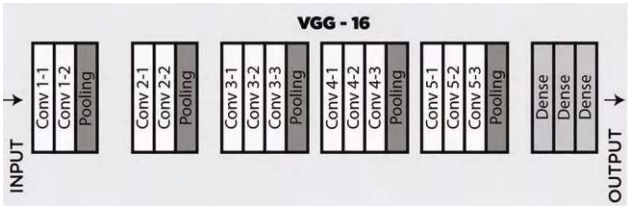

Fig. 67.2 Architecture of VGG-16

A localization based on bounding box position coordinates is used for the ocular image classification. This localization has two variants: one common among candidates and one class-specific. In addition, it investigates the feasibility of shifting loss from classification to regression loss functions, such as mean squared error (MSE), to identify deviations from the actual truth. Using VGG-16, the eye image space allows anybody to engage with the basic concepts of full homomorphic encryption (FHE) and apply them to image processing. The first step in the process involves using encrypted image filtering as a fake code for homomorphic encryption. Currently, the technique of constructing familiar image processing filters using Torch is a model that helps preserve privacy. These models can be readily converted into their corresponding FHE circuits with the help of the Concrete-NumPy library and Concrete-ML. After that, the circuit can be deployed using an interface. One possible use of this interface would be to provide a service enabling customers to apply any picture filter while maintaining the image's confidentiality concerning the location space. There is also the possibility of developing filters based on machine learning models. These filters might enable picture improvement or noise reduction.

Concrete-NumPy and Concrete-ML tools are developer-friendly tools for applying filters on X-ray images using Eye Image, enabling data processing and transfer using encryption. They allow Python routines to be converted to FHE-equivalent circuits and employ VGG models without cryptography knowledge. Create an image processing filter using Torch models and Concrete-ML utility functions, incorporating machine learning-related filters like noise reduction or eye image enhancement. Torch module simplifies filter building through convolution operators and eye image integration for VGG models. Convolution is crucial for popular filters like sharpening and blurring, with reshape functions added for non-numeric shape conventions in FHE. Concrete-NumPy's FHE implementation currently supports integer images and kernels, but more uncomplicated cases like inverting RGB image colours can be completed using more straightforward methods. Because filters cannot deal with such limits, the calculations in FHE need post-processing in the clear. This includes clipping output values to the appropriate RGB standards.

Concrete-ML tools should be used to combine the images to their equivalent FHE circuit to apply filters on encrypted ocular pictures. RGB eye pictures of the form (100, 100, 3) are used throughout the lesson. The compilation process considers a representative collection of inputs created randomly via synthetic RGB eye pictures made of integers (three channels, ranging from 0 to 255). The `sharpen filter` should be compiled. Following the execution of a filter in FHE, the system gets the encrypted output after sending an encrypted picture to a particular place using the system. In the location space, neither the input eye picture nor the output result are accessible to the user. The demonstration depicts the encrypted output, which enables authorized users to continue to use the service. Following the decryption of the output, a comparison is made to the initial ocular picture. The entire process has been shown in Table 67.1.

The algorithm eye image process was built with Concrete-ML, Zama's privacy-preserving machine learning open-source tool.

4. Results

VGG, or Visual Geometry Group, is a deep Convolutional Neural Network architecture used in object recognition and eye image classification, better baselines, and a popular choice for tasks and eye image datasets of Training and Validation. The eye image data Generation generated 464 authorized image filenames from two classes. 116 approved image computer filenames were belonging to two classifications. The pie chart shows the classification of normal eyes at 62.5% and jaundiced eyes at 37.5%, as shown in Fig. 67.3.

Counting each label, like Normal and Jaundice in Eye Image Classification, is a crucial aspect of the process, as shown in Fig. 67.4.

After pre-processing, various models were used for the dataset, like ResNet, DenseNet, MobileNet, and VGG16. After applying these models, some values were obtained, as shown in Table 67.2. After comparing the values with various metrics, various models observed that VGG16 has

Table 67.1 Algorithm for eye image classification for jaundice detection

ALGORITHM :	
Step 1:	Initially, we uploaded the input of the Eye image. The input image automatically resizes the shape. The image displayed here is, however, using its original resolution.
Step 2:	The image is encrypted after generating the necessary keys.
Step 3:	Generate the private key.
Step 4:	Encrypt the image using FHE. • Build image filters (like sharpening or noise reduction) that are compatible with FHE, ensuring they work on encrypted images using Torch and ConcreteML. • These filters enhance or modify image quality while maintaining the image's privacy. • Convert the filters and models into FHE circuits using tools like ConcreteNumPy and ConcreteML. This demo demonstrates a secure encryption process using a Classification System and a machine with 8 vCPUs. The demo is run on the same machine, but future demos will be on separate machines.
Step 5:	Train the Model • Train the models (ResNet, DenseNet, MobileNet, VGG16) using non-encrypted image data to extract features and develop classification rules. • Ensure the models are built around polynomial transformations, as FHE supports polynomial-based operations.
Step 6:	Federated Learning Setup: • Use Federated Learning, where multiple local models are trained on encrypted private data in different locations. Each model learns from its dataset without sharing raw data. Aggregation: • The encrypted models are aggregated on a central server without decrypting the individual models. • Local devices can then decrypt the aggregated model for further use.
Step 7:	The encrypted image should be sent to the model.
Step 8:	Apply FHEcompatible Filters and VGG Models: Process the encrypted image with pre-trained VGG models and image filters while maintaining encryption.
Step 9:	Run the FHE execution.
Step 10:	Obtain Encrypted Results, such as classification or filtered output, remain encrypted
Step 11:	Authorized users decrypt the output to access the final prediction or image data.

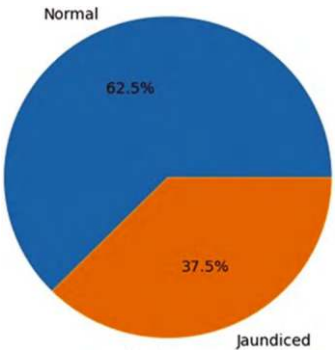

Fig. 67.3 Pie chart of eye image classification

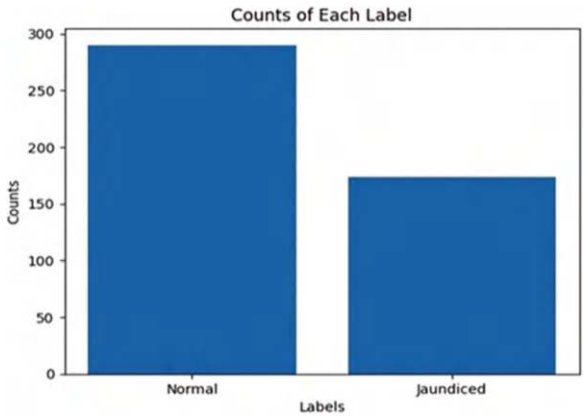

Fig. 67.4 Counts of eye image label bar chart

the highest values. By observing the Table 67.2 values, VGG16 has achieved the highest values for accuracy at 94.02%, precision at 93.44%, recall at 92.52%, f1 score at 91.08% and AUC has gained 66.44%.

The results from Table 67.2 show that the graph was drawn for accuracy, as shown in Fig. 67.5, the graph for various performance metrics with various models was shown in Fig. 67.6, and the graph for AUC with various models was shown in Fig. 67.7.

Table 67.2 Results obtained for various metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC
ResNet	86.85	84.47	81.07	82.14	81.03
DenseNet	89.09	75.24	69.45	69.63	68.65
MobileNet	79.87	79.74	71.23	72.08	71.21
VGG16	94.02	93.44	92.52	91.08	66.44

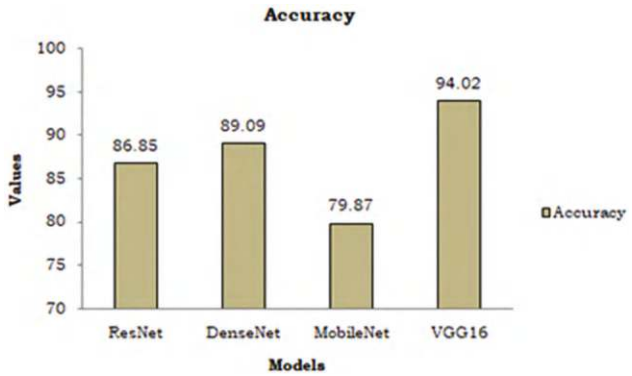

Fig. 67.5 Graph for accuracy

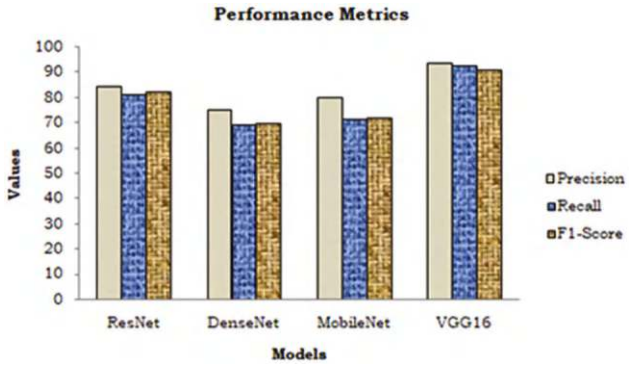

Fig. 67.6 Graph for various performance metrics

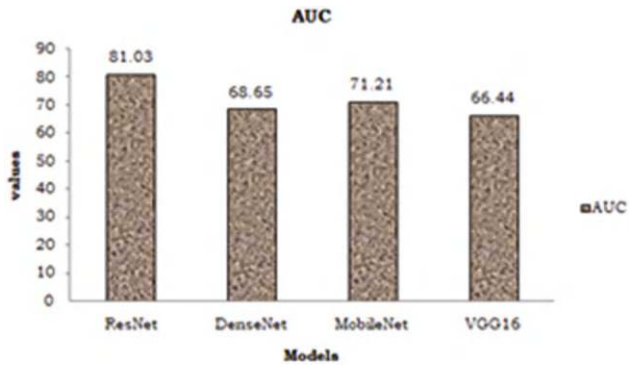

Fig. 67.7 Graph for AUV with various models

5. Conclusion

The proposed model anticipates jaundices in eye image categorization utilizing Full Homomorphic Encryption and the Visual Geometry Group. Jaundice are classified in ocular images using the Visual Geometry Group. The models enable deep learning to detect ocular image data used in an algorithm. VGG16 model got the highest values compared with the ResNet, DenseNet, and MobileNet. Accuracy got 94.02% for the VGG16, and AUC got 66.44% for VGG16. One solution to the data privacy issue could be to encrypt the eye image data, but typical encryption involves encryption of all training and validation data. The experimental results are based on the training and validation datasets for eye image classification to forecast disease and loss accurately. The proposed model demonstrates a promising approach to securely and accurately classifying jaundice in eye images, which could be expanded to detect a range of eye-related illnesses. Future research may further optimize encrypted model training and investigate additional architectures to improve classification performance, ultimately contributing to enhanced privacy-compliant diagnostic support in ophthalmology.

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Explainable Artificial Intelligence (XAI) for Lung Cancer Detection: A Framework for Early and Accurate Diagnosis

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Abstract: Lung cancer remains a leading cause of death globally, with early detection being crucial to improve patient survival rates. Traditional diagnostic methods are time-consuming and may overlook early-stage indications, prompting the need for advanced, automated solutions. This study presents an innovative deep learning-based framework leveraging Convolutional Neural Networks (CNNs) to enhance the accuracy and speed of lung cancer detection from CT scans. By employing Generative Adversarial Networks (GANs) for data augmentation and a specialized CNN architecture for feature extraction and classification, the model performs better in distinguishing malignant from benign nodules. Moreover, the framework incorporates Explainable AI (XAI) techniques, offering interpretability through visual explanations to support clinical decision-making. The proposed model demonstrates high recall and reasonable precision, balancing sensitivity and specificity to ensure effective detection of true positives while reducing false positives. Through model evaluation, including ROC analysis and comparisons with existing approaches, the study

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highlights the model's strengths and areas for refinement. This research contributes to the advancement of diagnostic accuracy in lung cancer detection, with a focus on creating robust, interpretable AI-driven tools for clinical integration and ultimately enhancing patient care. Future work will explore additional features and ensemble methods to further improve precision without compromising recall, addressing critical gaps in AI-driven medical diagnostics.

KEYWORDS: Lung cancer, Computed tomography CT images, Convolutional neural network (CNN), Supervised learning, Artificial intelligence (AI), Deep learning etc.

1. INTRODUCTION

Lung infections, especially cellular breakdown in the lungs, are a significant worldwide wellbeing concern, causing a huge number of passings every year. Early identification and treatment are basic for expanding patient endurance rates, yet conventional demonstrative techniques can be tedious and inclined to mistake. Progresses in clinical imaging, especially Registered Tomography (CT) examines, have changed the discovery and examination of lung anomalies. In any case, manual assessment of these pictures is tedious and may miss hidden indications of beginning phase cellular breakdown in the lungs. To address these difficulties, man-made brainpower (artificial intelligence) and profound learning advances have become integral assets in clinical diagnostics. By utilizing these advances, the productivity and precision of cellular breakdown in the lungs can be improved. This examination presents an original brain network model intended to recognize harmful cells in CT pictures, using profound learning methods like Convolutional Brain Organizations (CNNs) for precise cellular breakdown in the lungs grouping and organizing. With its focus on automation and precision, the proposed framework aims to reduce the time and cost associated with lung cancer diagnosis, providing an optimistic outlook for the future of cancer treatment. Convolutional brain organizations (CNNs) are generally applied to distinguish and group lung knobs from CT pictures. These models, for example, in the concentrate by Kanavati et al., utilize pitifully managed learning for lung carcinoma classification, improving precision through cutting edge imaging methods. Another popular method involves hybrid models combining CNNs with metaheuristic algorithms for higher accuracy. Deep reinforcement learning has also emerged as a valuable tool in medical applications. It is applied in lung cancer detection to improve decision-making processes, which helps predict mortality from CT images. Generative Antagonistic Organizations (GANs) are being utilized for information expansion, tending to the test of restricted clarified datasets. This method improves model robustness, allowing for better lung cancer classification. Some studies incorporate hybrid frameworks, combining classical machine learning techniques with deep learning methods to enhance diagnostic systems. For instance, a hybrid model combining CNNs and adaptive boosting is used to identify lung cancer types more efficiently.

2. REVIEW OF LITERATURE

The literature indicates a growing interest in applying deep learning and AI techniques for lung cancer detection. Key trends include the integration of multimodal data, the importance of explainability in AI models, and the exploration of hybrid and transfer learning approaches. The studies collectively emphasize the need for robust, interpretable, and clinically applicable models to improve diagnostic accuracy and patient outcomes. Future research should address current challenges, such as data diversity, bias in AI models, and the integration of AI into clinical practice.

Kanavati et al. (2020) implemented a weakly supervised CNN model for lung cancer classification from CT scans. Their model provided promising results in classifying carcinoma without needing fully annotated datasets, a common challenge in medical imaging. Further, transfer learning techniques have been used in various models to leverage pre-trained networks on general image datasets, achieving higher accuracy when applied to medical images (Cheng et al., 2021).

Hybrid models combining CNNs with traditional machine learning techniques like adaptive boosting or random forests have demonstrated enhanced performance. Lakshmanaprabu et al. (2020) proposed a mixture approach for cellular breakdown in the lungs discovery coordinated CNN with old style highlight combination strategies to further develop classification accuracy.

Li et al. (2022) also proposed a hybrid model combining CNNs and support vector machines (SVM) to further improve diagnostic precision, particularly in distinguishing between benign and malignant nodules.

Data augmentation using Generative Adversarial Networks (GANs) has become a widely adopted technique to

overcome the limitation of small medical datasets. Khalvati et al. (2021) used GANs to generate synthetic lung nodule images, improving the robustness of diagnostic models.

Using GANs in augmentation has enhanced the diversity of training data, which helps better generalise deep learning models in real-world settings.

Jiang et al. (2020) presented a robotized recognition framework for lung nodules in view of patch based profound learning. Their model focuses on identifying small nodules often overlooked during manual screening processes.

In 2023, Liu et al. extended this work by introducing an ensemble learning approach that further reduces false positives in automated systems, contributing to more reliable lung cancer screening in clinical applications.

3D CNNs have been increasingly utilized to reduce false positives in lung cancer detection. Jin et al. (2020) proposed a 3D residual CNN to bring down false positive rates, a vital improvement for diminishing superfluous patient subsequent methods.

Moreover, Zhang et al. (2023) extended this method by incorporating attention mechanisms, which improved the network's focus on relevant features of the images, leading to better accuracy in detecting lung cancer at an early stage.

Recent studies have explored integrating multimodal data, such as combining CT scans with other imaging modalities (e.g., MRI) or clinical data to improve diagnosis. A 2022 study by Lin et al. integrated radiomics features from multiple imaging modalities with deep learning networks, achieving significant improvements in sensitivity and specificity for lung cancer detection. This fusion of modalities allowed for a more comprehensive analysis of lung abnormalities.

There has been a growing focus on explainable AI in medical diagnostics in recent years. AI models must perform accurately and offer transparency and interpretability for medical professionals. Several works from 2021 to 2024, such as by Huang et al. (2022), have introduced interpretable deep learning frameworks that provide visual explanations for model decisions, enabling clinicians to understand how the system arrives at its conclusions.

There is a growing emphasis on the interpretability of AI models in healthcare, yet many current deep learning models for lung cancer detection remain "black boxes," offering little insight into how decisions are made. Explainable AI (XAI) techniques must be further integrated into these systems so medical professionals can understand and trust the model's predictions. Research into visualising important features and providing clear, interpretable explanations is still in its infancy. Future research should address these gaps, particularly the need for larger, more diverse datasets, improved sensitivity to early-stage cancer, reducing false positives, enhancing model explainability, and developing multimodal models for better diagnosis. Bridging these gaps is essential for the broader adoption of AI-driven lung cancer diagnostic systems in clinical practice.

Conducted clinical trials and validated AI models in real-world hospital settings, ensuring they could handle diverse patient populations and varying imaging systems. Integrate these models into clinical workflows for seamless use by healthcare professionals. The objectives focus on addressing the limitations of current models and advancing research in lung cancer detection to create more reliable, explainable, and accurate diagnostic tools that can be applied in clinical practice.

3. Proposed System Approach

The proposed framework is intended to upgrade the discovery and arrangement of cellular breakdown in the lungs from clinical imaging, for example, CT examines, utilizing progressed profound learning and computerized reasoning (man-made intelligence) procedures. This framework tends to current cellular breakdown in the lungs diagnosis challenges by further developing accuracy, early identification, and model logic displayed in Fig. 68.1. The framework evaluates the procedure steps are:

- **CT Image Dataset:** The system will utilize publicly available datasets such as LIDC-IDRI or hospital-specific datasets containing annotated lung CT scans.

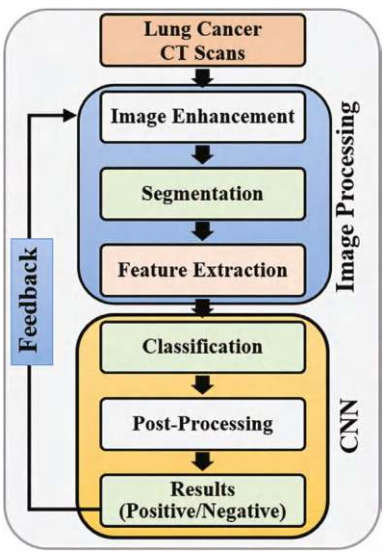

Fig. 68.1 XAI framework lung cancer prediction

- **Data Augmentation:** To address the limited size of datasets, Generative Adversarial Networks (GANs) will be used to generate synthetic data and improve model generalization and robustness. Image variations will be created using data augmentation techniques such as rotation, scaling, and noise addition.
- **Image Enhancement:** Images will undergo preprocessing steps, including pixel intensity normalization, denoising, and lung segmentation to enhance the quality of input data and reduce noise, which is crucial for accurate nodule detection.
- **Segmentation:** A dedicated segmentation network, like U-Net, will be integrated to locate and precisely segment lung nodules from the background. This segmentation will help isolate potentially cancerous regions from non-cancerous areas for further analysis.
- **Feature Extraction:** To minimize false positives, a post-processing stage involving a 3D residual CNN will be implemented to refine the model's predictions further and ensure that only true nodules are considered.
- **Classification and Post-processing:** After segmentation, the nodules will be classified as benign or malignant using a CNN-based classifier. The classifier will be trained using supervised learning techniques to recognize subtle differences between malignant and benign nodules.

XAI Frameworks: The model will provide explainable output, including visualizations of essential features or heatmaps, to offer transparency in decision-making. This is crucial for gaining the trust of healthcare professionals.

The XAI framework for lung cancer detection based on deep learning and visualized results is critical for interpreting model performance and providing insights into the approach's effectiveness. Here's a breakdown of the expected visualized outcomes and their implications.

A confusion matrix for a model labeled "XAI Model," displaying its performance in terms of predicted and actual labels as shown in Fig. 68.2. There are 639 true negatives (predicted negative, actual negative) and 73 false positives (predicted positive, actual negative). There are 24 false negatives (predicted negative, actual positive).True Positives (Predicted Positive, Actual Positive): 264

A shown in Fig. 68.3, the model correctly predicts(CPPK Hota.et.al, 2023) 90.3% of all instances, demonstrating overall accuracy in distinguishing between positive and negative classes. While the accuracy is high, it is critical to interpret it in terms of class distribution. If one class is significantly more prevalent than the other, accuracy alone may be deceptive, as the model may perform well simply by favoring the more common class. Precision of 78.3% indicates that the model correctly predicts a positive class 78.3% of the time. This metric is critical in research settings where false positives are costly. For example, in medical diagnostics, a false positive can result in unnecessary follow-up tests or treatments. The moderately high precision score indicates that the model is reasonably cautious when making positive predictions, though there is some room for improvement in reducing false positives. A recall of 91.7% indicates that the model is extremely effective at detecting true positives, capturing 91.7% of all actual positive cases. This high recall rate is particularly useful in applications where missing a positive case (false negative) would be problematic. For example, in fraud detection, failing to detect fraudulent cases can result in significant financial losses. The high recall rate reflects the model's ability to reduce false negatives, which is critical

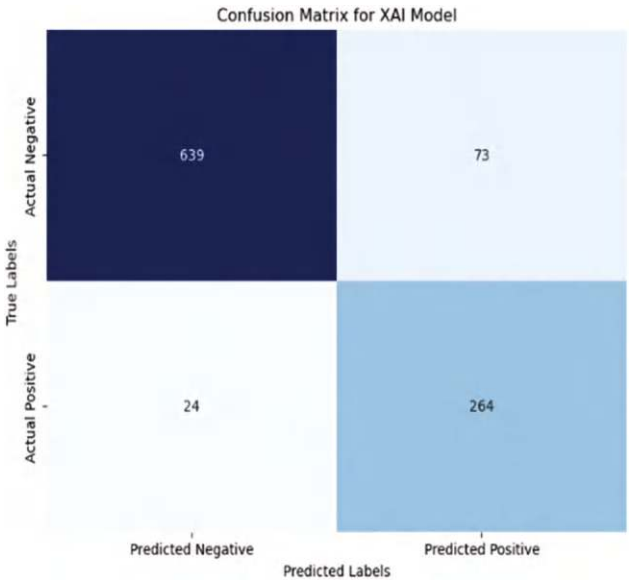

Fig. 68.2 Confusion matrix for XAI

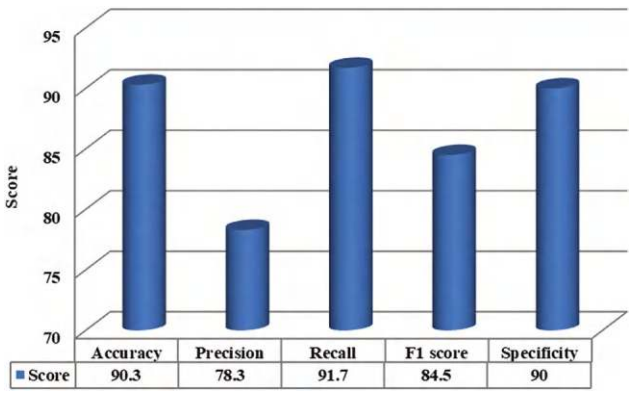

Fig. 68.3 Confusion matrix for XAI

for applications with high stakes for missing positive cases. The F1 score combines precision and recall, providing a balanced measure of the model's performance across both metrics. An F1 score of 84.5% indicates that the model captures positives while minimizing false positives. This balanced metric is especially useful when there is a trade-off between precision and recall, as it assesses how well the model performs when both types of errors (false positives and false negatives) are a concern.

Model Comparison Visualizations: Various charts can illustrate side-by-side comparisons of the proposed model's results(CPPK Hota et al., 2024) with those of existing state-of-the-art models such as traditional machine learning algorithms or other deep learning frameworks. Bar charts can show accuracy, precision, and recall for each model, emphasizing improvements achieved with the proposed system. Figure 68.3 shows such charts.

False Positive Reduction Visualization: Figure 68.4 shows visual representations of false positive rates across different models, showing how the proposed system reduces unnecessary alarms compared to traditional methods.

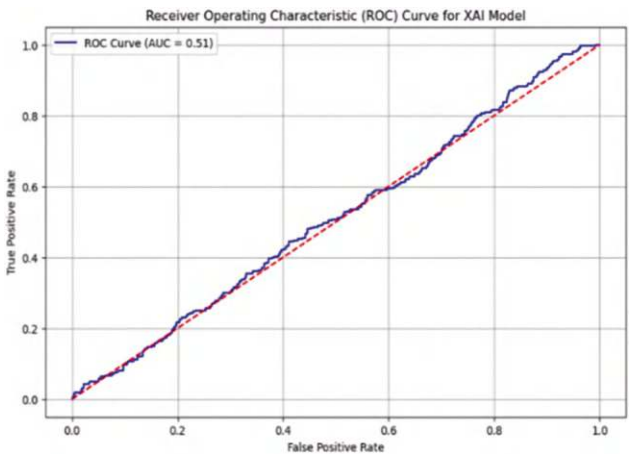

Fig. 68.4 ROC for XAI

Receiver Operating Characteristic (ROC) curve visualizes the performance of the XAI model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The Area Under the Curve (AUC) for this ROC curve is 0.51, which is only slightly higher than 0.5. In ROC analysis, an AUC of 0.5 indicates that the model has no discriminatory power, which is equivalent to random guessing. An ideal model would have an AUC near 1, indicating a high ability to distinguish between positive and negative classes. In this case, an AUC score of 0.51 indicates that the model has difficulty distinguishing between classes, implying limited effectiveness. The ROC curve's proximity to the diagonal (the red dashed line) emphasizes the model's poor discriminatory ability. A model with high performance would have a curve that rises sharply towards the top-left corner, maximizing TPR while minimizing FPR. The linear, diagonal shape of this curve implies that the model's predictions are no better than random chance, as there is no significant trade-off between TPR and FPR across thresholds.

By providing visual aids, the system enhances the interpretability of deep learning models in medical imaging. Clinicians can make more informed decisions when they understand why a model flagged a particular region as suspicious, leading to higher acceptance in clinical settings. The ability to visualize the model's performance through metrics and comparative analyses emphasizes the advancements made over existing methods. Demonstrating a significant reduction in false positives and improved sensitivity can lead to more trust in the technology, potentially improving patient outcomes. The discussion can also extend to potential limitations observed during the visualizations, such as areas where the model may still struggle. This can inform future iterations of the model, prompting refinements in architecture or training methodologies to enhance performance further.

4. Conclusion

This research contributes to the growing body of medical imaging and AI knowledge, offering a novel approach to lung cancer detection that combines high accuracy with interpretability. The proposed framework is valuable for healthcare professionals, paving the way for improved diagnostic practices and, ultimately, better patient care. The model has strong recall and reasonably high precision, indicating that it is highly sensitive to detecting positives while maintaining an acceptable level of specificity. This balance makes it appropriate for applications in which detecting as many true positives as possible is critical, but some false positives are acceptable. The precision rate indicates that there are a moderate number of false positives. In research applications where false positives are highly undesirable, this may necessitate additional tuning or even the exploration of different models to improve precision. Improving precision while maintaining high recall may be a priority. Possible approaches include: adjusting the classification threshold to favor precision. Feature engineering to increase the model's discriminatory power. If the dataset allows for it, consider using ensemble methods or more complex architectures. The future scope of the research is, more discriminative features could be investigated and included in the model to help it distinguish between classes better. Domain-specific knowledge may suggest additional features that improve model accuracy.

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ASLM-AQG: Attention-based Sequence Learning Model for Automatic Question Generation

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Abstract: This paper introduces an innovative Attention-based Sequence Learning Model (ASLM) for automatic question generating (AQG) that makes use of sentences extracted from reading comprehension literature. Using sequence-to-sequence learning to encode information at the paragraph and sentence levels, our data-driven approach surpasses the most advanced rule-based systems in automatic evaluations. The model is evaluated on the processed SQuAD dataset, which includes 536 articles and over 100,000 questions generated by crowd workers. To prepare this dataset, we first preprocess it using Stanford Core NLP for tokenization and sentence splitting, followed by converting all text to lowercase. Human evaluations confirm that our model generates more natural and challenging questions, requiring deeper reasoning and syntactic variation. Comparative analysis against competitive baselines demonstrates the model's superior ability to generate high-quality questions. Furthermore, ANOVA analysis reveals a strong correlation between evaluation metrics and question types, validating the model's robustness. This work marks a significant advancement in QG for reading comprehension, with potential applications in the educational domain, particularly for generating reading comprehension questions.

Keywords: Automatic question generation, Attention-based sequence learning model, Sequence-to-sequence learning, Reading comprehension, Data-driven approach, SQuAD dataset

1. Introduction

Humans have an innate curiosity that drives them to ask questions, seeking knowledge and connecting new information to their existing understanding. Asking questions is a crucial aspect of communication, particularly in learning, as it enables students to gain insights and evaluate their understanding (Hacker et al., 1998). However, many learners struggle to formulate effective questions, hindering their learning process. Automated question generation (AQG) systems can help overcome this challenge by identifying knowledge gaps and facilitating valuable inquiries.

IBM Watson and other question-answering systems are only a few of the numerous applications for AQG systems. By automating the self-training process, AQG helps to

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establish dependable responses and improves the overall performance of these platforms. By asking students to create questions based on what they have read, teachers can utilise Question Generation (QG) to assess their comprehension of a subject (Heilman and Smith, 2010).

The two primary categories of QG methods are rule-based (Lindberg et al., 2013; Mazidi et al., 2014) and deep neural network. approaches based on seq2seq models. The core of rule-based methods are template-based or human-designed transformation approaches, which change declarative statements into interrogative ones using well specified rules. These methods have the drawback of depending on rules that need to be manually created, which can be a laborious and time-consuming procedure. However, end-to-end trainable neural networks offer a possible way around these limitations.

Recently, AQG techniques have evolved substantially, shifting from traditional rule-based and template-based methods to more advanced neural network (Gao et al., 2019) and transformer-based approaches (Fabbri et al., 2020). The emergence of large language models (LLMs) like GPT, FLAN-T5, and LLaMA has set a new standard in natural language processing (Pedram Babakhani et al., 2024). By being trained on massive text datasets, these models can capture complex language patterns and structures, making them a potent tool for automatic question generation. The development of LLMs has led to the introduction of a personalized feedback question generation method, which utilizes T5 (Raffel et al., 2020) and BART transformer models (Lewis et al., 2019).

By directly mapping phrases from a text passage to matching questions, this research proposes a novel framework that reframes the QG task as a sequence-to-sequence learning problem. We have done away with the necessity for hand-crafted rules thanks to our data-driven approach. We employ cutting-edge huge language models with a focus on end-to-end subjective question production using fine-tuning strategies.

Our approach is motivated by the following reasons:

1. The suitability of RNNs for processing sequential data, such as natural language text, makes them an ideal choice for this task.
2. The encoder-decoder architecture is effective in capturing long-range dependencies and generating relevant questions.
3. According to Bahdanau et al. (2015), by including attention methods, the model may generate more accurate and context-aware queries by focusing on certain areas of the input for each token.
4. The use of bidirectional LSTMs allows the model to capture both forward and backward dependencies, considering the context and relationships between sentences.
5. The paragraph encoder is designed to capture sentence-level and paragraph-level information, enabling the generation of questions that are relevant to the paragraph as a whole.

2. Proposed Model

As seen in Fig. 69.1, the proposed ASLM architecture employs an attention-based sentence encoder and paragraph encoder to capture context-dependent token representations, calculate attention weights, and finally produce input paragraph-relevant queries.

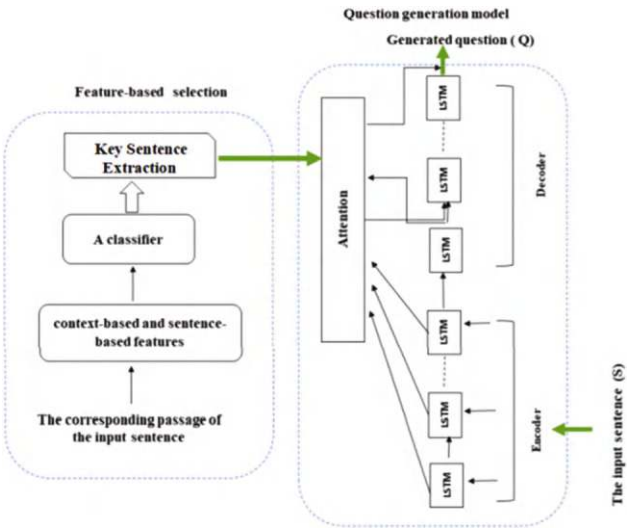

Fig. 69.1 Framework for automated question generation using key sentence extraction and an attention-based encoder-decoder model

You must take an input sentence x and use its contents to create a natural question y to finish the QG job. The enquiry y, which can be of any length, is represented as the set of tokens [y1,..., y|y|]. Finding y such that the anticipated question sequence y equals the greatest likelihood of the conditional logarithm of P(y|x) for every input x is our goal. To do this, our model employs an RNN encoder-decoder architecture with a global attention mechanism, which is based on the way individuals conceive and think about issues. In this work, we examine two model variations: one that encodes data at the paragraph level (PL) and another that encodes data at the sentence level (SL).

The decoder makes predictions at the word level using the conditional probability $\boldsymbol{U}(yZ \ni x, y \ll Z)$, where each predicted word yZ y t depends on the input sequence x x and the words that were generated earlier $y <\sim Z$ y. is equal to P(y|x) multiplied by the sum of all values of y from t=1^|y|. The input word x and the tokens y\t that have already been created are used to forecast each yt.

The encoder, which employs bidirectional LSTM to capture context-dependent token representation, calculates attention weights to focus on certain input segments, and produces questions relevant to the input paragraphs, is a crucial component of the proposed model. An integral part of attention-based sentence and paragraph encoders, its bidirectional LSTM architecture generates enquiries. While the PL model is unique in its use of the paragraph encoder, both the SL and PL models make use of the attention-based sentence encoder. The Sentence Encoder and Paragraph Encoder are two crucial components in the model architecture. The Sentence Encoder is responsible for encoding individual sentences, while the Paragraph Encoder takes the output from the Sentence Encoder to encode the paragraph-level information. Table 69.1 represents the components involved in both encoders:

Table 69.1 Mathematical framework for sentence encoder and paragraph encoder

Sentence Encoder:	• Forward and Backward LSTM layers to capture sequential information • Concatenation of LSTM outputs to form a single representation • Attention mechanism to compute context-dependent token representations
Paragraph Encoder:	• Takes sentence representations as input • Computes paragraph representation using a learned weight matrix and bias term

During training, we optimise the model by minimising the negative log-likelihood of the training corpus. We use a beam search to explore potential sequences during inference, utilizing a parameterized number of pathways of approximately k. Following Nayak et al.'s (2020) procedure, we replace the UNK tokens with the input token that has the highest attention score after processing is complete.

2.1 Experimentation

The processed SQuAD dataset, which includes 536 articles with more than 100,000 questions generated by crowd-workers, is used to test the neural question generation model. Before we convert all the text to lowercase, we pre-process the dataset by tokenizing it and dividing sentences using Stanford CoreNLP (Manning et al., 2014). Next, we use the answer offset to find the sentence that contains the answer for each question. In extremely rare instances (less than 0.17% of the dataset), we combine the relevant sentences to create the input sentence when the answer spans multiple phrases. Then, at the start of each sentence, special tokens <SOS> are inserted, and at the end of each sentence, special tokens <EOS> are added. To make sure the training data is good, remove sentence-question pairs that don't have at least one non-stop word. Annotation mistakes cause about 6.67 percent of these pairs to not overlap.

The SQuAD dataset is split randomly into 80% for training, 10% for development, and 10% for testing, with results reported on the 10% test set. The dataset statistics show that there are 70,484 training pairs, 10,570 development pairs, and 11,877 test pairs. The average sentence length is 32.9 tokens, the average question length is 11.3 tokens, and each sentence has an average of 1.4 corresponding questions. The model is implemented using Torch7 and built on the OpenNMT framework (Klein et al., 2017), details were shown in Table 69.2.

Table 69.2 Model configuration and training

Category	Description
Framework	Torch7, built upon OpenNMT framework (Klein et al., 2017)
Source Vocabulary	45,000 most frequent tokens i.e., <SOS>, <EOS>, and placeholders
Target Vocabulary	28,000 most frequent tokens, replacing others with UNK symbol
Word Embedding	300-dimensional GloVe embeddings (glove.840B.300d) b, fixed during training
LSTM Architecture	2 layers for both encoder and decoder, hidden units of size 600
Training	Starting in period 8, the learning rate of stochastic gradient descent (SGD) is halved.
Mini-batch Size	64
Dropout	Probability of 0.3 between LSTM layers
Gradient Clipping	When norm exceeded 5
Training Time	Up to 15 epochs (approximately 2 hours) on a single GPU
Model Selection	Based on lowest perplexity on development set
Decoding	A search using three beams is completed when each beam produces a <EOS> token.
Hyperparameter Tuning	Fine-tuned on development set

Evaluation Metrics for Question Generation Models

The evaluation framework shown in Table 69.3, which is used to assess the performance of the proposed question generation model.

Comparative Analysis of Question Generation Systems

Cella (2009) made a study on European firms to To evaluate the effectiveness of our system, we have conducted a

Table 69.3 Evaluation metrics for QG systems

Evaluation Type	Metric/ Aspect	Description	Evaluation Scale
Automatic Evaluation	BLEU (B1, B2, B3, B4)	Calculates precision, penalizes concise sentences	-
	METEOR	Emphasizes recall, considers lexical variations	-
	ROUGE-L	Measures recall, evaluates coherence and organization	-
Human Evaluation	Naturalness	Grammatical accuracy and fluency	1-5 scale
	Difficulty	Syntactic divergence and level of reasoning	1-5 scale

comparative analysis with several competitive approaches as given below.

a) IR Baselines (Rush et al., 2016): This model retrieves questions from the training set based on similarity metrics.

b) MOSES+ - A phrase-based statistical machine translation system that translates sentences to questions.

c) DirectIn is a simple method that builds its prediction using the longest sub-sentence. The use of delimiters such as "?", "!", ",", ".", and ";" divides the sentence into subsentences.

d) H&S – A system that generates and ranks questions based on rules.

e) Sequ2seq: We employed a simple sequence-to-sequence learning tool for machine translation. Using TensorFlow, we flipped the order of the inputs during training and inference to make the model work better. We tested the model that was the least perplexing after adjusting the hyperparameters with the development set's assistance. The results of these comparisons are shown in Fig. 69.2.

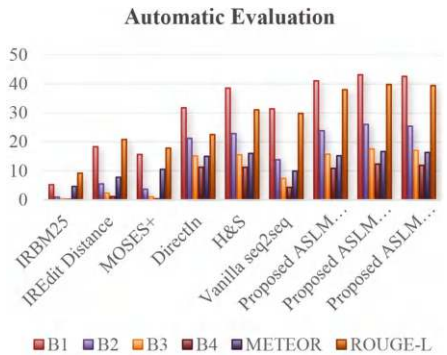

Fig. 69.2 Performance comparison of automatic evaluation metrics for QG systems

Result Analysis

The performance of various question generation models is thoroughly assessed using both automatic metrics and human evaluations, as shown in Fig. 69.3. The automatic metric evaluation results are represented in Fig. 69.2, showcasing the performance of each model across different metrics, including BLEU, METEOR, and ROUGE-L. Proposed ASLM model, which incorporates sentence-level information, achieves the highest performance across all metrics. In Fig. 69.3, we compare human evaluation results for naturalness, difficulty, and overall ranking of the questions generated by the models. The metrics are rated on a 1–5 scale, where 5 represents the best performance. Figure 69.3 reveals that proposed ASLM model outperforms the H&S model across all modalities, securing the highest rankings in 38.4% of the evaluations. This indicates that the questions generated by our system are generally of higher quality, in terms of both naturalness and difficulty.

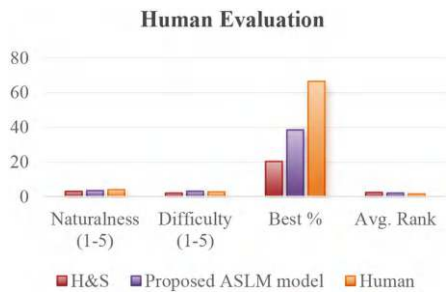

Fig. 69.3 Human evaluation results for question generation

Here are some examples that show how our ASLM model performs in comparison to the H&S model and queries that are supplied by humans. When you say "The largest of these is the Eldon Square shopping centre, one of the largest city centre shopping complexes in the UK," an enquiry from humans is: "What is one of the largest city centre shopping complexes in the UK?" To find out, the H&S model asks, "What is the Eldon Square shopping centre of?" But the ASLM model poses the question, "Which city centre shopping complex is among the largest in the UK?" which is rather different. Similarly, while reading, "The first significant amounts of free oxygen emerged between 3.0 and 2.3 billion years ago, during the Paleoproterozoic Aeon," a natural question to ask is, "When did free oxygen start to appear in larger quantities?" The model of H&S inquires: "What first appeared in significant quantities during the Paleoproterozoic Aeon?" "When did the Paleoproterozoic period begin?" is the output of the ASLM model.

The model's ability to generate queries that are both relevant and natural is further demonstrated by an

additional comparison. The natural follow-up question to the statement "Inflammation is one of the first responses of the immune system to infection" would be: "What other physiological responses does the immune system have to an infection?" Whereas the ASLM model inquires, "What is one of the immune system's initial responses to an infection?" the H&S model raises the question, "What does inflammation mean?" Just like in the previous example, "The fertile highlands, one of the most successful agricultural production regions in Africa, grow tea, coffee, sisal, pyrethrum, corn, and wheat," a question that is generated by humans asks, "What crops are grown in the fertile highlands of Africa?" "What do the fertile mountains often produce?" is the output of the H&S model, but the ASLM model frames the question as "Which regions in Africa have the highest agricultural production?" The ASLM model can produce queries that are exact, contextually accurate, and syntactically diversified, as seen in these instances.

The generated question tokens and input tokens are slightly aligned, as can be shown in Fig. 69.4, which is a confusion matrix of the attention weight matrix. Our attention-based paradigm works so effectively because key concepts like "introduced" and "teletext" are closely linked to the input and output. A thorough study of the model's performance for different question kinds is provided in Table 69.4. We demonstrate that our paragraph-encoding methodology is highly effective at generating questions that need more context than just the phrase, further confirming its ability to handle increasingly complex queries.

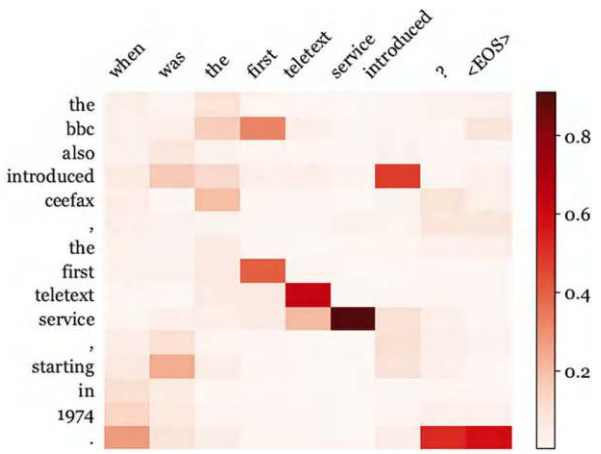

Fig. 69.4 Confusion matrix illustrating Input a sentence and generate a question softly aligned

To find out how well the evaluation criteria distinguished between different kinds of queries, we used analysis of variance (ANOVA). We used this statistical test to test the hypothesis that different types of questions do not affect the four evaluation criteria—difficulty, ambiguity, accuracy, and relevance. Except for one criterion, the results demonstrated that the p values were sufficiently low to reject the null hypothesis, suggesting a notable association between the types of questions and the evaluation criteria. Three criteria, namely difficulty, correctness, and relevance, strongly supported the capacity to distinguish performance variations across question types. Table 69.4 shows that all but one of these exceptions failed to provide a p-value that could be considered statistically significant: ambiguity.

Table 69.4 ANOVA analysis, showcasing the p-values for each evaluation criterion

Criteria	p-value
Difficulty	9.10E-10
Ambiguity	0.0485
Correctness	1.14E-09
Relevance	4.22E-10

3. Conclusion

Automated question generating (QG) was one component of our data-driven strategy to improve readers' understanding of text. To investigate encoding on both the sentence and paragraph levels, the suggested ASLM approach employs a model based on attention-based neural networks. Based on every metric for both automated and human evaluation, our top model achieves state-of-the-art performance. A few things could be better, though, including making better use of information at the paragraph level. Improving the model's capacity to produce high-quality questions across different types of enquiries could be the focus of future effort. Incorporating mechanisms from other natural language generation tasks could enhance question quality. The copy mechanism from dialogue generation systems could help generate more precise and contextually appropriate questions. Integrating such techniques could significantly boost the model's performance. Our approach marks a significant advancement in QG for reading comprehension. Future research directions are key to pushing the boundaries of automatic question generation systems.

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Used Car Price Forecasting: A Machine Learning-Based Approach

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Abstract: Forecasting used car prices is an important area of research. The demand for second-hand cars is increasing. This study offers a comparative analysis of different supervised Machine Learning (ML) algorithms for predicting costs. We evaluate Linear, Lasso, Ridge, XGBoost and Random Forest Regression models. Our findings show that Random Forest Regression performs well for individual car brands. It also significantly outperforms traditional regression models overall. This demonstrates the effectiveness of ensemble methods in handling complex data. We assessed each regression model's performance using the R-Squared (R2) metric. Among all the models studied, Random Forest regression achieved the highest R^2 value of 0.90. Compared to earlier studies, our model considers more factors related to used cars and shows greater predictive accuracy.

Keywords: Linear regression, Random forest regression, Lasso regression, Ridge regression, XGBoost regression

1. Introduction

In the automotive industry, new car prices are determined by manufacturers, with additional costs such as taxes imposed by the government. This ensures that customers purchasing new vehicles feel assured of the value of their investment. According to a recent report by Indian Blue Book on India's pre-owned car market (breen, 2024) nearly 4 million used cars were bought and sold in 2018-19. This market has created business opportunities for both buyers and sellers. However, with the rising prices of new cars and the financial constraints faced by many buyers, the demand for used cars has been increasing worldwide. Consequently, there is a need for an accurate used car price prediction system that evaluates the car's value based on various factors. Many people prefer purchasing used cars due to their affordability, and they can resell them after a few years, often at a profit.

The following factors affect a used car's price: including fuel type, color, model, mileage, transmission, engine specifications, and seating capacity. Since the price of used cars fluctuates in the market, a predictive evaluation model is essential to estimate their prices (Monburinon et al.,

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2018), (Satapathy, Vala, & Virpariya, 2022), (Narayana, Madhuri, NagaSindhu, Aksha, & Naveen, 2022).

The existing system often involves dealers setting prices arbitrarily, leaving buyers unaware of the car's true worth, and sellers uncertain about the appropriate price to ask. To address this problem, we have developed an efficient model utilizing regression algorithms, which generate continuous values to estimate the exact price of a car rather than providing a price range. Furthermore, a user-friendly interface has been designed to take input from users and display the predicted car price based on the provided information.

This study explores the following sections, Section II reviews the literature related to used car price prediction. Section III outlines the proposed study methodology. Section IV discusses the evaluation of the model's performance and the cross-validation of the proposed model for predicting used car prices. Finally, Section V summarizes the conclusions and provides recommendations for future research.

2. Literature Review

Danh Phan proposed ML techniques to analyze the historical house transaction data in Australia and created a model for predicting property prices. The analysis indicated a notable disparity in housing prices between the highest-priced and the most economical suburbs in Melbourne. (Jin, 2021a). While the focus differs from property prices, the regression models and methodologies presented can provide valuable references The author reviewed multiple factors associated with properties, such as location and condition, to construct the prediction model. Similarly, this research can take advantage of different attributes of used cars as features or indicators for constructing a predictive model.

In 2019, O Celik and UO Osmanoglu conducted a study focused on predicting the prices of second-hand cars (Celik & Osmanoglu, 2019). They utilized online data to build their model, mainly applied LR and experimenting utilizing various data splits (70-30% and 80-20%). Their highest R2 value reached 89.1%, which is quite impressive. They selected R2 as a metric for evaluating model performance, believing it offers a more detailed analysis than prediction accuracy alone. This suggests opportunities for enhancement, as adding factors like mileage and transmission could improve the model's effectiveness.

Prashant Gajera (Gajera, Gondaliya, & Kavathiya, 2021) proposed Old Car Price Prediction with ML, which illustrates the difficulties in valuing old cars due to a variety of characteristics. The analysis is based on five ML algorithms: KNN Regressor, Random Forest Regressor, Linear Regression, XGBoost Regressor, and Decision Tree Regressor, all of which are trained on 92,386 records. It assumes that a Random Forest Regressor is the optimal choice. Some of the analyses performed include comprehensive dataset evaluation, categorical variable tagging, and correlation coefficient ranking. The study's goal is to outline future research that will be undertaken to improve model accuracy through retraining with larger datasets or the incorporation of more predictive variables. In summary, it clarifies the role of ML in the challenges surrounding used car pricing and outlines how it might be improved further. Random forest had the highest test accuracy (93.11%).

Chuyang Jin (2021b) proposed a Price Prediction of Used Cars Using ML. They trained on 100,000 UK used cars' scraped data. The R2 for each regression was computed for this project in order to show how well it performed. With an R2 of 0.90416, random forest regression has the best among all five regressions. Thus, the used vehicle prediction model was built using random forest regression.

Nitis Monburinon et al. (2018) suggested predicting used car prices through the use of regression models. In this paper, the authors utilized data from a German e-commerce platform. The primary objective of the study is to identify an effective predictive model for used car prices. Various ML techniques were applied for comparison, using Mean Absolute Error (MAE) as the evaluation metric. The authors proposed that their gradient boosting regression model achieved superior performance with a lower MAE of 0.28, compared to LR with an MAE of 0.55 and random forest with an MAE of 0.35.

3. Proposed Methodology

The "Used Cars" data set has been processed and filtered to obtain the data values and remove any superfluous data. The model is trained with pre-processed data using several supervised ML techniques to produce a more accurate prediction of used car sales and to provide a model evaluation. Figure 70.1 displays the proposed methodology outline.

3.1 Dataset Collection

This refers to the process of collecting data from a source for estimation purposes. The Used Cars dataset, available in CSV format, was downloaded from the Kaggle website. It includes nine variables: Car_Name, Year, Selling_Price, Fuel_Type, Present_Price, Kilometres_Driven, Seller_Type, Transmission, and Owner, as illustrated in Fig. 70.2.

3.2 Data Preprocessing

ML approaches perform better when preprocessed data is used, especially for categorization. It includes the following items.

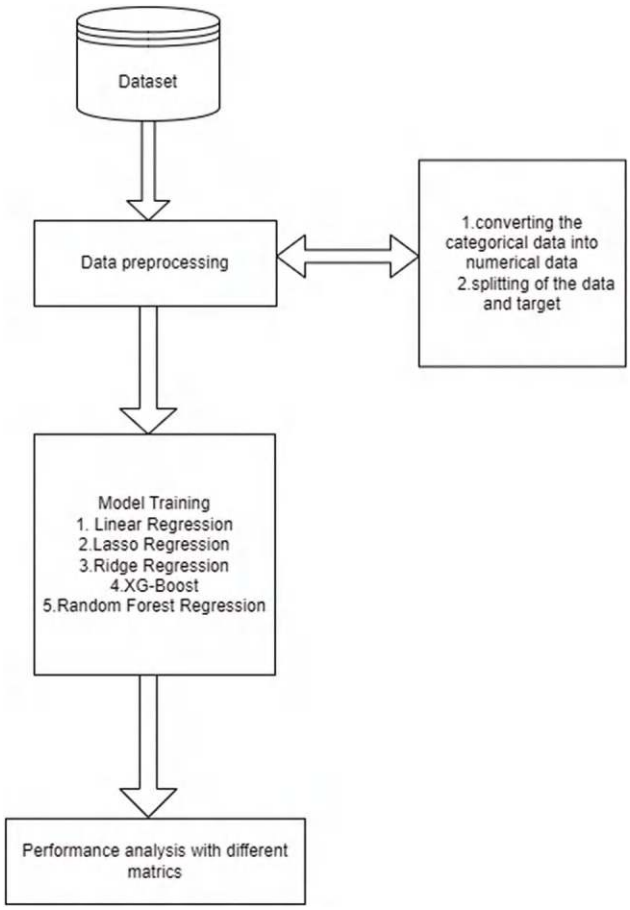

Fig. 70.1 Proposed methodology

Looking for Values that are Null

This step detects non-numerical words within the dataset, such as 1.Car_Name, 2.Selling_Price, 3.Present_Price, 4. Year of Manifacuring, 5. No of Kilometres_Driven, 5. Car Fuel_Type, 6.Seller_Type, 7.Car Transmission, and 8.Owner for data processing.

Encoding (Transforming Numerical Data from Categorical Data): Here, ML algorithms will convert the dataset's categorical features—such as fuel type, seller type, transmission, and owner type — to numerical values because numerical values are easier for machines to handle in machine readable form. As seen in Fig. 70.3, this is accomplished by substituting numerical values for categorical values. Step 1: Choosing categorical values from the dataset requires consideration of its datatype. Step 2: Substituting numbers for the category values to convert them to numerical values.

Data Splitting in the Target Variable: In this instance, we need to separate the objective feature that we are going to predict. In this instance, the target variable is the selling price. Step 1: The selling price, the target variable, is assigned to the variable "y". Step 2: All variables other than the target variable and the car name are allocated to the pre-processed data set, including the variable "X".

3.3 Model Training

Splitting of data into training and testing sets using the 80%-20% rule to evaluate the model performance.

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

Fig. 70.2 Before the data preprocessing this is the sample data

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	0	0	0	0
1	sx4	2013	4.75	9.54	43000	1	0	0	0
2	ciaz	2017	7.25	9.85	6900	0	0	0	0
3	wagon r	2011	2.85	4.15	5200	0	0	0	0
4	swift	2014	4.60	6.87	42450	1	0	0	0
...	...	...	...	...	...	...	...	...	...
296	city	2016	9.50	11.60	33988	1	0	0	0
297	brio	2015	4.00	5.90	60000	0	0	0	0
298	city	2009	3.35	11.00	87934	0	0	0	0
299	city	2017	11.50	12.50	9000	1	0	0	0
300	brio	2016	5.30	5.90	5464	0	0	0	0

301 rows × 9 columns

Fig. 70.3 After the data preprocessing this is the sample data

1) ***Linear Regression:*** LR analysis serves as a method for forecasting the value of one variable relative to another variable. The variable being predicted is designated as the dependent variable, while the variable used for the prediction is termed the independent variable..

   This technique involves both training and test datasets, with accuracy assessed using metrics such as R2, Mean Squared Error (MSE), and MAE. To gauge the model's accuracy, it compares actual prices with the predicted values. The formula for the LR model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon \quad (1)$$

2) ***Lasso Regression:*** It is a kind of LR that simulates the relationship between one or more independent variables and a dependent variable, also known as the target or response. Lasso's capacity to perform both variable selection and regularization improves prediction accuracy and model interpretability. The goal is to develop a linear equation that fits the data while reducing some coefficients to zero, resulting in only the most significant features.

   We use lasso regression to forecast used car prices by simplifying the model and selecting relevant features to avoid overfitting. The formula for the Lasso regression model is:

$$\text{minimize}\left(\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 + \alpha \sum_{j=1}^{p} \left|\beta_j\right| \right) \quad (2)$$

3) ***Ridge Regression***: It is an effective tool for finding associations between parameters in a dataset, particularly when there is multicollinearity. It also helps control overfitting by including a penalty term. Large coefficients in LR models are penalized using Ridge Regression in order to lessen overfitting and enhance generalization. The ridge regression model formula is as follows: (Hoerl & Kennard, 1970)

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \lambda \sum_{i=1}^{n} \beta_i^2 \quad (3)$$

4) ***XGBoost regression***: It is an effective ML technique based on the concept of gradient boosting framework. It is used to predict a continuous target variable by combining the predictions of several weaker models, typically decision trees. XGBoost is known for its efficiency, speed, and performance, particularly in handling large datasets and complex data patterns. The approach includes regularization techniques aimed at mitigating overfitting and enhancing the generalization capabilities of the model. The formulation of the objective function for XGBoost regression is expressed as: (Chen & Guestrin, 2016)

$$\text{Obj} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\left(f_k\right) \quad (4)$$

5) ***Random Forest Regression:*** This technique involves generating multiple decision trees and aggregating their predictions to enhance accuracy and mitigate overfitting. It is particularly useful for estimating used car values since it can handle significant associations between details like vehicle age, mileage, brand, fuel type, and transmission type. Random Forest minimizes variation and increases the model's capacity to generalize to new data by averaging the predictions of multiple decision trees.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(X) \quad (5)$$

4. Experimental Results

In this Work, we applied five different regression models on a car dataset to forecast the price of used cars. We have used 80-20 rule for training and testing and computed R2, MAE, and Mean Square Error (MSE). Random Forest is the best model of all, with a R2 of 0.90, MAE of 0.36, and MSE of 0.31. Table 70.1, shows all of the estimated values for all models.

Table 70.1 Comparison of model performance metrics

S. No	Model	R2	MAE	MSE
1	Linear Regression	0.83	1.15	2.15
2	Lasso Regression	0.83	1.15	2.15
3	Ridge Regression	0.85	1.16	2.37
4	Random Forest	0.91	0.36	0.31
5	XGB-Boost	0.87	0.32	0.25

4.1 R-squared (R2)

An important statistic for any regression model, it shows how well the independent variables explain the variation in the dependent variable. It can take on values between 0 and 1, with 0 signifying no explanatory power and 1 a perfect fit. The following is the formula for calculating R2, where RSS is the sum of squared residuals and TSS is the total sum of squares..

$$R^2 = 1 - \frac{RSS}{TSS} \quad (6)$$

4.2 Mean Absolute Error (MAE)

A regression model's performance can be evaluated using MAE, a statistical measure. It takes the absolute

discrepancies between the expected and actual numbers and averages them out. Without considering if the model is overly optimistic or pessimistic, it essentially measures the degree to which its forecasts match the actual. MAE offers a simple and intuitive way to understand the size of prediction errors. By using absolute values, it ensures that errors don't cancel each other out, as could happen when using squared differences. A smaller MAE suggests a more precise model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{7}$$

4.3 Mean Squared Error (MSE)

Mean Squared Error (MSE) is a commonly utilized metric for evaluating the precision of a regression model.

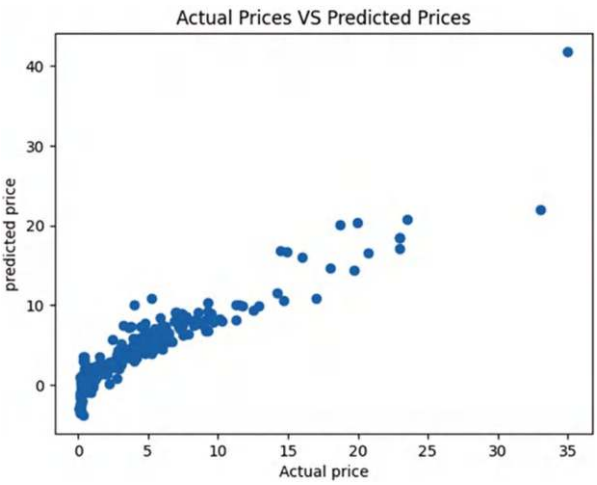

Fig. 70.4 Linear regression actual versus predicted prices in the training data

Fig. 70.5 Linear regression actual versus predicted prices in the test data

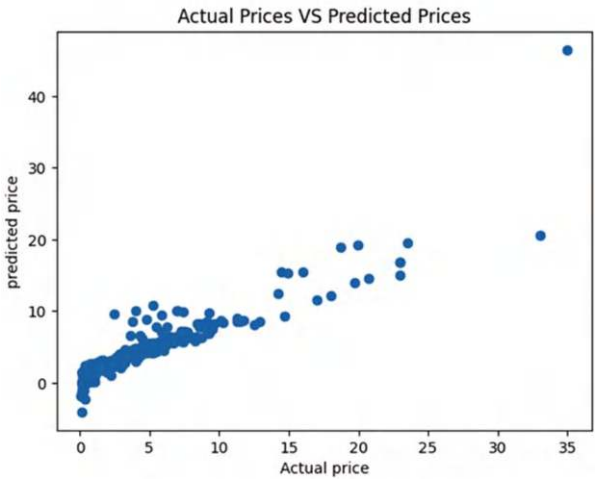

Fig. 70.6 Lasso regression actual versus predicted prices in the training data

Fig. 70.7 Lasso regression actual versus predicted prices in the test data

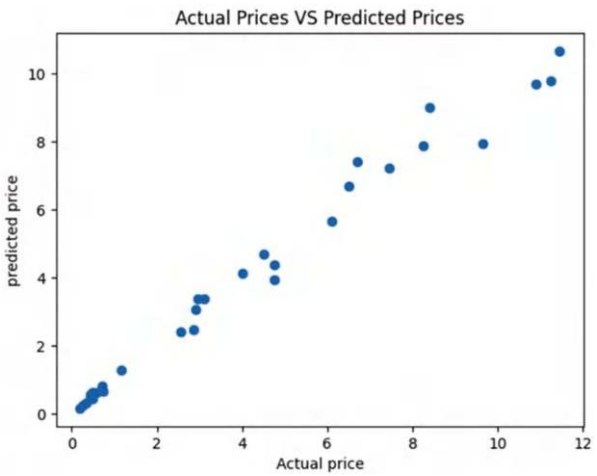

Fig. 70.8 Random forest regression actual versus predicted prices in the test data

Fig. 70.9 XGBoost actual versus predicted prices in the test data

It computes the mean of the squared deviations between the observed and forecasted values. By squaring these discrepancies, MSE accentuates larger errors, rendering it particularly susceptible to outliers. As a result, models with larger prediction errors will have a higher MSE. It serves as a useful measure to determine how well a model fits the data, with a lower MSE indicating better model performance. The formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{8}$$

5. Conclusion and Future Work

In this paper, we trained models on a used car dataset to predict prices. We employed five supervised ML models for comparison: LR, Lasso Regression, Ridge Regression, Random Forest, and XGBoost Regression. The random forest model achieved an accuracy of 91.0%, while LR reached 83.0%, lasso regression 83.4%, ridge regression 85.0%, and XGBoost 87.0%. Collecting more data could lead to more reliable predictions. To enhance model optimization and improve accuracy, we plan to use advanced ML techniques such as Extra Tree Regressor and Bagging Regressor, evaluating the models through various approaches.

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Water Potability Prediction: A Comprehensive Comparison of Machine Learning Models

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Abstract: Water potability is a critical aspect of public health and safety, and accurate prediction of water quality is of utmost importance. Machine learning algorithms have shown promising results in various domains, including water quality assessment. This study aims to examine several machine learning methods for water potability prediction. The goal is to evaluate the performance of these algorithms and identify the most effective approach for accurately predicting water potability. Out of its 1.3 billion inhabitants, 91 million people (or 6% of the total) lack access to clean water, and 746 million people (or 54% of the total) lack access to properly run residential sewage systems [2]. Present issues include severe water stress, contaminated surface water, and restricted access to piped water supplies. Most of the families in India are also impacted by the consequences of climate change, such as droughts and increasing sea levels, on access to clean water and sanitary facilities. In this study, we will utilize a dataset containing various water quality parameters such as pH, hardness, chloride levels, and more. The dataset will be preprocessed to handle missing values, outliers, and feature scaling. After that, we'll put a number of machine learning algorithms into practice and assess them, such as Random Forest, Gradient Boosting, Decision Trees, and Logistic Regression. The performance of each

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algorithm will be evaluated using appropriate evaluation metric accuracy. By determining the best machine learning method for predicting water potability, the study's findings will advance the field of water quality management. The findings will help environmental organizations, water treatment plants, and legislators make well-informed decisions about water quality monitoring and guaranteeing the public has access to clean drinking water.

KEYWORDS: Machine learning, Water potability, Comparative study, Prediction, Water quality, Evaluation, Logistic regression, Decision tree, Random forest etc.

1. INTRODUCTION

The purity of water has a direct impact on human health and is a necessary resource for maintaining life. The water quality standards are clearly mentioned in the Environmental Protection Agency (EPA) website[5]. According to the data, about 2,111,794 individuals die each year from water-related ailments.[6] Ensuring the potability of water, which refers to its safety and suitability for consumption, is of paramount importance. In India, the Bureau of Indian Standards (BIS) sets the standards for drinking water quality in the country [7]. These standards are outlined in the Indian Standard IS 10500:2012. Conventional techniques of assessing water quality usually include manual testing and analysis, which can be expensive, time-consuming, and prone to mistakes. In recent years, the use of machine learning algorithms to water potability prediction has attracted a lot of attention due to the possibility of accurate and efficient analysis.

The objective of this project is to develop a water potability prediction system using machine learning algorithms. By utilizing a dataset of water samples with corresponding chemical and physical parameters, the system aims to classify whether given water sample is potable or non-potable based on its characteristics. Accurate predictions for unseen samples are made possible by the application of machine learning algorithms, which enable the discovery of intricate patterns and correlations within the dataset.

Several machine learning methods, such as decision trees, logistic regression, gradient boosting classifier, and random forests, will be investigated in this study. With an emphasis on obtaining excellent prediction accuracy and robustness, these algorithms will be trained and assessed using the dataset of collected water samples. The project's potential to totally alter the way water quality is judged and monitored is what makes it essential. A system that can quickly and accurately assess the potability of water can be created by utilizing machine learning, enabling prompt intervention and preventive steps as needed. This can greatly contribute to public health by ensuring the availability of safe and clean drinking water.

2. LITERATURE SURVEY

Heming Gao et al., [1] use a Kaggle dataset on Indian water potability to analyze the potability of the water. This study specifically discusses each water quality aspect that affects water potability using binomial distribution and k-nearest neighbour algorithms. Additionally, the authors develop a model that enables users to forecast a water resource's potability using data from each of the resource's contributing factors. The characteristics of water are not connected to one another, according to the research. To obtain drinkable water, every feature must adhere to a set standard.

Dalal S et al., [3] proposes a machine learning-based model with the capacity to classify and assess the drinking water quality rate using the adaptive boosting technique. The study used a dataset taken from Kaggle. An experimental study of the several machine learning approaches (ensemble) was carried out in order to build a general water quality classifier. The results show that the presented ensemble model (96.4%) greatly improved the multi-layered perceptron (95.3%), XGBoost tree (94.3%), Chi-square Automatic Interaction Detector (93.1%), and logistic regression model (88.6%) forecast accuracy. The study shows that, in comparison to other relevant approaches, ensemble modeling provides more accurate water quality predictions.

Samir Patel et al., [4] proposed various methods for predicting the potable water measures by looking at the physicochemical measures of water samples taken from the Drinking Water quality dataset. Potential of hydrogen, hardness range, solids presence, chlorine and halogen disinfectants, sulfates, chloramines, organic carbon, conductivity, and turbidity are the nine metrics that comprise this dataset. To assess the potability of drinking water, they use a variety of methods, including Logistic Regression, SVM, Random Forest, XGBoost, and KNN. With an accuracy of above 99 and precision of near 0.99, sensitivity of 0.99, specificity of 1.0, and F1 score

of 0.99, the XGBoost approach specifically outperforms conventional machine learning models. Additionally, the Random Forest approach performs well, as evidenced by its 74% accuracy rate. As a result, there is great potential for this research to produce accurate data on water quality.

3. METHODOLOGY

3.1 Problem Description and Data Collection

We suggest using machine learning algorithms to create a reliable and accurate water potability prediction system. The purpose of the system is to provide users an accurate assessment of water safety so they can decide whether or not water is drinkable based on its quality characteristics. The system will aim for high prediction accuracy by using a variety of features and popular classifiers as Random Forest, Gradient Boosting, Decision Trees, and Logistic Regression. The system will follow a systematic approach, starting with data collection from the Kaggle dataset on water potability [8]. Thorough data preprocessing, including handling missing values and outliers, will ensure data integrity.

By dividing the dataset into training and testing sets and using suitable evaluation measures like accuracy, precision, recall, F1-score, and ROC-AUC, we will put in place a thorough evaluation procedure. The best-performing model(s) will be selected based on rigorous hyper parameter tuning and comparison.

The water potability dataset, sourced from Kaggle [8], comprises 3,276 records and acts as a useful tool for researching drinking water safety. Each record represents a water sample and contains multiple features associated with its quality. The dataset's primary objective is to predict water potability, classifying water as either potable (safe for consumption) or non-potable (unsafe for consumption). The dataset likely includes various attributes that influence water quality, such as follows

1. **pH:** Determines the water's acidity or basicity. A score below 7 indicates acidity, a value equal to 7 indicates neutrality, and a value above 7 indicates basicity.
2. **Hardness:** Indicates how much calcium and magnesium are present in the water. More minerals are indicated by higher values.
3. **Solids:** Represents the total dissolved substances in the water, including minerals and salts.
4. **Chloramines:** Indicates the amount of disinfectant used to treat the water.
5. **Sulfate:** Shows the concentration of sulfate in the water.
6. **Conductivity:** Measures how well water can conduct electricity, influenced by dissolved ions.
7. **Organic_carbon:** Represents the concentration of organic carbon from decaying plants and animals.
8. **Trihalomethanes:** shows the amount of byproducts chlorine produces when disinfecting organic water.
9. **Turbidity:** Measures the haziness or cloudiness of the water caused by particles.
10. **Potability:** The target column, 1 means water is safe to drink (potable), and 0 means it is not safe to drink.

3.2 Architecture of the System

Data Collection

The 'water_potability' dataset was acquired from Kaggle[8], a well-known site for materials related to data science and machine learning. The dataset contains 3276 records, with each record representing information about a different water source. It encompasses a number of water quality measures, including conductivity, organic carbon, trihalomethanes, turbidity, particulates, pH, hardness, sulfate, and chloramines. The main target is to predict water potability, which is represented by a binary variable, where 1 indicates safe (potable) water, and 0 indicates unsafe (non-potable) water. With this dataset, I can explore the water quality characteristics and create machine learning algorithms that forecast the suitability of water for human use. Here the dataset is imbalanced, with 1998 instances classified as Not Potable (0) and 1278 instances classified as Potable (1).

By applying SMOTE (Synthetic Minority Over-sampling Technique), the dataset now contains 1586 instances for both classes (Not Potable and Potable). This indicates that the dataset has been successfully balanced, with each class having an equal number of samples. The following

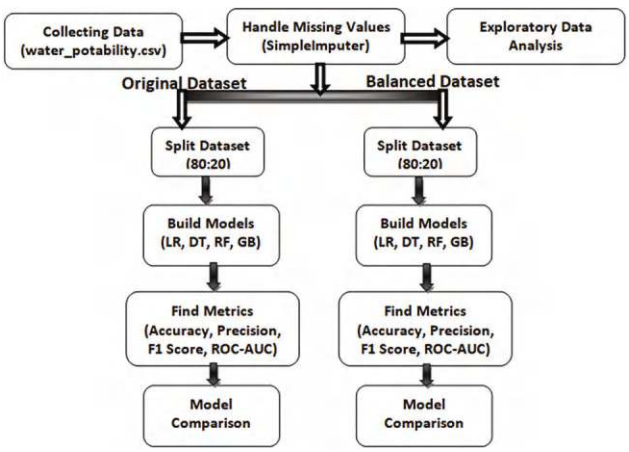

Fig. 71.1 Architecture of the system

Table 71.1 describes the distribution of dataset for both balanced and unbalanced.

Table 71.1 Distribution of dataset

	Original Dataset	Balanced Dataset
Potable(1)	1278	1586
Non Potable(0)	1998	1586
Total	**3276**	**3172**

The balancing process using SMOTE did not remove any records from the original dataset but rather created synthetic instances of the minority class (Potable).

As a result, the total count of records in the dataset decreased slightly due to the adjustment in the counts of the classes.

The following Fig. 71.2 shows the probability distribution among original and balanced datasets.

Pre-processing and Handling Missing Values

Preprocessing and handling missing values are essential steps in preparing the "water_potability" dataset for building accurate and reliable machine learning models. The collection includes details on a number of water quality factors, but it may have missing values due to measurement errors or data collection issues. To address missing values, we use the "most frequent" strategy in the SimpleImputer from the scikit-learn library. This strategy replaces missing values with the most frequently occurring value in each column. By doing so, we ensure that the data remains representative of the overall distribution, minimizing the impact of missing data on our analysis.

We can divide the dataset into features (X) and the target variable (y) for model training when the data preprocessing is finished. From there, we can investigate other machine learning methods, including Random Forest, Gradient Boosting, Decision Trees, and Logistic Regression, to create models that precisely forecast the potability of water.

Algorithms

1. **Logistic Regression:**

   One statistical technique for binary classification tasks is logistic regression, such as determining if water is potable or not. It simulates the connection between the likelihood that the water is drinkable and the water quality characteristics (features). The algorithm calculates a weighted sum of the features, applies a sigmoid function to the result, and generates a number between 0 and 1, which is the likelihood that the water is drinkable. By choosing a threshold (commonly 0.5), it classifies the water as safe (potable) if the probability is above the threshold and unsafe (non-potable) if it's below the threshold. In the feature space, it determines the best-fitting line (or hyperplane) that divides the data points that are drinkable and those that are not.

2. **Random Forest:**

   In order to make predictions, Random Forest, an ensemble learning technique, generates many decision trees where each decision tree is trained using a random subset of the attributes and a random subset of the data. This unpredictability enhances generalization and lessens overfitting. For water potability prediction, each tree would use different combinations of water quality parameters to determine if the water is potable or not. Through majority voting, the outcomes of each individual tree are combined to provide the final prediction. The most common prediction among the trees becomes the final prediction.

3. **Decision Tree:**

   Each node in a decision tree, which resembles a flowchart, represents a question based on a feature (for example, "Is pH < 7?"). The tree recursively splits the data into subsets based on the answers to these questions until it reaches leaf nodes with

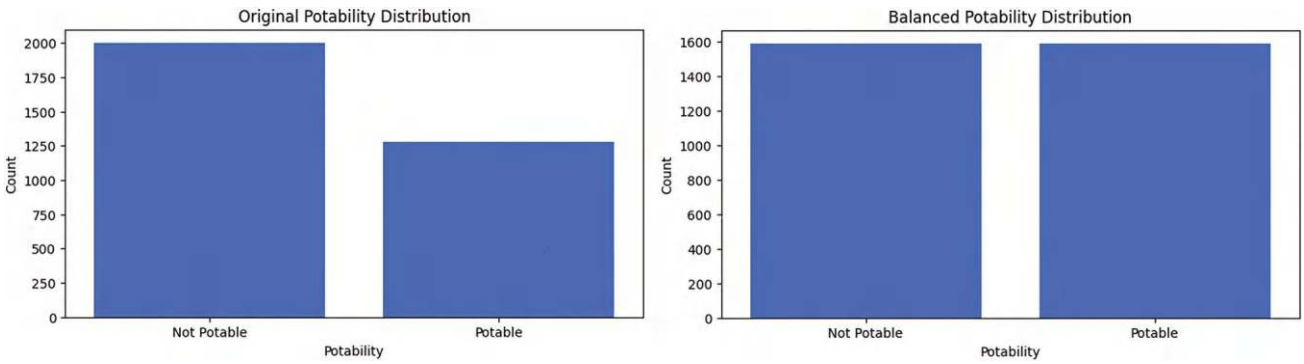

Fig. 71.2 Original vs balanced probability distribution

final predictions. In order to determine whether water is potable or not, the decision tree would take into account many water quality criteria, like pH, hardness, etc.

4. **Gradient Boosting:**

   Another ensemble learning technique is gradient boosting, which builds a powerful predictive model by combining several weak learners, usually decision trees. It constructs trees one after the other, training each new tree to fix the mistakes of the ones that came before it. In the case of predicting water potability, gradient boosting would start with a simple decision tree and then iteratively add more trees, each focusing on the mistakes of the previous trees. This iterative process continues until the model achieves high accuracy in predicting potability. Gradient Boosting often results in highly accurate models and is less likely than individual decision trees to overfit.

4. Results

4.1 Correlation Heatmap

A correlation heatmap is a visual representation of the correlation matrix in which the direction and intensity of the correlation between two variables are shown by the color of each cell. It is a powerful visualization tool to quickly identify patterns and relationships between variables in a dataset.

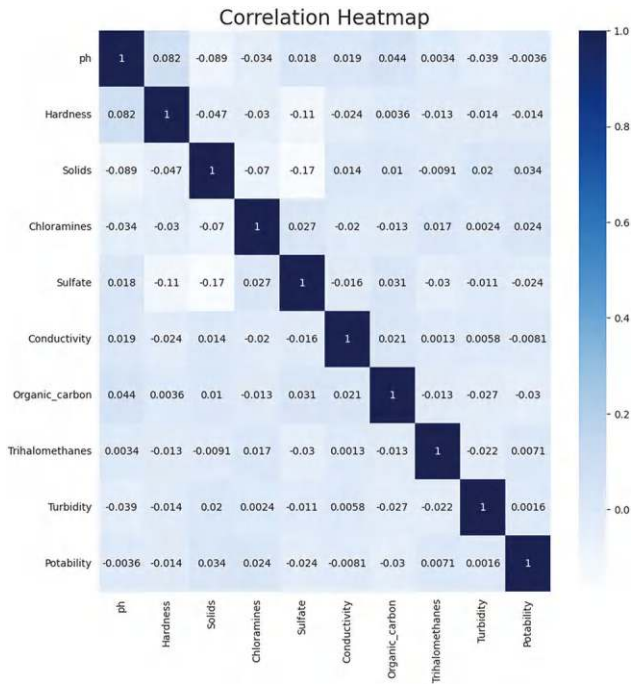

Fig. 71.3 Correlation heatmap

From the above correlation heatmap the most significant correlation observed is between Hardness and Solids (0.479) and most other pairs of features exhibit weak correlations, indicating that the physicochemical properties measured may largely act independently of each other in this dataset.

4.2 Comparison of Models before and after Balancing

The following Table 71.2 gives the comparison of different machine learning models before and after balancing the dataset.

Table 71.2 Comparison of machine learning models before and after balancing

Model	Accuracy	F1 Score	Precision	ROC-AUC	Dataset
Logistic Regression	0.63	0.00	1.00	0.52	Original
Random Forest	0.68	0.44	0.64	0.67	Original
Decision Tree	0.57	0.43	0.42	0.54	Original
Gradient Boosting	0.67	0.38	0.63	0.65	Original
Logistic Regression	0.49	0.41	0.36	0.51	Balanced
Random Forest	0.67	0.54	0.55	0.67	Balanced
Decision Tree	0.56	0.47	0.43	0.56	Balanced
Gradient Boosting	0.62	0.50	0.49	0.64	Balanced

The following Fig. 71.4 gives the graphical view of comparison of model accuracy before and after balancing the dataset.

According to the results above, Random Forest is the best model for forecasting the potability of water, demonstrating the highest accuracy, F1 score, and ROC-AUC score both before and after balancing the dataset. Its robust performance indicates a strong ability to distinguish between potable and non-potable water, making it a reliable choice for this prediction task.

5. Conclusion

We can clearly see how each model performed after examining the outcomes of water potability prediction using various machine learning methods. This analysis's primary goal was to identify the best algorithm for

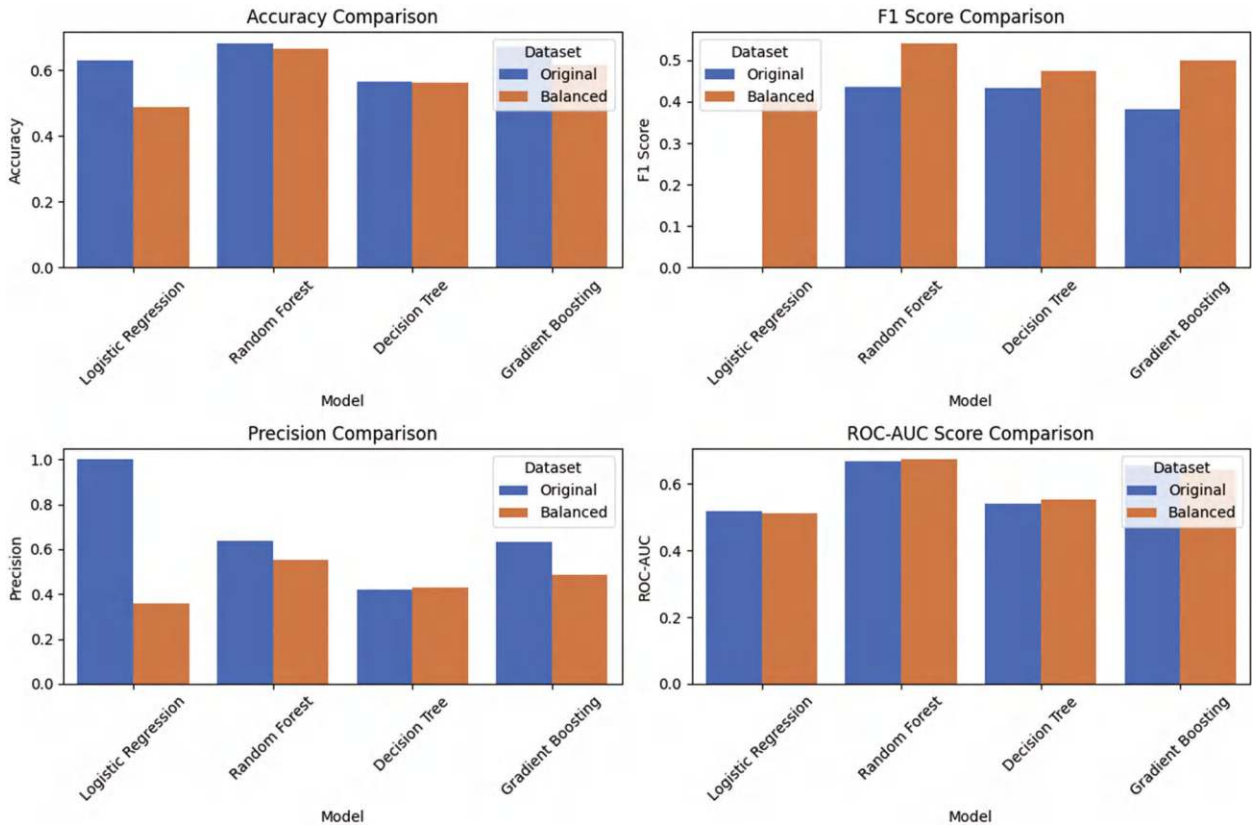

Fig. 71.4 Comparison of models evaluation metrics before and after balancing

determining whether or not water is potable, or safe to drink. Random Forest emerged as the top-performing algorithm with the highest overall accuracy among the models that were tested. This means that Random Forest was able to correctly classify water sources as potable or non-potable more accurately than the other models.

It's crucial to remember, though, that every model had potential for development. The accuracy values for all models were not extremely high, which indicates that they struggled to make precise predictions for water potability. This suggests that there are complexities in the data that the models have not fully captured. Further hyper parameter tuning, feature selection, and feature engineering may help enhance the models' predictive power and robustness. Additionally, considering ensemble methods or exploring other advanced algorithms might yield even better results for this important water potability prediction task.

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An Optimized Ensemble Machine Learning Framework for Pumpkin Seed Classification using Sequential Feature Engineering to Boost Agricultural Productivity with Sustainable Food Strategies

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Abstract: Agricultural productivity and sustainable food production are hindered by numerous challenges, including limited resources, climate change, pest outbreaks, and inefficiencies in crop management. Traditional seed classification

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methods often fail to deliver timely and accurate results, which are essential for improving crop yields and minimizing waste. Furthermore, class imbalances and feature redundancy in agricultural datasets severely limit the effectiveness of machine learning models in precision agriculture. To address these issues, this research presents an optimized ensemble machine learning framework for pumpkin seed classification aimed at enhancing agricultural productivity. The framework integrates and refines existing classification techniques, including Boosted Trees, RUS-Boosted Trees, and Bagged Trees. Utilizing Sequential Feature Engineering with the Minimum Redundancy Maximum Relevance (MRMR) method, the framework efficiently selects relevant features while minimizing redundancy, improving both accuracy and computational efficiency. The optimized ensemble approach tackles class imbalance issues inherent in Boosted and Rus-Boosted Trees, resulting in enhanced classification precision. Additionally, Bagged Trees contribute to model robustness by reducing variance. Comprehensive analyses reveal that the optimized ensemble significantly outperforms individual models, demonstrating notable improvements in classification accuracy on real-world agricultural data and ultimately fostering more sustainable and efficient agricultural practices.

KEYWORDS: Pumpkin seed classification, Ensemble machine learning models, Agricultural, Feature selection

1. INTRODUCTION

Agricultural productivity plays a critical role in ensuring sustainable food production globally [1]. However, it faces numerous challenges that threaten its efficiency, including limited resources, climate change, pest outbreaks, and the inefficiencies associated with traditional crop management techniques. In particular, seed classification is a pivotal aspect of crop management that impacts overall agricultural yield and sustainability. Unfortunately, traditional methods of seed classification often fall short in delivering timely and accurate results, which are crucial for enhancing crop yields and minimizing waste. This inefficacy can be attributed to class imbalances and feature redundancy prevalent in agricultural datasets, which significantly hinder the effectiveness of machine learning models [2].

To overcome these challenges, this research presents an innovative optimized ensemble ML framework specifically designed for pumpkin seed classification. The primary aim of this framework is to enhance agricultural productivity by leveraging advanced ML techniques that are both efficient and effective.

To address these issues, the proposed framework integrates and refines existing classification techniques, specifically Boosted Trees, RUS-Boosted Trees, and Bagged Trees [4]. Each of these methods has unique strengths that contribute to the overall performance of the ensemble framework.

Boosted Trees enhances the classification accuracy by combining the predictions of several weak models, focusing more on previously misclassified instances. However, it can suffer from overfitting, especially in the presence of class imbalances. RUS-Boosted Trees modifies the Boosted Trees approach by incorporating random under sampling of the majority class during training. This strategy helps mitigate class imbalance, improving the model's ability to generalize from the training data. Bagged Trees reduces variance by averaging the predictions from multiple models trained on different subsets of the data. It is particularly effective in increasing the robustness of the classification process, making it less sensitive to noise in the data.

The integration of these techniques within a single framework allows for a more comprehensive approach to seed classification, capitalizing on the strengths of each method while addressing their individual weaknesses. An integral component of the proposed framework is the Sequential Feature Engineering process, which employs the MRMR method. MRMR is a powerful feature selection technique [14] that efficiently identifies relevant features while minimizing redundancy. By focusing on features that provide the most significant information gain while reducing overlapping information, MRMR enhances both the accuracy and computational efficiency of the ML models. This targeted feature selection is particularly vital in agricultural datasets, where the number of potential features can be overwhelming and often includes irrelevant or redundant data.

The optimized ensemble approach effectively tackles the class imbalance issues [25] prevalent in traditional classification techniques, particularly in the Boosted and RUS-Boosted Trees models. By ensuring a more balanced representation of classes during the training phase, the framework improves classification precision. This is critical in agricultural applications where accurate classification of underrepresented seed types can lead to better crop management decisions and ultimately improved agricultural outcomes.

In addition to addressing class imbalances [27], the incorporation of Bagged Trees within the ensemble contributes to model robustness by reducing variance. This increased stability is essential for achieving reliable classification results, especially when dealing with real-world agricultural data that may exhibit noise and variability.

The challenges faced in agricultural productivity and sustainable food production necessitate innovative solutions that leverage advanced technology. The optimized ensemble machine learning framework presented in this research addresses critical issues in traditional seed classification methods, such as class imbalances and feature redundancy. By integrating and refining existing techniques like Boosted Trees, RUS-Boosted Trees, and Bagged Trees, and employing effective feature selection through MRMR, this framework enhances classification precision and model robustness. The positive outcomes demonstrated through comprehensive analyses highlight the potential of this approach to transform agricultural practices, leading to improved yields and more sustainable food production systems. As the agricultural sector continues to evolve, the adoption of such advanced methodologies will be crucial in overcoming the challenges posed.

This research paper is organized into five main sections, each providing an in-depth examination of various aspects of the study. The second section offers a comprehensive review of existing literature on the application of machine learning techniques in sustainable agriculture. The third section describes the proposed framework, including data preprocessing steps, feature engineering strategies, and the machine learning algorithms used. In the fourth section, the experimental results and outcomes from the applied methodologies are discussed in detail. Lastly, the fifth section provides a summary of the research conclusions, emphasizing the key contributions and insights this study adds to the domain of sustainable agriculture.

2. Literature Review

The rise in the global population underscores the importance of creating sustainable agricultural approaches that ensure food security while also preserving the environment. Machine learning (ML) is emerged as crucial tools in modern agriculture to optimize crop production, enhance food quality, and promote sustainability. For example, Mana et al. [1] highlight the applications of AI in agricultural practices that aim to balance productivity with environmental concerns by utilizing intelligent systems for precision agriculture and crop management. Similarly, Researchers [2, 3, 4, 5] emphasize the transformative role of machine learning (ML) in sustainable agriculture. They address the challenges of data scarcity and the necessity for domain-specific models while highlighting how ML can enhance decision-making and optimize agricultural supply chains. Additionally, the importance of effective data preparation techniques is underscored, ensuring that big data can be leveraged to improve agricultural practices and productivity.

Intelligent systems have been employed not only in agriculture but also in food processing and health, enabling automated processes, quality control, and efficient resource utilization. Mavani et al. [6] outline how AI applications can improve efficiency in food production while ensuring product quality. These systems are particularly relevant in processing seeds, such as pumpkin seeds, where classification based on quality is crucial for market competitiveness and health benefits. Mahesh et al. [7] discuss the innovative applications of mining techniques in food systems, enhancing data processing capabilities. Additionally, Vijayan et al. [8] explore strategies for mobile robotics in food exploration, contributing to intelligent automation. Additionally, Reddy et al. [9] demonstrate the empirical approach in developing models for predictive tasks, which can be analogous to agricultural applications. Dheer and Singh [10] illustrate the successful classification of wheat varieties using ML models, highlighting the potential for similar methodologies in pumpkin seed classification. Furthermore, Mahesh et al. [11] explore algorithmic approaches in optimizing content delivery systems, suggesting that similar techniques could enhance data management and processing in agriculture.

Pumpkin seed classification has gained importance due to its economic and nutritional value, and ML techniques have been widely applied in this domain. Qasimi [12] provides an extensive analysis of ML methods for the classification of pumpkin seeds, presenting a comparative performance evaluation of different models. The study emphasizes the importance of feature engineering in improving classification accuracy. Similarly, Kumar et al. [13] highlight the use of ensemble techniques like voting classifiers, which outperform traditional models. Rao et al. [14] contribute by exploring a sequential feature selection approach in developing an innovative ML-based system, enhancing the classification process of pumpkin seeds by identifying the most relevant features. The work of Koklu et al. [15] centers on utilizing neural networks for classifying seeds, underscoring how high-dimensional data and optimized models contribute to improved performance. Additionally, the authors [16] emphasize the significance of enriched big data pre-processing techniques in ML, which is critical for effective pumpkin seed classification, as it ensures that the data used in models is well-structured and

relevant. Furthermore, Demir et al. [17] investigate neural networks for predicting physical parameters of pumpkin seeds, which supports classification efforts.

In classification challenges, selecting the right features is vital for improving the performance and efficiency of machine learning models. In their study, Siddique et al. [18] evaluate multiple feature selection approaches to enhance the classification of pumpkin seeds and determine those sequential methods, particularly MRMR, greatly enhance model effectiveness. Additionally, Silpa et al. [19] highlight the benefits of combining feature selection strategies with ML techniques to analyze employee retention, showcasing the effectiveness of these methods across varied domains. Demir et al. [20] further support this by predicting physical parameters of pumpkin seeds using neural networks, indicating the relevance of precise data selection in achieving accurate outcomes. Bonthu et al. [21] analyze the application of neural networks for multi-class prediction, emphasizing the capability of machine learning models to address complex datasets relevant to agricultural contexts. Suganthi and Sathiaseelan [22] discuss novel feature extraction methods that focus on identifying quality seed attributes through optimized selection techniques. These approaches not only enhance classification but also contribute to sustainable agricultural practices by optimizing the selection of high-quality seeds. Additionally, Rao et al. [23] present team-building recommendation ML model utilizing personality type, illustrating the importance of personalized approaches in data-driven decision-making across diverse fields.

The optimization of hyperparameters is critical for enhancing ML model performance. Lilhore et al. [24] explore how hyperparameter tuning improves model accuracy in medical applications, a concept that can be transferred to agricultural classification problems. Arnold et al. [25] detail the role of hyperparameters in ML models and emphasize the significance of tuning them to achieve optimal results. Furthermore, Simaiya et al. [26] demonstrate the application of deep learning and optimization techniques in prediction methods, showcasing the effectiveness of hyperparameter optimization across diverse fields. Hossain and Timmer [27, 28, 29, 30] highlight the importance of model optimization through hyperparameter tuning to enhance classification precision, which is crucial for high-stakes applications like pumpkin seed classification. Additionally, Lilhore et al. [31] analyze risk factors in postpartum depression using a hybrid deep learning model, emphasizing the critical role of optimized models in healthcare. By optimizing model parameters and combining feature selection methods, the classification of pumpkin seeds can be significantly improved, leading to higher accuracy and better productivity outcomes. The researchers [32] also investigate predicting web user behavior using advanced techniques, illustrating the broad applicability of hyperparameter tuning in various domains.

The integration of machine learning into agriculture, particularly for the classification of crops like pumpkin seeds, has the power to modernize agricultural practices. By employing optimized ensemble models and sequential feature engineering, this research aims to boost productivity while promoting sustainability in food production. The reviewed literature provides a strong foundation for leveraging ML techniques in pumpkin seed classification, setting the stage for further advancements in this field.

3. Proposed Methods and Materials

The proposed study aims to develop a ML-driven Optimal Pumpkin Seed Classification System (ML-OPSCS) as premeditated in Fig. 72.1, contributing to sustainable agricultural practices by optimizing seed selection for enhanced crop yield. The methodology employs a comprehensive data-driven approach, beginning with data acquisition and exploratory data analysis to extract key attributes and generate visual insights. Advanced data preprocessing addresses missing values, normalization, and outlier detection to ensure data quality. The MRMR algorithm is used for feature selection, prioritizing relevant features to improve model accuracy. Several ML models, including Boosted Trees, Bagged Trees, RUS-Boosted Trees, and an optimized ensemble, are applied. The system aims to support sustainable food strategies by boosting agricultural productivity through precise seed classification. Model optimization via cross-validation and hyperparameter tuning ensures robust performance, while metrics like precision, recall, F1-score, and accuracy assess its efficacy.

To effectively implement the ML-OPSCS, researchers have developed a detailed nine-step algorithm, as illustrated in Table 72.1 (Algorithm 1). This structured methodology includes crucial nine phases such as data collection, preprocessing, feature engineering, model selection, training, evaluation, optimization, deployment, and ongoing monitoring. Each step is designed to create a systematic framework that enhances seed classification accuracy and supports sustainable agricultural practices, ultimately improving productivity and food security in the agricultural sector. The subsequent subsections provide a detailed explanation of each step outlined in the algorithm, ensuring clarity in the implementation process.

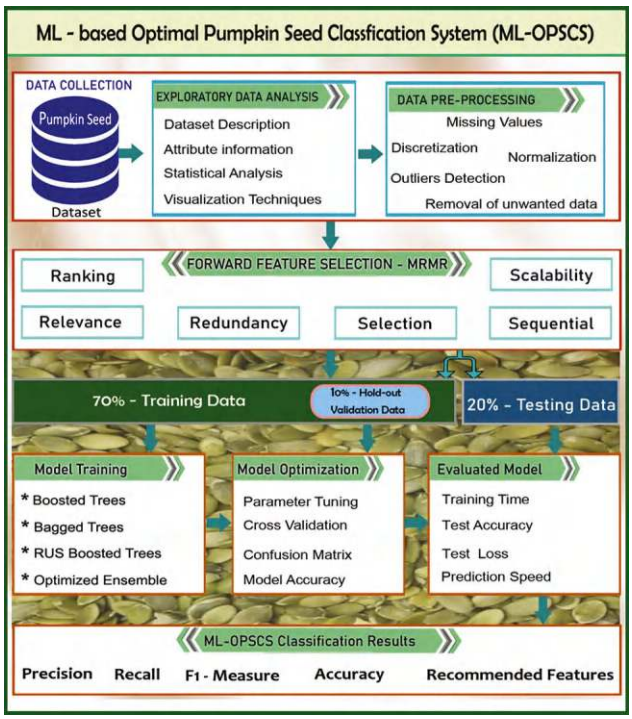

Fig. 72.1 Proposed framework for the ML-based optimal pumpkin seed classification system

3.1 ML-OPSCS: Dataset Explanatory Analysis

The first step involves gathering a well-curated and comprehensive pumpkin seed dataset, ensuring the inclusion of key attributes, which are crucial for seed classification. The dataset must be large enough and representative of diverse seed characteristics to allow for effective machine learning model training. It is essential to ensure data quality and relevance, as these factors significantly influence the model's ability to provide accurate classifications, ultimately enhancing agricultural productivity and sustainability in crop management. In addition, the authors presented correlation heatmap in Fig. 72.2, visually demonstrates the relationships among different features of pumpkin seeds, in relation to classification. This helps identify the key attributes that significantly influence the performance of ML models in seed classification tasks.

3.2 ML-OPSCS: Feature Engineering

In the Feature Engineering stage of the ML-OPSCS framework, the Minimum Redundancy Maximum Relevance (MRMR) method is crucial for boosting agricultural productivity and promoting sustainable food strategies. By selecting the most informative features from the pumpkin seed dataset, MRMR enhances model performance, enabling precise crop classification

Table 72.1 **Algorithm 1:** ML-based optimal pumpkin seed classification system (ML-OPSCS)

Input	: Pumpkin Seed Dataset, Feature Attributes, Classification labels, Model Parameters.
Output	: Optimal Classification Model, Optimal Feature Set, Evaluation Metrics
Phase 01.	**Data Acquisition**
1.1	Collect a structured pumpkin seed dataset from validated agricultural repositories.
1.2	Ensure that the dataset includes diverse and well-labelled attributes pertinent to Pumpkin seed classification, ensuring data integrity.
Phase 02.	**Data Exploratory Analysis**
2.1	Conduct in-depth exploratory analysis using statistical and visual techniques.
2.2	Perform attribute distribution analysis, correlation assessments, and hypothesis testing to derive initial insights into data patterns and feature relationships.
Phase 03.	**Data Preprocessing**
3.1	Apply advanced preprocessing techniques including imputation methods for missing data, normalization techniques and robust outlier detection mechanisms.
3.2	Ensure removal of noise and irrelevant features by dimensionality reduction techniques.
Phase 04.	**Feature Selection Using MRMR**
4.1	Implement MRMR for feature ranking.
4.2	Select features that optimize classification accuracy by balancing feature relevance against redundancy to enhance model scalability and interpretability.
Phase 05.	**Pumpkin Dataset Partitioning**
5.1	Employ stratified splitting techniques to partition the dataset into training (70%), validation (10%), and testing (20%) subsets
5.2	Ensure the distributions of target classes remain balanced across the subsets for model generalization.
Phase 06.	**ML-OPSCS Model Training**
6.1	Select machine learning classifiers—Boosted Trees, Bagged Trees, RUS-Boosted Trees, and Optimizable Ensemble.
6.2	Initialize them using appropriate hyperparameters.
6.3	Combine the classifiers into an Optimizable Ensemble model to improve overall accuracy, reduce overfitting, and enhance generalization to unseen data.
Phase 07.	**ML-OPSCS Model Optimization**
7.1	Perform hyperparameter tuning using hold-out validation techniques.
7.2	Evaluate models with confusion matrices and utilize accuracy, precision, recall, and F1-score as performance metrics.
Phase 08.	**ML-OPSCS Model Evaluation**
8.1	Test the trained models using the hold-out testing dataset.
8.2	Measure model performance using comprehensive metrics such as training time, prediction speed, test accuracy, and test loss.
Phase 09.	**Interpretation of ML-OPSCS Results and Agricultural Application**
9.1	Analyze the optimized model's output, emphasizing its classification efficacy and feature importance.
9.2	Correlate the results to agricultural productivity, and recommend the top features that contribute to pumpkin seed quality assessment.
9.3	Highlight the model's potential to support sustainable food strategies, addressing real-world agricultural challenges.

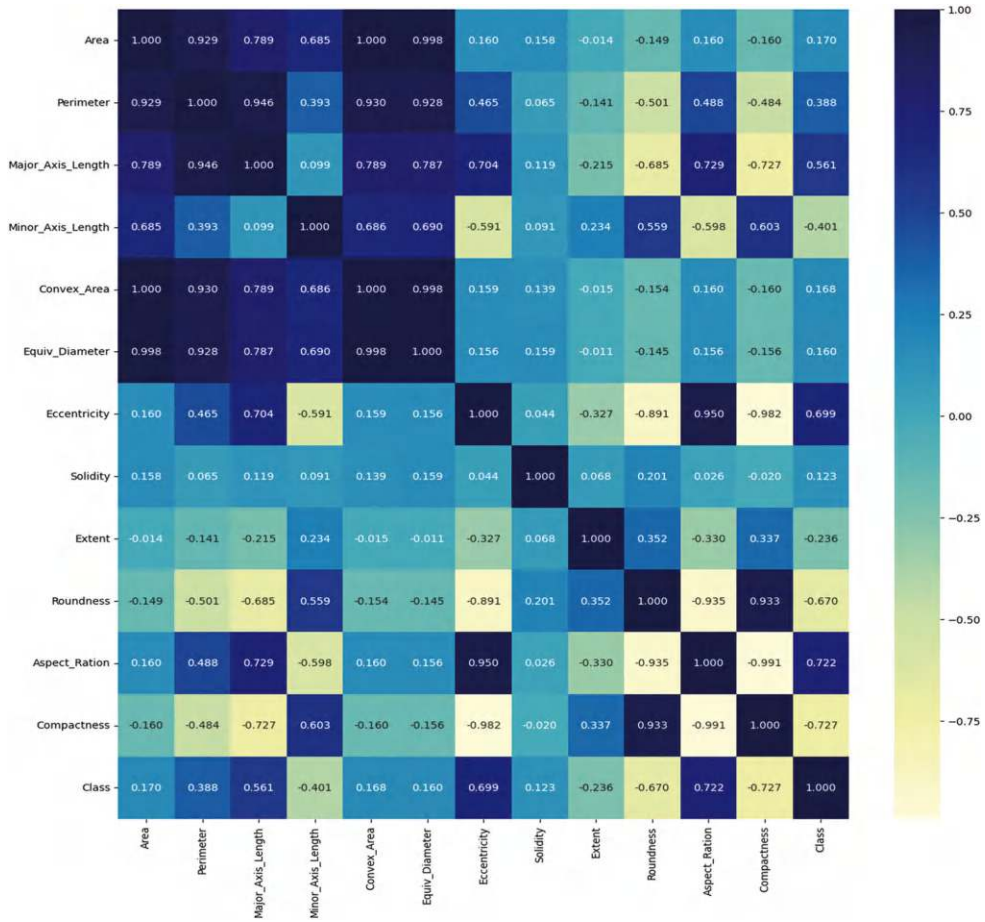

Fig. 72.2 Correlation heatmap of key features for pumpkin seed classification

and management. The MRMR approach maximizes the relevance of features to the target variable while minimizing redundancy among them. Mathematically, this can be represented as:

$$MRMR(S) = \max\{I(s,Y) - \frac{1}{|S|}\sum_{s' \in S} I(s,s')\}$$

where (s, Y) denotes the mutual information between feature s and the target Y, and $I(s, s^!)$ indicates the mutual information between features s and $s^!$. This strategic selection of features ensures that critical attributes contributing to yield and sustainability are prioritized, thus supporting informed decision-making in agricultural practices.

3.3 ML-OPSCS: Dataset Partitioning

Pumpkin dataset partitioning involves dividing the dataset into training, testing, and hold-out validation sets, commonly in a 70:10:20 ratio. Mathematically, let the dataset be represented as $D = \{X, Y\}$, where X denotes the features and Y represents the labels. The dataset D is split into D_{train}, $D_{hold\text{-}out}$, and D_{test}. The training set builds the model, the testing set evaluates performance, and the hold-out set provides unbiased validation for minimizing overfitting.

3.4 ML-OPSCS: Model Training

This stage focuses on training multiple machine learning classifiers, such as Boosted Trees, Bagged Trees, RUS-Boosted Trees, and an Optimizable Ensemble, to improve model accuracy and performance. Boosted Trees leverage gradient boosting, which iteratively enhances weak learners by minimizing loss functions and improving prediction accuracy. Bagged Trees utilize bootstrap aggregating (bagging), where multiple models are trained on random samples to reduce variance, thus increasing model robustness. RUS-Boosted Trees address class imbalance by applying Random Under-Sampling with boosting to focus on minority classes. The Optimizable Ensemble integrates these classifiers, enabling the model to automatically

tune parameters and optimize feature selection, further improving performance. This combination of techniques strengthens the classifier's ability to generalize to unseen data while minimizing overfitting. The optimized approach is crucial for effective pumpkin seed classification.

3.5 ML-OPSCS: Model Optimization and Evaluation

In this Phase of the ML-OPSCS framework, model optimization is achieved by tuning hyperparameters to enhance performance. Hold-out validation techniques are employed, where the dataset is split into distinct training and validation subsets. This approach ensures that the model's hyperparameters, such as learning rate and depth of trees, are optimized for improved accuracy. Performance evaluation during optimization is conducted using confusion matrices and key metrics, including accuracy, precision, recall, and F1-score, which provide a detailed understanding of the model's effectiveness, especially in handling class imbalances.

It focuses on model evaluation using the hold-out testing dataset, ensuring the trained model's robustness. Evaluation metrics include not only traditional measures such as test accuracy and loss but also training time and prediction speed, providing a comprehensive assessment of model efficiency. These metrics guarantee that the optimized ML-OPSCS model performs well in real-world agricultural scenarios, offering reliable and fast seed classification for enhancing agricultural productivity.

3.6 ML-OPSCS: Deployment Agricultural Application

In this phase, the optimized ML-OPSCS model's output is meticulously analysed to assess its classification efficacy and the significance of different features used in the model. By employing techniques such as feature importance scores, it becomes evident which attributes contribute most significantly to accurate pumpkin seed classification. The findings lead to specific recommendations regarding the top features that should be prioritized for pumpkin seed quality assessment, thereby enabling farmers to make informed decisions based on data-driven insights.

4. Empirical Results and Analysis

The results from the implementation of the ML-OPSCS for pumpkin seed classification reveal significant improvements in agricultural productivity and sustainability. The subsequent subsections present detailed findings and analyses for each technique at every stage, elucidating their impact on the overall classification framework.

4.1 Performance of Bagged Trees with MRMR

The Fig. 72.3, illustrates the performance of Bagged Trees with MRMR across varying feature counts (12, 10, 8, and 6). The performance metrics, including precision, recall, F1-score, and accuracy, fluctuate with different numbers of features. The highest precision is observed with 8 features, reaching over 92%, while recall and F1 remain relatively balanced across feature counts. Notably, the accuracy remains consistent above 86% for all feature sets but dips notably with the 6-features, suggesting a trade-off between feature reduction and model performance. Overall, the 8-feature model appears to provide the optimal balance.

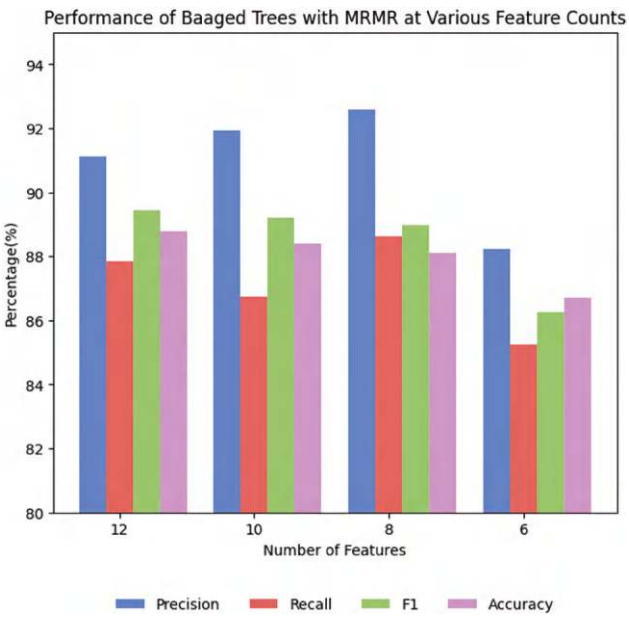

Fig. 72.3 Performance of bagged trees at various feature counts

4.2 Performance of RUS-Boosted Trees with MRMR

Figure 72.4 visualizes the performance of RUS-Boosted Trees with MRMR at various feature counts (12, 10, 8, and 6). From the analysis, precision peaks at over 94% when 10 features are used, highlighting the model's capability to correctly classify positive instances. In contrast, recall is lowest with 6 features, reflecting a drop in sensitivity as fewer features are included. The overall F1-score, which balances precision and recall, performs best with 8 features. Accuracy remains fairly stable across the 12, 10, and 8-feature sets but declines with 6 features. The optimal performance in this case is achieved with 8 features, where the precision and accuracy are at their highest, providing a more reliable model.

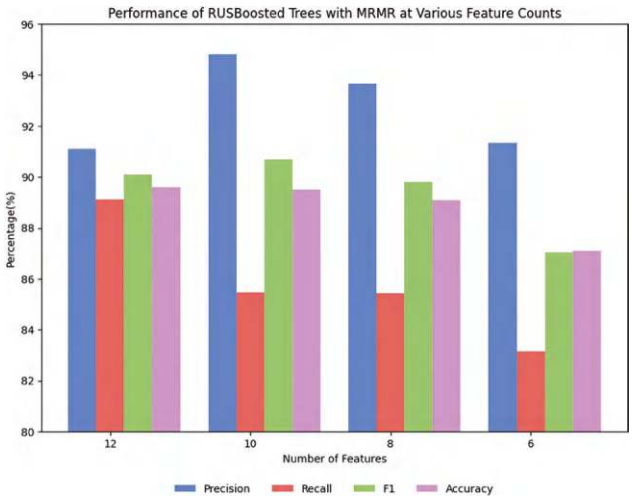

Fig. 72.4 Performance of RUS-boosted trees at various feature counts

4.3 Performance of Boosted Trees with MRMR

The graph presented in Fig. 72.5, illustrates the performance of Boosted Trees with MRMR at different feature counts (12, 10, 8, and 6), focusing on metrics like precision, recall, F1-score, and accuracy. With 12 features, precision is high at over 93%, but recall shows a dip, indicating some missed positive cases. As the number of features reduces to 10 and 8, precision remains strong, while F1 and accuracy also show consistent performance. However, with 6 features, both recall experience significant declines, suggesting a drop in the model's ability. The highest accuracy is observed with 8 features, but the overall results suggest that using fewer than 8 features negatively impacts the model's overall performance.

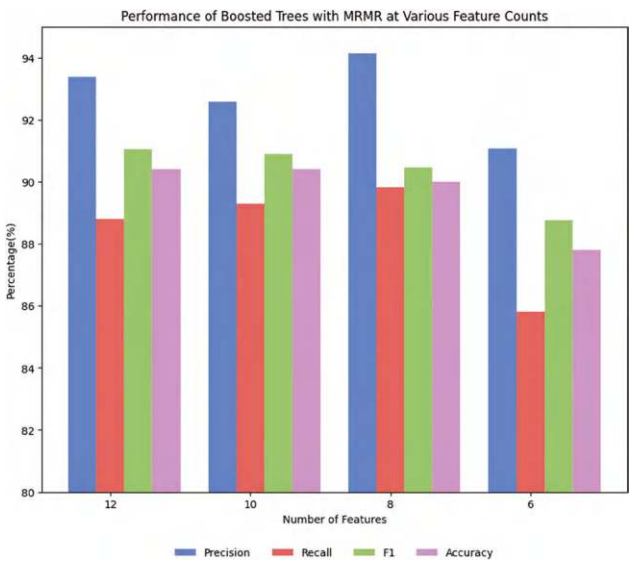

Fig. 72.5 Performance of boosted trees at various feature counts

4.4 Performance of Optimized Ensemble with MRMR

The graph in Fig. 72.6 displays the performance of the Optimizable Ensemble model, which utilizes the MRMR technique for feature selection. It evaluates how the model performs with varying numbers of features: 12, 10, 8, and 6. The performance metrics used are precision, recall, F1-score, and accuracy. With 12 features, precision is notably high, approaching 92%, indicating that the model is strong in correctly identifying true positives. As the feature count decreases to 10, the precision slightly improves, going beyond 92%. Despite this, the F1-score and accuracy remain stable, showing that the model can still provide strong. At 8 features, the performance across all metrics, precision, recall, F1-score, and accuracy are generally well-balanced, each staying at or around 90%. This suggests that 8 features may be an ideal number, as it maintains a good balance between all the evaluation metrics, showing reliable prediction strength. When the feature count is further reduced to 6, the model's performance starts to degrade across the board, especially in recall and accuracy.

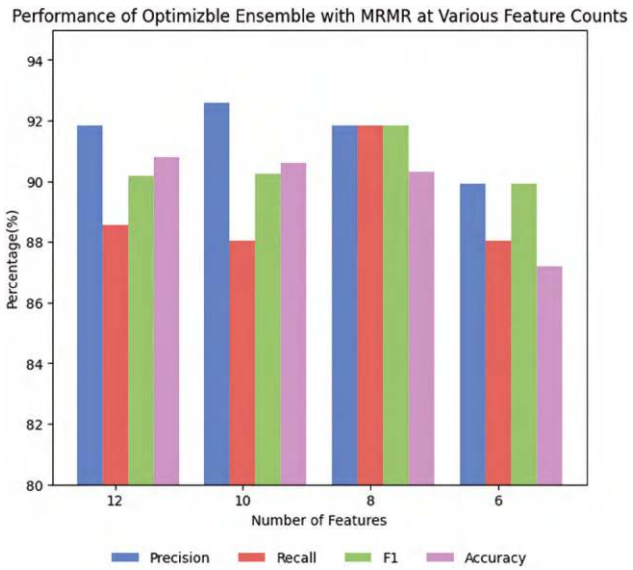

Fig. 72.6 Optimized ensemble at various feature counts

4.5 Performance of Comparison of ML Techniques

The research study systematically compares four ML techniques—Bagged Trees, RUS-Boosted, Boosted Trees, and Optimizable Ensemble—at the optimal feature set of 8 proven by all, using key evaluation metrics: precision, recall, F1-score, and accuracy. The results, illustrated in Fig. 72.7, reveal that the Bagged Trees technique yields an accuracy of around 88%, showing moderate performance.

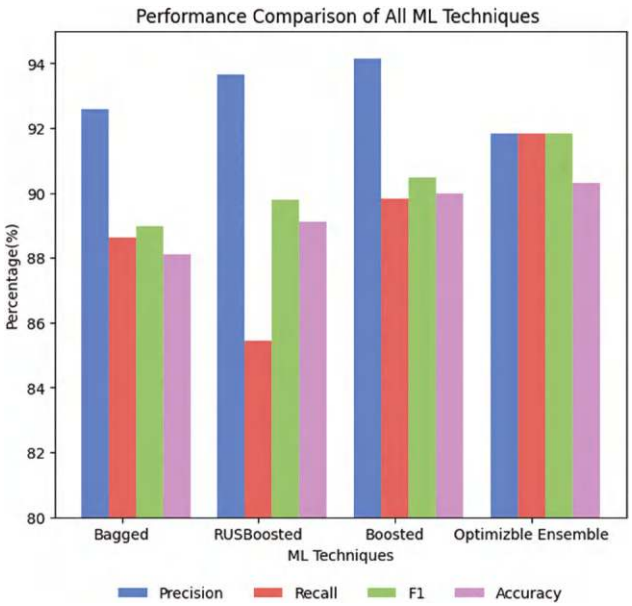

Fig. 72.7 Comparison all four ML techniques at optimal feature set

The RUS-Boosted technique demonstrates improved accuracy, reaching 89%, although its handling of class imbalance remains a challenge. In contrast, the Boosted Trees model outperforms both with an accuracy surpassing 90%, highlighting its strength in classification tasks. The Optimizable Ensemble method, however, surpasses all other techniques with an accuracy of 91.3%, owing to its ability to integrate multiple classifiers. This model demonstrates a balanced and robust performance across varying conditions, ensuring that it consistently achieves high classification accuracy. As such, the Optimizable Ensemble stands out as the optimal choice for complex agricultural tasks like pumpkin seed classification, effectively addressing issues like class imbalance and feature optimization.

4.6 Ranked Optimal Feature Set

The study identified the optimal feature set, ranked in Table 72.2, using the Optimized Ensemble Method within the ML-OPSCS model, integrated with MRMR. By applying backward sequential feature selection, the method improves classification accuracy and boosts overall model performance. This combination enhances the ML-OPSCS model's efficiency and reliability for agricultural seed classification, especially in seed quality assessments.

5. Conclusion

In conclusion, this research presents an optimized ensemble machine learning framework tailored for pumpkin seed classification, addressing key challenges in agricultural productivity, such as class imbalances and feature redundancy. By integrating advanced techniques like Boosted Trees, RUS-Boosted Trees, and Bagged Trees, and incorporating the MRMR method for feature selection, the framework significantly enhances model accuracy and computational efficiency. Sequential Feature Engineering plays a pivotal role in refining the classification process.

Table 72.2 Ranked optimal feature set

S. No.	Feature	MRMR Score	Rank
1	Aspect_Ratio	0.3654	R01
2	Equiv_Diameter	0.2996	R02
3	Solidity	0.2986	R03
4	Extent	0.2799	R04
5	Major_Axis_Length	0.1899	R05
6	Minor_Axis_Length	0.1778	R06
7	Roundness	0.1357	R07
8	Compactness	0.0858	R08

The optimized ensemble approach demonstrates superior performance compared to individual models, effectively improving classification accuracy while ensuring robustness. This research contributes to precision agriculture by advancing seed classification methods, ultimately supporting sustainable food production practices and enhancing agricultural efficiency.

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ECG Analysis Based VGG 16 Heart Attack Approach Using Federated Learning

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Abstract: Federated Learning is a privacy-preserving technology (PET) that lessens the dangers connected to private information. Differential privacy, homomorphic encryption, federated learning, secure enclaves, secure multi-party computation, synthetic data, and tokenization are just a few of the uses for it. Heart attacks occur every five minutes, with several people currently surviving one, and are caused by sudden blood supply loss in the heart muscle. Abnormal ECG can indicate heart conditions like irregular heartbeats, electrical issues, enlarged hearts, reduced blood supply, or sudden heart attacks, aiding in emergency treatment and requiring additional tests. The study aims to address the issue of ECG image classification using advanced deep learning techniques. This paper analyses ECG waves, identify ethnic differences, and develop an ECG database to improve heart attack definitions and treatment plans based on age and sex. Exploratory data analysis (EDA) is crucial for identifying outliers of abnormal heartbeat in the dataset, including ECG image size, dimensions, blurriness, and aspect ratio. This discusses the use of Transfer Learning and Convolutional Neural Networks for advanced ECG analysis Using VGG-16. The empirical result can be integrated into ECG machines to interpret rhythm, conduction abnormalities, and heart enlargement, based on age, sex, and race.

Keywords: Convolutional neural network (CNN), Electrocardiogram (ECG), Heart attacks, VGG-16.etc

1. Introduction

Coronary heart disease (CHD) is a situation where coronary arteries becomes compressed due to fatty deposits called atheroma. If the plaque ruptures, a blood clot produces blocking the coronary artery which causes a heart attack (Baranowski et al., 2016). Heart attack symptoms are similar for men and women, but doctors may differ. Women are under-treated for CHD, and doctors need to be educated. Symptoms include persistent chest pain, light-headedness, dizziness, shortness of breath, nausea, or vomiting. It's possible to witness a heart attack without chest pain, especially in diabetes patients. It's crucial to call 999 immediately if you suspect a heart attack. Rapid

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treatment is crucial for heart damage, aiming to restore blood flow to damaged heart muscle. Primary angioplasty or thrombolysis are common treatments, reopening blocked coronary arteries or dissolving blood clots. Heart attacks have evolved from painkillers and bed rest in the 1980s to thrombolysis, aspirin, and post-attack medication. These treatments prevent future attacks, treat angina, strengthen the heart, reduce heart failure risk, and reduce cardiovascular disease risk factors. Cardiac rehabilitation promotes recovery. Heart attacks, often misunderstood as fatal, can be life-saving if treated promptly. Proper management can lead to heart failure, symptom relief, and satisfaction in the field of primary angioplasty (Vereckei A et al., 2007).

An electrocardiogram (ECG) is a non-invasive test that measures the heart's electrical activity, aiding in diagnosing heart conditions, monitoring treatments, and assessing overall health. Normal ECG results show a consistent heart rate of 60-100 beats per minute. Abnormal results may indicate heart damage, electrolyte changes, or heart attack. Pregnant individuals should avoid oily skin creams and hosiery. Results are returned for review by a specialist. Professor Peter Macfarlane explains the process of an electrocardiogram (ECG), a test that calculates the heart's rate, rhythm, and electrical activity. An ECG is a common heart test used to identify issues with the heart's electrical impulses, such as irregular heartbeats, shortness of breath, high blood pressure, palpitations, or suspected heart valve problems, and can rule out other issues. The ECG test uses electrodes to record heart views, with patients lying flat with their heads and chest raised for reliable recording and patient details. Rarely may a slight skin reaction occur due to electrodes, but typically, there are no after effects. An abnormal ECG can indicate irregular heartbeats, electrical activity issues, enlarged hearts, reduced blood supply, or a silent heart attack. In an emergency, it can help determine treatment by locating the source of high heart rate (Baranowski R et al., 2016).

ECG results and symptoms may require additional tests, such as exercise ECG or CT angiogram, depending on the condition. Additional investigations may include coronary angiograms to determine heart blockage. Palpitations may require longer ECG recordings, called ambulatory ECG or Holter ECG, using a wearable monitor. Holter recorders detect random ECG changes, while CT angiograms and coronary angiograms may be necessary for further diagnosis. Advances in miniaturizing ECG equipment, particularly for long-term recording, have led to the development of wearables, such as T-shirts with electrodes for daily activities and devices recording single ECG leads on mobile phones. Computers can interpret ECGs, including rhythm, conduction abnormalities, and heart enlargement, based on age, sex, and race (Dariusz Kozłowski et al.,2018). Automated ECG interpretation offers a second opinion, but may also give inaccurate interpretations due to noise issues, which experienced eyes can identify. Computers can store normal limits based on these factors. Many researchers discovered differences in normal ECG waves between men and women and age (Soar J et al.,2015). They developed ECG databases, revealing ethnic differences. Their work improved the internationally agreed definition of heart attacks, incorporating age and sex, and modifyingtreatment plans based on ECG appearances by Thygesen K2018[4].

2. Related Methods

2.1 Convolutional Neural Network (CNN)

CNN use two- or three-dimensional input to recognize objects and classify visuals.Using dimensional input, CNNs are ML algorithms that can identify objects and categorize images. These networks consist of node layers with weights and thresholds and are used for many different applications such as NLP and speech recognition. CNNs provide a scalable approach to object recognition and picture classification through the use of matrix multiplication and other techniques from linear algebra. However, they can be computationally demanding, needing GPUs for model training.

Convolutional, pooling, and fully-connected layers make comprise the three primary layers of convolutional neural networks, which perform better with picture inputs. While the final layer identifies larger parts or shapes, the first layer concentrates on simpler details. The network gets increasingly complicated as it develops.

The convolutional layer in a CNN is the main component, involving input data, a filter, and a feature map. The input is a 3D color image, and a feature detector checks if a feature is present. The output is a feature map, activation map, or convolved feature, with parameters affecting volume size.

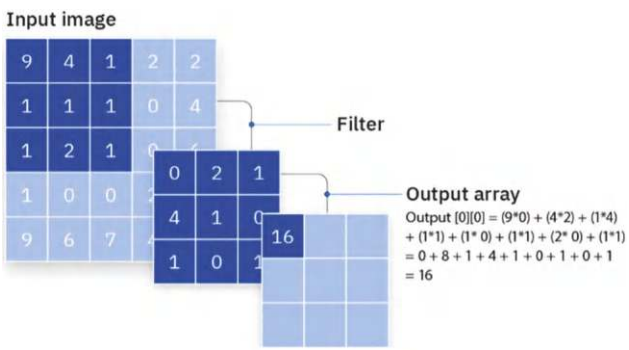

Fig. 73.1 The CNN uses a rectified linear unit (ReLU) transformation to transform the feature map

2.2 Visual Geometry Group (VGG)

VGG-16 is a 16-layer convolutional neural network able to classify the images into 1000 object categories, learning rich feature notations for a deep scope of images, with an image input size of 224-by-224. A 16-layer convolutional neural network called the VGG-16 model was created by the University of Oxford's Visual Geometry Group. Because of its depth, it can learn intricate visual characteristics and make precise predictions. VGG-16 is still a well-liked option for deep learning applications because of its performance and versatility, despite its simplicity.

VGG16 is a deep learning model with 16 weight layers, 13 convolutional layers, five Max Pooling layers, and 3 Dense layers. It uses 224, 244 input tensors with 3 RGB channels and uses a 3x3 filter with stride 1 padding and maxpool layer. The architecture has 64 filters, 128 filters, 256 filters, and 512 filters.

2.3 Privacy X-Ray Data Using Federated Learning

AI's integration into healthcare faces challenges due to the need for data privacy. Healthcare data face challenges in convincing hospitals to lend data for model training due to strict regulations, making the benefits of such data unworthwhile.

Federated Learning is a solution where the model is brought to the data instead of the data being brought to the model. The method trains query suggestions on the system, crucial for continuous training of CNN and VGG-based x-ray prediction in machine learning applications.The summary can be summarized in the following steps:

- A pre-trained model is sent to user devices along with related software applications on a centralized server.
- Users can interact with local models that are continuously refined locally.
- The models or aggregated gradients are sent back to a centralized platform after a certain time, where they are averaged into one model.
- The remote model is then synchronized with the local models on the devices.

Developing a framework that enables training on millions of users' data without storing it, a trend expected with increasing data principles.

3. METHODOLOGY

The study looks into how to use transfer learning and convolutional neural networks for more in-depth ECG analysis with Federated Learning. The goal is to leverage federated learning to improve the privacy of centralized medical testing operations using above principles.

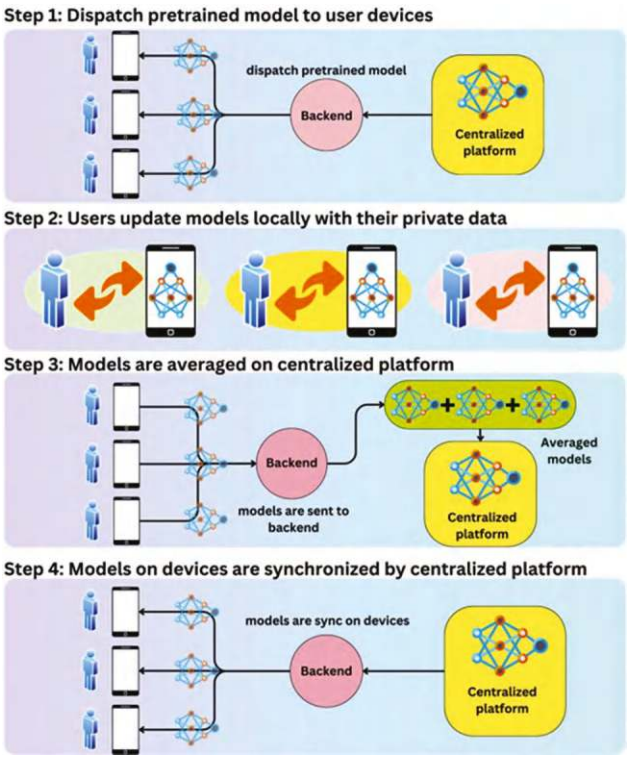

Fig. 73.2 Steps of train on private healthcare data using federated learning

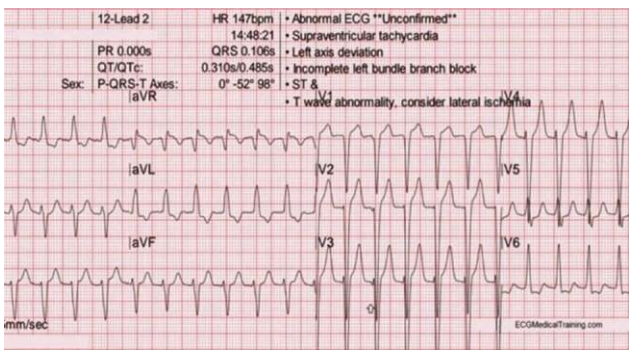

Fig. 73.3 Sample ECG data

ECG Data exploration: We examine into how the ECG picture datasets are distributed among several classifications, like normal ECGs and those that display heartbeats that are irregular or myocardial infarction. There are 2420 training and 928 testing photographs spread over four distinct categories.

ECG Data Visualization: Leveraged matplotlib to visualize samples from each category, providing a clear view of the dataset and ensuring balanced representation across classes.

3.1 Model Development

Baseline Model: Implemented a custom CNN model from scratch with layers of Conv2D and MaxPooling2D, achieving an initial test accuracy of 64.22%.

Transfer Learning: Enhanced the model by incorporating VGG16 pre-trained weights. This approach significantly improved performance, with a final accuracy reaching up to 87.50% on the validation set.

Methodical Highlights: Utilized TensorFlow and Keras for building and training models. Employed data augmentation and normalization strategies for robust training and evaluation. Implemented GPU acceleration to optimize training times and efficiency.

Main Results: Achieved notable improvements in classification accuracy using transfer learning compared to the baseline model. Successfully demonstrated how pre-trained models can be adapted for specialized tasks, leading to superior results with less training data.

This paper methodology not only deepened my understanding of convolutional neural networks but also highlighted the power of transfer learning in real-world applications. I'm excited about the potential impact of this approach in medical diagnostics and eager to explore further innovations in this field.

3.2 Input

Let the input ECG data be represented as:

X = {x1, x2, ..., xn}, where each **xi** is an ECG image sample.

Y = {y1, y2, ..., yn}, where **yi ∈ {0, 1, 2, 3}** represents the class labels (e.g., normal ECG, irregular heartbeat, myocardial infarction).

Dataset split:

- Training set: **X_train** and **Y_train** with 2420 images.
- Testing set: **X_test** and **Y_test** with 928 images.

3.2 Data Preprocessing

1. Image Normalization: Normalize the ECG images to ensure all values fall within a range [0, 1]:

   xi' = (xi – min(X)) / (max(X) – min(X))

   where xi is an image and xi' is the normalized image.
2. Data Augmentation: Apply DA techniques (rotation, scaling, flipping):

   X_augmented = {augment(xi) | xi ∈ X}

   This ensures model's robustness.

3.3 Model Development

Baseline Model (Custom CNN):

- Define a CNN model with layers of Conv2D, MaxPooling2D.

  Conv2D(f, s): convolution with f filters, stride s. MaxPooling2D(p): pooling with pool size p. The output for each image xi is computed as: **f(xi') = MaxPooling2D(Conv2D(W, b, xi')) for all i.** The final prediction is made using softmax: ŷi = softmax(h(xi')).

Transfer Learning (VGG16):

- Use pre-trained VGG16 weights for feature extraction.

  Fine-tune layers to specialize on ECG classification:

  fVGG(xi') = VGG16(xi').

  The final classification is:

  ŷi = softmax(hVGG(xi')).

3.4 Loss Function and Optimization

Minimize cross-entropy loss function:

$$L(\hat{y}i, yi) = -\sum c = 1 \text{ to } C \ (yic \log(\hat{y}ic))$$

where C represents number of classes, yic is the true label for class c, and ŷic is the predicted probability for class c.

Optimize by SGD:

$$\theta(t+1) = \theta(t) - \eta \nabla\theta L(\hat{y}i, yi)$$

where θ are the model parameters, η is the learning rate.

4. Experimental Result

To find outliers in the ECG dataset, such as ECG image dimensions and size, as well as other ECG image-related characteristics including aspect ratio and blurriness, exploratory data analysis (EDA) is required. The experimental study explores the use of Transfer Learning and Convolutional Neural Networks for advanced ECG analysis. The experimental result displays 10 ECG images of a patient with an abnormal heartbeat, totalling 2796.

The search yielded 2420 images categorized into four classes.

The search yielded 603 images categorized into 4 classes.

The search yielded 928 images categorized into 4 classes.

Class indices: {'ECG images of Myocardial Infarction Patients

(240x12=2880) `:0,'ECG Images of Patient that have History of ML.

The ECG images of patients with a history of ML are available in a total of 2880.

(172x12=2064) `:1,' ECG Images of Patient that have abnormal heartbeat.

The patient has an abnormal heartbeat, as shown in the ECG images (172x12=2064).

(233x12=2796) `:2,' Normal Person ECG Images(284x12=3408)',3}

The number of normal person ECG images, which is equal to the sum of the squares of the numbers 233 and 284 respectively.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      896

 max_pooling2d (MaxPooling2D)  (None, 111, 111, 32)    0

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18,496

 max_pooling2d_1 (MaxPooling2D)  (None, 54, 54, 64)    0

 conv2d_2 (Conv2D)           (None, 52, 52, 128)       73,856

 max_pooling2d_2 (MaxPooling2D)  (None, 26, 26, 128)   0

 flatten (Flatten)           (None, 86528)             0

 dense (Dense)               (None, 128)               11,075,712

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 11,169,476 (42.61 MB)
Trainable params: 11,169,476 (42.61 MB)
Non-trainable params: 0 (0.00 B)
```

The user is notified that their input has run out of data, causing the training to be interrupted.

```
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 2s 30ms/step - accuracy: 0.4062 - loss:
1.3729 - val_accuracy: 0.2593 - val_loss: 1.3756
Epoch 3/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 106s 842ms/step - accuracy: 0.2715 - loss:
1.3723 - val_accuracy: 0.3160 - val_loss: 1.3743
Epoch 4/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 8ms/step - accuracy: 0.2812 - loss:
1.3906 - val_accuracy: 0.3333 - val_loss: 1.3648
Epoch 5/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 70s 861ms/step - accuracy: 0.2932 - loss:
1.3739 - val_accuracy: 0.3229 - val_loss: 1.3651
Epoch 6/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 8ms/step - accuracy: 0.4375 - loss:
1.3386 - val_accuracy: 0.1852 - val_loss: 1.3593
Epoch 7/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 67s 835ms/step - accuracy: 0.3384 - loss:
1.3640 - val_accuracy: 0.3194 - val_loss: 1.3614
Epoch 8/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 8ms/step - accuracy: 0.3438 - loss:
1.3261 - val_accuracy: 0.2593 - val_loss: 1.3993
Epoch 9/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 69s 853ms/step - accuracy: 0.2996 - loss:
1.3689 - val_accuracy: 0.6163 - val_loss: 0.9847
Epoch 10/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 8ms/step - accuracy: 0.5938 - loss:
0.9071 - val_accuracy: 0.6667 - val_loss: 0.8890
29/29 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 29s 1s/step - accuracy: 0.6225 - loss:
0.9828
```

The test has an accuracy of 0.64.

The ECG data is download from the storage platform VGG16 with a time of 58889256 seconds.

```
Epoch 1/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 99s 1s/step - accuracy: 0.3515 - loss:
2.7575 - val_accuracy: 0.5347 - val_loss: 1.0871
Epoch 2/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 15s 201ms/step - accuracy: 0.5312 - loss
1.0371 - val_accuracy: 0.4444 - val_loss: 1.1161
Epoch 3/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 68s 838ms/step - accuracy: 0.5206 - loss
1.0426 - val_accuracy: 0.6944 - val_loss: 0.8787
Epoch 4/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 7ms/step - accuracy: 0.7188 - loss:
0.8200 - val_accuracy: 0.6667 - val_loss: 0.7633
Epoch 5/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 68s 828ms/step - accuracy: 0.7323 - loss
0.8072 - val_accuracy: 0.7882 - val_loss: 0.6549
Epoch 6/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 8ms/step - accuracy: 0.6562 - loss:
0.7927 - val_accuracy: 0.9259 - val_loss: 0.6732
Epoch 7/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 68s 844ms/step - accuracy: 0.7879 - loss
0.5928 - val_accuracy: 0.8351 - val_loss: 0.5085
Epoch 8/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 6ms/step - accuracy: 0.8125 - loss:
0.6428 - val_accuracy: 0.8148 - val_loss: 0.5687
Epoch 9/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 71s 872ms/step - accuracy: 0.8382 - loss
0.4735 - val_accuracy: 0.8750 - val_loss: 0.4377
Epoch 10/10
75/75 ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1s 7ms/step - accuracy: 0.8750 - loss:
0.4130 - val_accuracy: 1.0000 - val_loss: 0.2808
```

The model is evaluating of Test Accuracy by Test Generator. Test Accuracy:0.871.

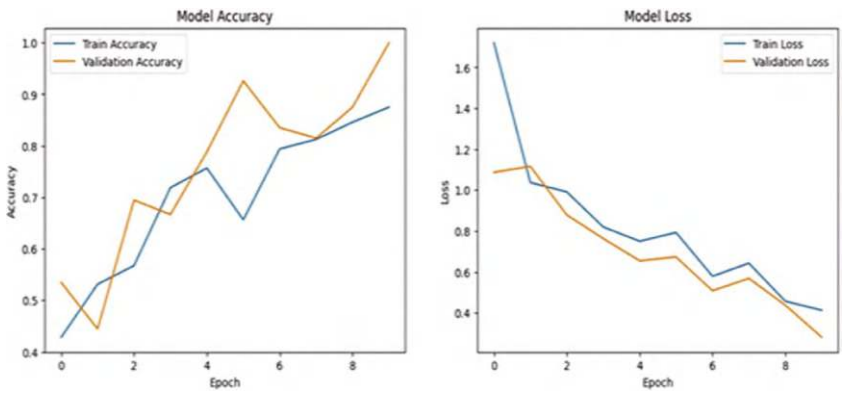

Fig. 73.4 Model accuracy and loss of train and validaation

To do predictions on the trained model, it is good to use the best saved model, pre-process the ECG image, and provide it to the model for output.

Classification Report:	precision	recall	f1-score	support
ECG Images of Myocardial Infarction Patients (240x12=2880)				
	0.29	0.33	0.31	239
ECG Images of Patient that have History of MI (172x12=2064)				
	0.24	0.16	0.20	172
ECG Images of Patient that have abnormal heartbeat (233x12=2796)				
	0.21	0.19	0.20	233
Normal Person ECG Images (284x12=3408)				
	0.31	0.36	0.33	284
accuracy			0.27	928
macro avg	0.26	0.26	0.26	928
weighted avg	0.27	0.27	0.27	928

5. Conclusion

Federated Learning is a privacy-preserving technology that uses differential privacy, homomorphic encryption, secure enclaves, secure multi-party computation, synthetic data, and tokenization to mitigate privacy risks. Heart attacks occur every five minutes due to sudden blood supply loss in the heart muscle. Abnormal ECG images can indicate heart conditions, aiding emergency treatment. This studiedused the advanced deep learning techniques to classify ECG images, identify ethnic differences, and develop an ECG database. The transfer learning and convolutional neural networks to interpret rhythm, conduction abnormalities, and heart enlargement based on age, sex, and race.

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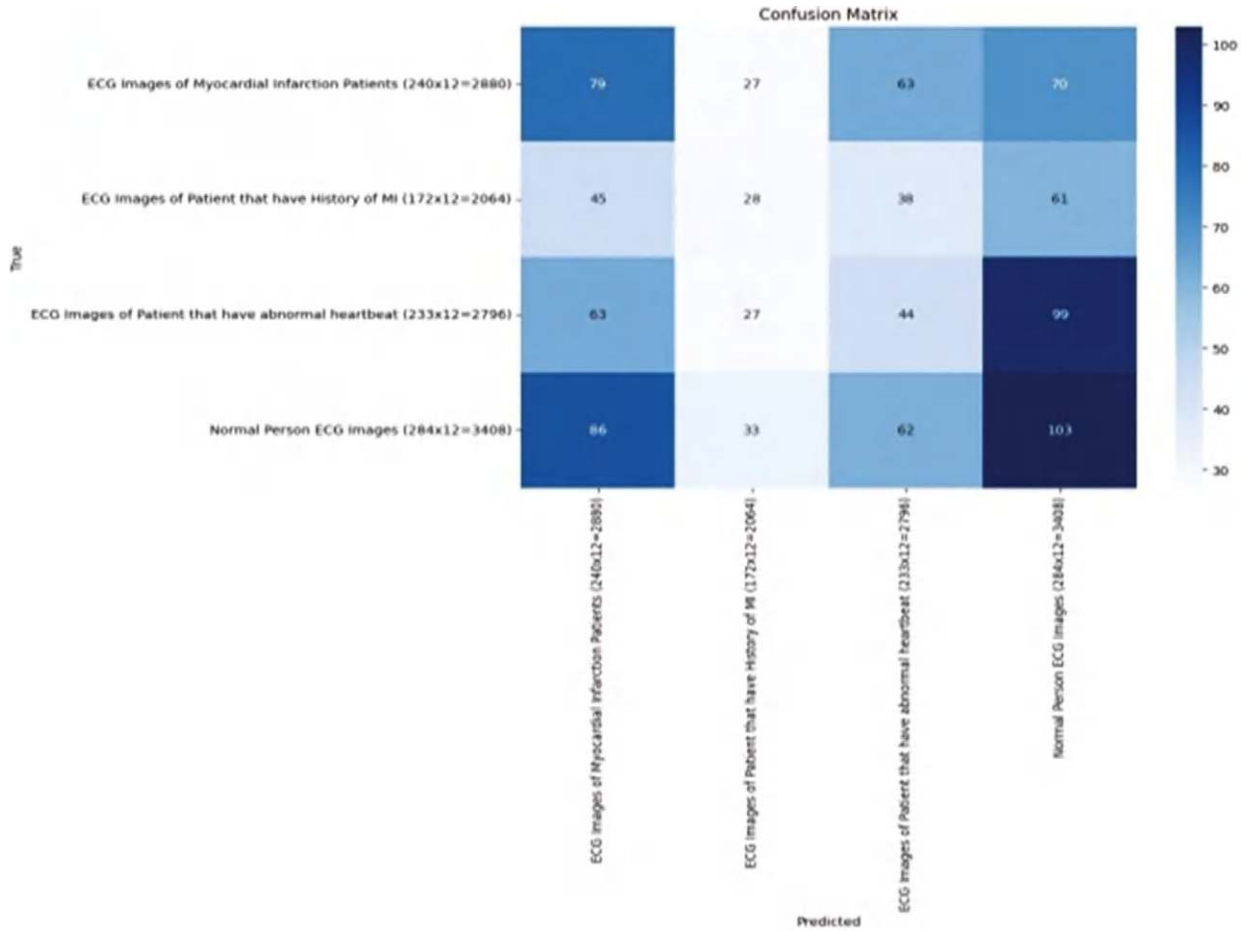

Fig. 73.5 Confusion matrix of heartbeat ECG analysis

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Note: All the figures in this chapter were made by the authors.

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Multiclass Classification of DDoS Attacks using HSOFS Algorithm in IoT Networks

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Abstract: The fast growth of Internet of Things (IoT) applications, like those in smart cities, healthcare, and industrial automation, has greatly increased the risk of networks facing Distributed Denial of Service attacks. These attacks present critical threats to the reliability and security of IoT ecosystems. This research introduces a robust methodology for detecting DDoS attacks in IoT networks utilizing machine learning models. By leveraging the CICIoT2023 dataset, the most relevant features for accurate detection were identified using the Hierarchical Self-Organizing Feature Selection (HSOFS) technique. Various machine learning models were benchmarked to evaluate their effectiveness in detecting different DDoS attacks in IoT. The models tested include DT, RF, KNN, XGB, and MLP. The models were trained and tested on two different classification scenarios: 34 attack classes and 12 DDoS classes. Among the five models, XGBoost delivered the best performance, achieving an accuracy of 99.97% for the 12-class DDoS detection task. In contrast, Random Forest achieved 99.16% accuracy for the 34-class task

Keywords: DDoS, Machine learning, RF, KNN, XGB, DF, MLP, and HSOFS

1. Introduction

The swift advancement of Internet of Things (IoT) technologies is reshaping numerous fields, such as smart city infrastructure, healthcare systems, and industrial automation Bhayo, et al. (2022). These advancements bring substantial benefits, such as increased efficiency and enhanced quality of life. However, these advancements bring additional vulnerabilities, especially affecting the security and stability of IoT networks. Distributed Denial of Service (DDoS) attacks pose a major concern among the many threats facing IoT ecosystems. These attacks flood a network with excessive traffic, causing service interruptions and hindering normal operations. The scale and impact of these attacks have escalated with the growth of IoT devices, which are often characterized by their large

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number, heterogeneity, and varying levels of security. As a result, traditional defense mechanisms frequently fall short in addressing the unique challenges posed by DDoS attacks in IoT environments.

Advanced detection and mitigation approaches are urgently needed to counter these threats effectively. Recent developments in machine learning and deep learning provide valuable pathways for improving DDoS attack detection. These techniques can utilize the extensive data generated by IoT devices to identify patterns and anomalies that may signal malicious activities.

Our approach addresses the urgent need for strong security in IoT networks by offering a reliable, data-based framework for detecting DDoS attacks. The results of our study show that advanced deep learning methods are effective in achieving high detection accuracy, reducing false positives, and maintaining strength across different IoT environments. Ultimately, this research contributes valuable insights into enhancing the security posture of IoT networks and fortifying them against the growing threat of DDoS attacks Elsaeidy et al. (2021).

The number of DDoS attacks increased significantly in the first half of 2024. With 445,000 attacks reported in Q2 2024 alone, the number of attacks increased by 46% over the same period in 2023. This is a 34% increase over the preceding six months (Q3–Q4 2023) [11]. Figure 74.1 shows the number of DDoS attacks that increase quarterly from 2023-2024.

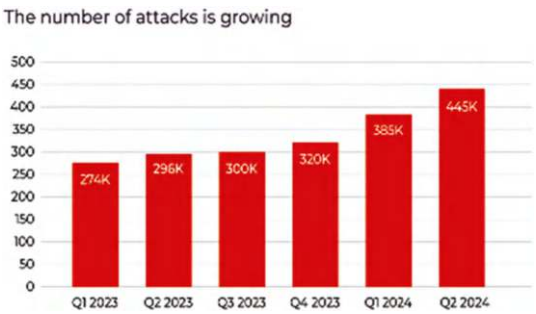

Fig. 74.1 Quarterly-wise number of DDoS attacks from 2023-24

Source: https://gcore.com/blog/radar-q1-q2-2024-insights/

2. Literature Review

In the literature review, we examined various research articles on detecting DDoS attacks in IoT networks using machine learning and deep learning models. We found that most studies used binary classification, with very few authors exploring multiclass classification of DDoS attacks. Additionally, those that did focus on multiclass classification did not target a specific number of DDoS attack categories.

Elsaeidy et al. (2021) combined restricted Boltzmann machines with CNNs to enhance IoT device detection in smart cities, achieving over 98% accuracy. This unique approach to DDoS attack identification remains unexplored by other researchers using similar datasets.

Xie et al (2024) introduced the Multidimensional Reconstruction Encoder (MrE) with Function Mapping (MRFM), tested on CIC-DDoS2019 and BOT-IoT datasets, achieving 94.6% accuracy for binary and 97% for multiclass classification with favorable resource requirements.

Aguru, A. D., and Erukala, S. B. (2024) developed a queuing model to simulate multi-vector DDoS attacks on EHR systems in mobile healthcare networks. Using feature selection from CICIoT2023 and CICDDoS2019, they examined bandwidth and resource impacts, achieving 97.3% accuracy in binary and 98.17% in multiclass classification.

Yaras, S., and Dener, M. (2024) enhanced DDoS attack detection in IoT networks using a hybrid CNN-LSTM model on CIC-IoT2023 and TON-IoT datasets. Their approach achieved 96.5% accuracy in binary and 98.36% in multiclass classification, demonstrating effective attack classification in complex IoT environments.

Lv et al. (2023) introduced KG-SMOTE, an oversampling algorithm to enhance DDoS detection in IoT by addressing data imbalance, which often lowers accuracy due to limited attack packets. Using hybrid ML models on CIC2023 and Edge-IoT datasets, the study achieved up to 99.10% accuracy in detecting DDoS attacks.

In the study by Pande et al. (2021), the CICDDoS2019 dataset is widely utilized for both training and testing purposes, providing a comprehensive foundation for evaluating model effectiveness. Using this dataset, the LSTM and decision tree models achieve an accuracy rate of 99.32%..

Nuhu et al. (2024) highlights the urgent need for smart methods to tackle DDoS attacks in the fast-growing IoT field, showing that deep learning and combining features can help detect these attacks. Similarly, Jaber and Kadhim demonstrate that Deep Neural Networks (DNNs) can effectively identify DDoS activities, reaching a high detection rate of 96.5%.

Dash, S. K., et al. (2024) executed a forest algorithm aimed at identifying Distributed Denial of Service (DDoS) attacks, particularly through the application of machine learning methodologies, utilizing the command-based Ping of Death technique, which yielded an impressive detection rate of 99.76%.

Kumar, R., & Singh, P. (2023). proposed a Deep Belief Network method for effective DDoS detection. impressive

accuracy, with some exceeding 99.97% in detection accuracy and F1-score, highlighting real-time applications.

3. METHODOLOGY

In the proposed methodology, the CICIoT2023 Neto, et al. (2023) dataset, developed by the University of New Brunswick (UNB) in 2023, was utilized to comprehensively analyze various DDoS attacks in IoT environments. A novel feature selection approach, Hierarchical Self-Organizing Feature Selection (HSOFS), was employed to extract the most pertinent features from the dataset. Following the feature selection process, the model was trained using four machine learning algorithms alongside a deep learning model to evaluate performance. Figure 74.2 shows a detailed step-by-step explanation of our proposed model.

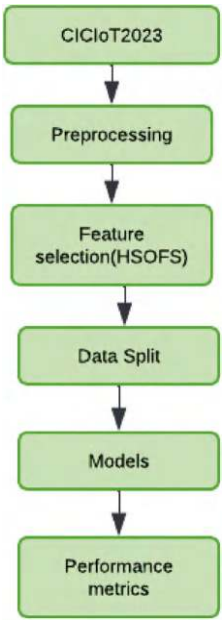

Fig. 74.2 Architecture of proposed methodology

Source: Author

3.1 Dataset Description

The CICIoT2023 Neto, et al. (2023) dataset is a comprehensive dataset containing features representing network traffic and several attack categories, with a particular focus on Distributed Denial of Service (DDoS) attacks. This dataset consists of 46 features, where the last feature corresponds to the output label (attack type). This dataset mainly contains 34 classes in seven different categories. The seven categories are DDoS, DoS, Mirai, Brute Force, Web spoofing, and Reconn. The primary goal of the research is to build a machine learning model that can accurately classify DDoS attacks, using feature selection techniques to reduce dimensionality and improve model performance.

3.2 Feature Selection

Feature selection plays a vital role to improving model efficiency and performance by reducing the number of irrelevant or redundant features. In this research, the Hierarchical Self-Organizing Feature Selection (HSOFS) technique is applied to the dataset, specifically targeting features that are most relevant to detecting DDoS and DoS attacks.

HSOFS identifies and selects a subset of optimal features based on hierarchical structures and self-organizing principles. This method not only reduces the computational burden but also enhances the interpretability of the model by eliminating noisy features that do not contribute to attack detection.

We retrieved the top twenty features using HSOFS algorithms. Among all the features, the IAT feature got the highest score, followed by magnitude, syn-count, protocol type, header length, etc. Here, we consider the top 10 features and trained model, and we also take the top 20 features and train the model. The accuracy in both cases is the same.

HSOFS Algorithm:

i) Input:
Load the Dataset $X \in R^{n \times d}$ and target labels $y \in \{0,1\}^n$, where $d = 47$

ii) Initialize Population:
Create an initial Population $S_I \in \{0,1\}^d$, $i = 1,2,...P$, representing binary feature subsets

iii) Hierarchical Clustering:
Apply Clustering on X to form clusters C_1, C_2,....., C_K, where k is the number of clusters

iv) Feature Selection within Clusters:
For each Cluster C_i, select the features f_i^* with the highest relevance

v) Self-Organization Process:
For each Particle S_i, refine feature selection by organizing within its cluster C_i, and maintaining hierarchical constraints.

vi) Velocity update:
Update velocity for each particle S_i, based on its personal best pBest and global best gBest:

$$v_{ij}(t+1) = w \cdot v_{ij}(t) + c_1 \cdot r_1 \cdot (\mathbf{p}Best_{ij} - S_{ij}(t) + c_2 \cdot r_2 \cdot (\mathbf{g}Best_{ij} - S_{ij}(t))$$

vii) Position Update:
Update particle positions S_i, using the sigmoid function applied to $v_{ij}(t+1)$

$$S_{ij}(t+1) = signoid(v_{ij}(t+1)) > \theta$$

where θ is a threshold

viii) Fitness Evaluation:
Compute fitness $f(S_i)$ using performance metrics:

$$f(S_i) = \alpha \,.\, Acc + \beta \cdot \Pr e + \gamma \cdot \mathrm{Re}\, c + \delta \cdot F1$$

ix) Update pBest and gBest:
Update personal best pBest and global best gBest based on fitness values.

x) Convergence check:
Stop when convergence criteria are met or after a maximum number of iterations.

xi) Output:
Return the optimal feature subset gBest for model training.

3.3 Model Training and Evaluation

We evaluate the performance of model in terms of accuracy, precision, recall and F1-score.

- Precision Precision is how many of the positive predictions were actually correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- Recall shows how well the model correctly detects all real positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- Accuracy measures how many predictions were correct out of all predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

- F1 Score combines precision and recall into one value, useful for imbalanced data.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4. Results and Discussion

This study assesses the CICIoT2023 dataset across two distinct categories using four machine-learning algorithms and one deep-learning model. In the first

4.1 Performance Measurements with all 46 Features

Initially, we trained and tested with all the features in 34 classes and 12 DDoS classes. In 34 classes, we got a maximum accuracy of 99.15% for the XGBoost algorithm, followed by the decision tree with an accuracy of 99.13%.

In twelve DDoS classes, we got an accuracy of 99.41% for XGBoost and 99.15 % for Decision Tree, respectively.

Table 74.1, shows the all performance metrics for CICIoT2023 dataset data in terms of 34 and 12 classes clearly.

Table 74.1 Performance measurements with 46 features

Classes	Model	Acc	Pre	Rec	F1
34	RF	0.9908	0.9903	0.991	0.99
	DT	0.9913	0.9915	0.991	0.991
	XGB	0.9915	0.9907	0.992	0.991
	KNN	0.9361	0.9347	0.936	0.934
	MLP	0.9796	0.9785	0.98	0.979
12	RF	0.9912	0.9956	0.996	0.997
	DT	0.9915	0.9979	0.999	0.998
	XGB	0.9941	0.9608	0.964	0.961
	KNN	0.9800	0.9806	0.981	0.980
	MLP	0.9993	0.9986	0.998	0.999

Note: Acc: Accuracy, Pre: Precision, Rec: Recall, F1: F1-score
Source: Author

Figure 74.3 shows the performance bar graph with 34 and 12 DDoS classes with all 46 features. In this graph, the x-axis indicates model name and the y-axis indicates metrics score.

Fig. 74.3 Performance metrics with all features

Source: Author

4.2 After Applying the HSOFS Algorithm

In this section, we evaluate our work with the novel HSOFS algorithm. With the help of this novel algorithm, the most relevant top 20 features from the list of all 46 features were extracted. In this, we trained and tested our models using all five algorithms. We saw a tremendous change in the results in both 34 and 12 classes. Table 74.2 shows the performance results with our proposed model. Among all AI models, XGBoost (XGB) achieves the highest accuracy of 99.45% and 99.98% for 34 classes and 12 DDoS classes. XGBoost also shows good performance in terms of precision, recall, and F1-score which is 99.98% for 12 classes and 99.14% for 34 classes. Decision tree

Table 74.2 Performance metrics with HSOFS algorithm

Classes	Model	Acc	Pre	Rec	F1
34	RF	0.9916	0.9812	0.9721	0.9656
	DT	0.9917	0.9852	0.8594	0.8445
	XGB	0.9945	0.9914	0.9928	0.9915
	KNN	0.9784	0.8417	0.6815	0.7815
	MLP	0.9461	0.9456	0.9479	0.9485
12	RF	0.9989	0.9989	0.9989	0.9989
	DT	0.9994	0.9994	0.9994	0.9994
	XGB	0.9998	0.9998	0.9998	0.9998
	KNN	0.9947	0.9947	0.9947	0.9947
	MLP	0.9975	0.9975	0.9975	0.9975

Note: Acc: Accuracy, Pre: Precision, Rec: Recall, F1: F1-score

Source: Author

performance has an accuracy of 99.94% and 99.17 in 12 and 34 classes.

KNN and MLP exhibit a little bit lower accuracy 99.75% and 99.47%, respectively in the 12-class task, while all models, including XGBoost, perform exceptionally well in the simpler 12-class task, achieving near-perfect metrics across the board. In 12 DDoS classes, all models perform excellent results which is above 99.47% in all measures.

Figure 74.4 shows the performance bar graph with the HSOFS algorithm. In this x -axis indicates model names and the y-axis indicates metrics score.

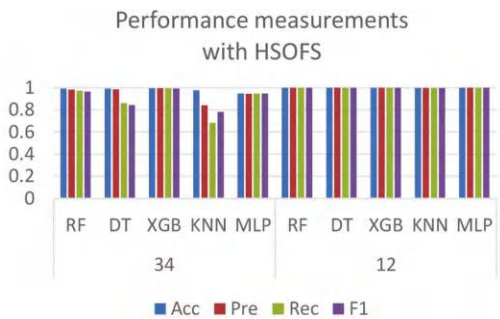

Fig. 74.4 Performance bar graph with HSOFS algorithm
Source: Author

After applying the HSOFS we almost reduced the features by more than half and we achieved good accuracy and precision for all models.

Finally, we compared our work with existing works. Our proposed model achieved outstanding results in terms of performance metrics. Our model got an accuracy of 99.98% for identifying DDoS attacks in IoT networks and in 34 classes we got an accuracy of 99.45%. Table 74.3 shows the results comparison between proposed model with existing works. Our proposed model performance exceptionally well in all areas.

Table 74.3 Comparison of proposed model with existing work

Ref	Acc	Pre	Rec	F1
Elhoseny et al. (2023).	97.0	96.8	97.2	96.9
Kumar, et al. (2023)	95.5	94.3	95.0	94.6
Lv, et al. (2023)	99.32	98.7	99.0	98.8
Our model	99.98	99.98	99.98	99.98

Note: Acc: Accuracy, Pre: Precision, Rec: Recall, F1: F1-Score.

Source: Author

5. Conclusion

This research demonstrates the critical need for advanced detection mechanisms to safeguard Internet of Things (IoT) networks from the escalating threat of DDoS attacks using the CICIoT2023 dataset and machine learning approaches. We were able to identify important features with the help of the HSOFS algorithm and selected the top 20 features that improve detection accuracy. In this, we trained and tested with five AI models: RF, DT, KNN, XGBoost, and MLP out of all these models, especially XGBoost, has a remarkable accuracy of 99.97% for 12 DDoS classes and 99.51% for 34 classes. Here, machine learning algorithms got more significant results than deep learning algorithms.

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Weather-Augmented Traffic Sign Classification with YOLOv3: A Custom Dataset Approach

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Abstract: Advanced driver-assistance systems (ADAS) and autonomous driving systems depend on the identification of traffic signs, however ,unfavorable weather patterns such as rain, dust, snow, and sunlight pose substantial challenges for accurate detection. This paper presents a novel custom dataset simulating these extreme climatic conditions and employs a YOLOv3-based classification model to detect traffic signs. The model obtained an accuracy of 92.74%, with a recall of 92.74%, precision of 93.55%, and F1-score of 92.62%. These findings demonstrate the strength of the model in handling challenging real-world conditions and present an effective approach to improving traffic sign detection in adverse climate scenarios.

Keywords: Traffic sign detection, Adverse weather conditions, YOLOv3, Deep learning, Custom dataset, Classification, Weather-augmented dataset

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1. Introduction

Traffic signs plays an important role in road safety, providing significant information to drivers and autonomous vehicles. Traditional algorithms for detecting traffic signs typically rely on features like shape, edges, and color. For example, color features might be matched using HSV and HSI mod-els, or shape features can be detected through techniques such as histograms of oriented gradients and scale-invariant feature transform Cao et al., 2021Wali et al., 2019Flores- Calero et al., 2024. While these methods work well in simple environments, their limited feature extraction capabilities make them inadequate for identifying small traffic signs in complex backgrounds. In contrast, Object detection algorithms with Deep learning have emerged as the preferred models due to their superior feature extraction power. Accurate traffic sign detection is a fundamental prerequisite for autonomous driving systems and advanced driver-assistance systems. However, bad weather patterns such as heavy rain, dust storms, snow, and intense sunlight present significant challenges to accurate detection. These weather conditions reduce visibility, cause reflections or obstructions, and distort the appearance of traffic signs, making detection more difficult. Existing techniques like

YOLO, Faster R-CNN, and SSD have established great success in detecting traffic signs in normal weather conditions, but their performance tends to degrade under extreme weather. This paper proposes a novel approach that incorporates a custom dataset augmented with realistic weather conditions and uses a simplified YOLOv3-based classification model to address the detection problems posed by adverse weather conditions.

2. Literature Survey

The authors Liu et al., 2020 in their paper proposed an enhanced form of YOLOv5 for small traffic sign detection for improved performance in challenging weather conditions. This model should have different features like anchor box op- timization and multi-scale detection, which raise the accuracy of detection. Real-time performance with increased precision in detection was achieved while limitations pertaining to de- graded performance under extremely adverse conditions were observed. Based on this, the authors Shen et al., 2023 propose the YOLOv5-TS model for real-time small and extra small traffic sign detection. They proposed a Multi-Scale Feature Fusion Mechanism, with anchor box generation enhanced by the k-means. The model has shown obvious improvements in the accuracy of discovering small objects, The challenge, however, remains with increased computational complexity. The authors Dang et al., 2023 of the current paper, thus, proposed an enhanced YOLOv5 model for real-time traffic sign detection particularly under poor weather. The authors incorporated a convolutional block attention module, into the YOLOv5 architecture to improve the ability of the model towards paying attention to small and different traffic signs to suppress irrelevant features. The model achieved noticeable improvements in accuracy, especially with challenging weather conditions. Nevertheless, there are still limitations concerning the detection of heavily occluded signs. The authors Zhang et al., 2023 proposed an advanced YOLOv5-based Traffic Signs Detection method with particular emphasis on adverse weather conditions and occlusions. The study included several enhancements: the presence of the Convolutional Block Attention Module and the ACONC activation function; all improvements were combined to enhance feature extraction and generalization in YOLOv5. Besides, the training process was further optimized using the SIoU loss function to favor much better detection performance for small traffic signs. The study showed that, as a result of these modifications, an mAP boost from 75.7% to 81.9% on the TT100k dataset and from 90.2% to 92.5% in the GTSDB dataset, there- fore indicating that the detector generalizes across different datasets. Limitations included handling occluded traffic signs, future work is planned on enhancing computational efficiency, maintaining the accuracy of detection in varied conditions of the road. The authors Wang et al., 2023 proposed an enhanced YOLOv5 model for real-time, multiple traffic sign detection. The authors used feature pyramid network and a data augmentation method to improve the detection of small signs at different scales. These resulted in a much higher detection accuracy while keeping the model real time. Conclusions: The model was validated on the TT100K dataset and demonstrated notable improvements in the performance of detection. However, the authors conceded that ”more complex weather conditions and occlusions may challenge the system”. Further work is planned to develop the model’s performance for such gradient. For this reason, the authors, Chu et al., 2023 proposed TRD-YOLO, which further improves YOLOv5 with a Transformer mechanism for global feature extraction ability and a light weight decoupled detection. Some enhancements handle the challenging tasks of deformations, occlusions, and poor lighting conditions often captured in real-world traffic scenes.This model achieved very high accuracy and robustness with enriched data using data augmentation techniques. At 73 FPS, it achieved an accuracy of 86.3%, a recall of 82.1%, and a mAP of 86.5% on the TT100K dataset and, therefore, is suitable for real-time applications.

The authors, Qu et al., 2023 further proposed an improved version of the YOLOv5-based detector. This model had a

Convolutional Attention-inspired module for the detecting small-size traffic signs within complicated weather. This led to its very high performance, especially under rain, fog, and snow conditions and achieved a precision of 88.1% and recall of 79.8%, which increased by 12.5% and 23.9% respectively. Besides, the model has kept a high frame rate at 115 FPS for real time detection. The authors showed that the model still had its limitation regarding occluded object detection and would like to improve it in further work by data augmentation and object persistence. The authors Kandasamy et al., 2024 of the paper developed a deep learning model specifically designed to recognize traffic signs under various lighting conditions, such as natural daylight and artificial light scenarios like vehicle headlights with white and yellow bulbs. The study noted that many existing datasets lack extensive coverage of complex lighting situations, which can limit recognition accuracy. To address this gap, the authors created a custom dataset that spans a wide range of lighting environments, enhancing the model's robustness in real-world driving situations. The research underlines the importance of accurate traffic sign recognition, which is vital for improving road safety and au-tonomous vehicle systems. This custom dataset contains traffic signs captured at multiple angles and distances under different lighting scenarios, and the images were categorized to assist the model's training in differentiating between sign types. The methodology also employed augmentation techniques like rotation and resizing to improve the model's generalization capabilities. The results showed a notable improvement in the model's ability to detect traffic signs in diverse and challenging lighting conditions..

The Nartey et al., 2020 introduces an innovative semi-supervised approach to traffic sign recognition. It combines weakly-supervised learning with self-paced learning to improve training on small and imbalanced datasets. By using un-labeled data and generating reliable pseudo-labels, the method enhances accuracy while reducing annotation costs. The model is effective at handling rare classes and small sample sizes, yielding competitive results on two benchmark datasets and demonstrating robustness in real-world traffic sign detection.

2.1 Inference from Literature

Results through a conducted literature survey show many of the models for traffic sign detection under bad weather and occlusion conditions, such as Enhanced YOLOv5 (2023) and TRD-YOLO (2023), although powerful in performance, still present some challenges in detecting small or occluded traffic signs under complex environments. Beyond, models have recently gone a step further by simulating more varied weather conditions, such as Weather-Augmented YOLOv5; how- ever, those may not contain all real-world complexities, and their generalization might be limited. From the literature, we can see that such restrictions result in a lack of robust detection of traffic signs under very bad, realistic weather. We then developed a novel dataset that best represented typical extreme weather conditions while being sensitive to the Indian road context. Using a classification model based on YOLOv3, the performance in detection greatly improved as compared to a single-shot detector over this dataset. The model achieved an accuracy of 92.74%, precision of 93.55%, and recall of 92.74%. These findings highlight that the model is strong and effective enough to address rigorous, real-world situations. Our proposed custom dataset and YOLOv3-based solution can fill the gap in the literature regarding more realistic and challenging datasets to model real-world applications. This is the effective step forward for better traffic sign detection systems, especially in complex weather conditions, ensuring overall safety and reliability in driving technology.

3. METHODOLOGY

The methodology employed in this research includes the following key stages: *dataset creation and augmentation*, *model architecture*, *training setup*, and *evaluation metrics* shown in Block diagram. These stages are designed to enhance traffic sign detection under adverse weather conditions on Indian roads.

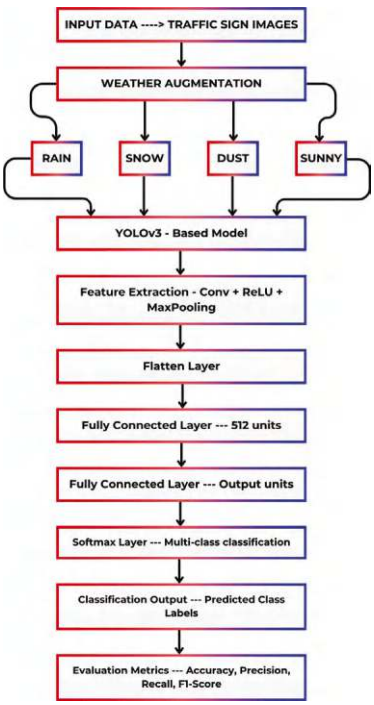


Fig. 75.1 Block diagram

3.1 Dataset Creation and Augmentation

Traffic signs across Indian roads were collected and augmented with weather filters to simulate extreme conditions such as rain, snow, dust, and sunny conditions. The filters were applied using transformations to create a diverse dataset.

Weather Simulation

Each image in the dataset was augmented with rainy, snowy, dusty, and sunny filters, using OpenCV-based methods. The transformations applied include Gaussian noise and motion blur to simulate raindrops, and color shifts to add bluish or orange tints, mimicking real-world weather effects.

a) Rainy Condition:: The rainy condition is modeled using streaks added to the image by drawing random lines. For each streak, the pixel values at position (x, y) is altered to simulate rain:

$$\text{rain_intensity}(x, y) = R(x, y) \cdot \alpha + \beta,$$

where $R(x, y)$ is the original intensity at pixel (x, y), α controls brightness, and β adjusts contrast.

b) Dusty Condition:: A dusty environment was simulated by adding Gaussian noise. An orange tint was applied to simulate the hue typically seen in dust storms, along with a decrease in contrast:

$$\text{dust_tint}(x, y) = \text{clip}(R(x, y) \cdot r_{\text{dust}}, 0,255),$$

where r_{dust} represents the reduction factor for blue channel intensity to simulate the dusty conditions.

c) Snowy Condition:: Snowflakes were modeled by adding noise to the images to represent snow. The overall brightness was reduced, and a bluish tint was applied to simulate snow:

$$\text{snow_intensity}(x, y) = R(x, y) \cdot \alpha_{\text{snow}},$$

where α_{snow} is the factor for reducing brightness to simulate snow.

d) Sunny Condition:: For sunny conditions, the filter brightened the overall image and added warm yellowish tones, simulating a bright and sunny day:

$$\text{sunny_intensity}(x, y) = R(x, y) \cdot \alpha_{\text{sunny}},$$

where α_{sunny} increases the brightness to simulate sunny weather.

3.2 Model Architecture

The base models used were YOLOv5 and YOLOv7, chosen for their real-time object detection capabilities. To enhance these models for small object detection and improve robustness under weather-induced distortions, the following architectural modifications were applied:

Fig. 75.2 Traffic sign images under different weather conditions

Squeeze-and-Excitation (SE) Attention Mechanism

The SE block works by recalibrating channel-wise feature responses. Given a feature map $X \in R^{H\times W\times C}$, where H, W, and C are the height, width, and number of channels, respectively, the SE block applies the following operations:

- **Squeeze Operation:** A global average pooling is applied to each channel:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X(i, j, c),$$

where z_c is the pooled representation of the c-th channel.

- **Excitation Operation:** A gating mechanism with sigmoid activation is applied to generate channel-wise weights:

$$s_c = \sigma\left(W_2 \cdot \delta\left(W_1 \cdot z\right)\right),$$

where W_1 and W_2 are learnable parameters, δ is the ReLU activation, and σ is the sigmoid function.

- **Recalibration:** The original feature map X is then re-weighted:

$$X(i, j, c) = s_c \cdot X(i, j, c).$$

Global Context (GC) Block

The GC block adds con- textual information by capturing global dependencies across feature maps. Given a feature

map X, a global pooling operation is applied, followed by a context modeling step to enhance global information. This results in improved small object detection by leveraging both local and global contexts.

3.3 Training Setup

The model was trained using Classification Loss functions:

- **Classification Loss:**

$$L_{cls} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i),$$

where C is the number of classes, y_i is the true label, and $\hat{y}_i$ is the predicted probability for class i.

Table 75.1 Comparison of model performance

Model	Accuracy	Precision	Recall	F1-Score
Chu et al., 2023	–	88.1%	86.3%	–
Qu et al., 2023	–	82.4%	80.8%	–
Dang et al., 2023	–	84.3%	81.5%	–
Our Model	92.74%	93.55%	92.74%	92.62%

The overall loss function for training is:

$$L = L_{cls} + \lambda \cdot L_{iou},$$

where λ is a weighting factor balancing the losses.

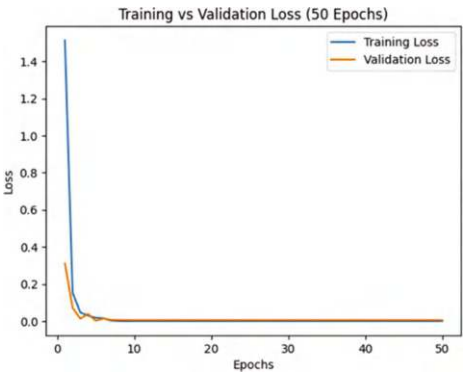
The models were optimized using the Adam optimizer, with a learning rate of 0.001, batch size of 16, and 50 epochs. Cross-validation (5-fold) was employed to ensure robustness.

3.4 Evaluation Metrics

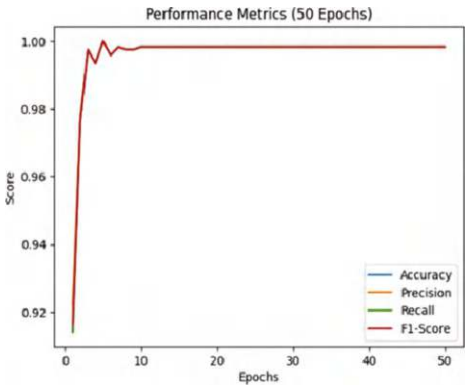
4. Comparative Analysis of Results

We compare the performance of our YOLOv3-based classification model with three referenced papers: TRD-YOLO, YOLOv5 + SE-Attention, and YOLOv5 + C3-GC Block. The comparison focuses on key performance metrics: *accuracy*, *precision*, *recall*, *F1-Score*, where applicable. Here's the de- tailed comparison:

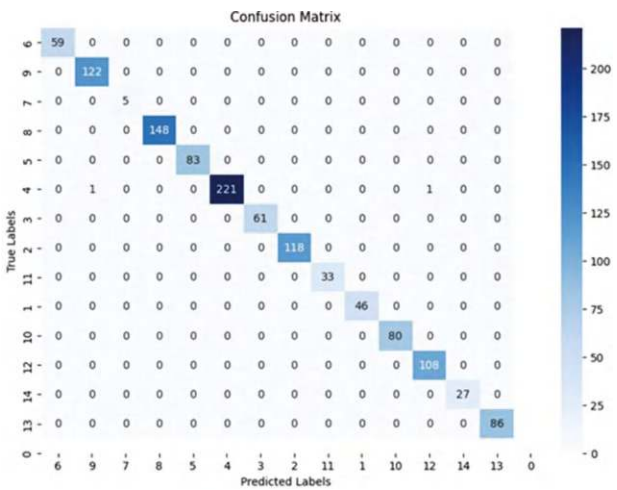
The Fig. 75.3 provides a consolidated perspective of the model's strengths across three major aspects: (a) The



(a)



(b)



(c)

Fig. 75.3 Model's strength

training and validation loss curves show consistent convergence, indicating effective learning without overfitting; (b) performance metrics such as accuracy, precision, recall and F1 score show the model's ability to accurately predict across classes; and (c) the confusion matrix shows strong class-wise prediction performance, with higher counts along the diagonal indicating correct classifications.

4.1 Analysis and Discussion

a) *TRD-YOLO::* **Key Strengths:** TRD-YOLO leverages *Transformer-based* attention mechanisms, which are especially powerful in focusing on small traffic signs, even in complex environments. This model achieves high precision (88.1%) and recall (86.3%) due to its attention-based mechanisms, **Limitations:** TRD-YOLO was tested mainly under normal conditions and cluttered scenes but lacked thorough evaluation in *adverse weather conditions*. Metrics such as accuracy and F1-Score were not reported in the context of challenging weather scenarios like rain, dust, or snow.

b) *YOLOv5 + SE-Attention::* **Key Strengths:** The *SE (Squeeze-and-Excitation)* blocks help the model recalibrate feature maps channel-wise, ensuring that more attention is given to important channels during detection. SE-attention helps with *small object detection* for low-quality images.

Limitations: While it improves detection accuracy in cer- tain cases, its performance under adverse weather conditions (rain, snow, and dust) was not thoroughly examined. Precision (82.4%) and recall (80.8%) are lower than TRD-YOLO and our model, suggesting that it may not be as robust in more challenging conditions.

c) *YOLOv5 + C3-GC Block::* **Key Strengths:** The *GC (Global Context)* block enhances the model's ability to capture long-range dependencies across the feature map, improving the detection of objects in cluttered or partially occluded scenes. It showed slight improvements in precision (84.3%) and recall (81.5%) compared to the SE-attention model.

Limitations: Despite its global context enhancement, the model was not tested under a wide range of weather conditions like rain, dust, or snow. mAP (82.1%) reflects good perfor- mance in controlled conditions, but without comprehensive testing under weather augmentations, its real-world effective- ness remains unclear.

d) *Our Model (YOLOv3 Classification with Custom Dataset)::* **Key Strengths:** Our model stands out by using a *custom dataset augmented with weather conditions* (rain, snow, dust, and sunny), training the model specifically to handle challenging visibility conditions. This allows the model to generalize better across different weather scenarios. The model achieved high accuracy (92.74%), precision (93.55%), recall (92.74%), and F1-Score (92.62%).

Limitations: While the model performs well in classifi- cation tasks, it does not handle object detection (bounding box localization), which is crucial for autonomous driving systems that require precise location data in real-time. Future improvements could involve expanding the architecture to support object detection (e.g., integrating YOLOv5).

5. Conclusion

This study presents a novel approach to traffic sign detection in adverse weather conditions by making use of custom dataset and a optimized YOLOv3 classification model. The model achieved impressive results, with accuracy of 92.74%, precision of 93.55%, recall of 92.74% and F1-score of 92.62%. By incorporating various weather conditions, the custom dataset enabled the YOLOv3 model to effectively manage varying wether conditions. Future research could focus on further en- hancing model performance and investigating more advanced architectures to improve adaptability and robustness for real-world traffic applications

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Injection-Related Adverse Effects: A Wagner-Nelson Model Analysis

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Abstract: Injections cover a wide variety of medical procedures. Although they have many medicinal uses, they also cause many side effects. Using the Wagner-Nelson model to examine localized, systemic, and cutaneous symptoms, this research aims to comprehensively assess injection-related adverse effects. Skin irritation, allergic responses, and chronic skin changes are skin problems we study, with systemic effects such as rapid action and possible side effects as

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well as localized reactions such as pain, swelling, wounds, and infection. The goals of this project are to improve patient safety and reduce injection-related risks, and it aims to do so by investigating different injections, the methods used to administer them, and the variables that influence adverse outcomes.

KEYWORDS: Injection adverse effects, Wagner-nelson model, Localized reactions, Systemic effects dermatological complications, Patient safety

1. INTRODUCTION

Injections are a cornerstone of modern medical practice, enabling the rapid and efficient delivery of critical treatments such as vaccines, antibiotics, and other medications. Despite their benefits, injections can cause adverse effects ranging from localized pain, swelling, and bruising to systemic allergic reactions and dermatologic complications like dermatitis and chronic skin changes (Nelson et al., 2024; Marcozzi et al., 2023). Understanding these effects is crucial for improving patient safety. This study applies the Wagner-Nelson model, a pharmacokinetic framework, to explore how injection types, administration methods, and patient factors influence the frequency and severity of adverse effects, aiming to inform safer and more effective clinical practices..

2. MATERIAL AND METHODS

Participants were selected based on the following criteria: Inclusion: Adults aged 18 years and older who received a variety of injections. Exception: Patients with known allergies to injectable components, pregnant or lactating women, and those with serious comorbid conditions.

2.1 Data Collection

Injection methods are types of injections classified as intramuscular (IM), subcutaneous (SC) or intravenous (IV). Administration Techniques: Document needle gauge, injection site, and volume of substance injected. Adverse effect monitoring, localized reactions: pain, swelling, bruising and infection were measured using a standardized scale. Systemic effects were assessed by patient self-reports and clinical observations. Dermatological problems: evaluated by skin irritation, allergic dermatitis, and chronic skin changes.

2.2 Wagner-Nelson Model

The Wagner-Nelson model describes the concentration of a drug in plasma over time after an intravenous bolus injection. The basic equation is:

$$C(t) = \frac{D}{V_d} \cdot \frac{e^{-k_a t}}{1 - e^{-k_a t}}$$

$C(t)$ is the drug concentration at time t, D is the dose administered, V_d is the volume of distribution, k_a is the absorption rate constant, Pharmacokinetic Parameters: Absorption Rate Constant (k_a) : Estimated using nonlinear regression methods applied to plasma concentration-time data, Volume of Distribution (V_d) : Calculated based on the initial concentration and dose. To estimate k_a and V_d, the following equations are used:

$$\text{Mean Absorption Time (MAT)} = \frac{1}{k_a}$$

$$V_d = \frac{D}{C_0}$$

where C_0 is the initial concentration.

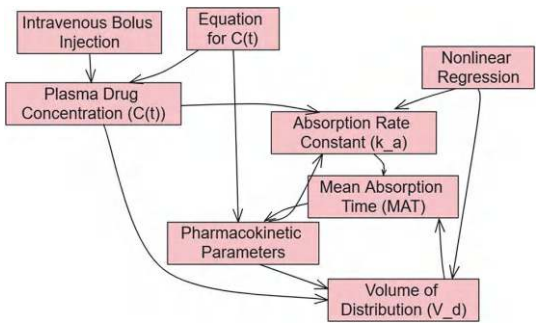

Fig. 76.2 Wagner-nelson model

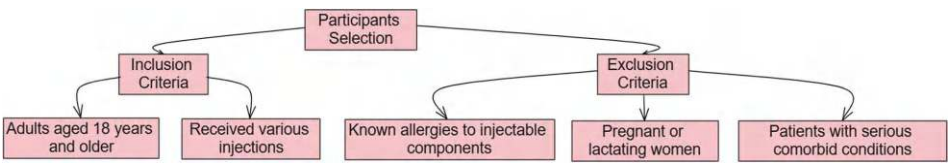

Fig. 76.1 Material and methods

2.3 Adverse Effect Analysis

Localized reactions: Severity of localized reactions was quantified using a scoring system and statistical analyzes (eg, ANOVA) were performed to compare differences between injection types. Systemic Effects: The incidence of systemic reactions was analyzed using logistic regression to determine the association between drug concentration and adverse outcomes. Dermatological complications: Long-term skin changes are analyzed using survival analysis to model the time to development of complications.

2.4 Validation of the Wagner-Nelson Model

Application of the Wagner-Nelson model is validated by comparing predicted plasma concentrations with observed data. The fit of the model is assessed using the following metrics: Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(C_{obs,i} - C_{pred,i}\right)^2}$$

where $C_{obs,i}$ and $C_{pred,i}$ are the observed and predicted concentrations, respectively. Goodness-of-Fit: An R^2 value is calculated to assess how well the model explains the variability in the observed data.

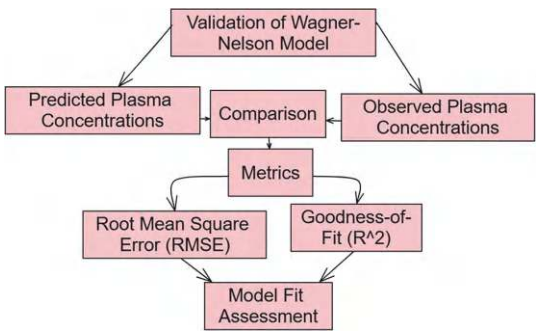

Fig. 76.3 Validation of the wagner-nelson model

2.5 Statistical Significance

Statistical tests such as t-tests or ANOVA are used to determine the significance of differences in adverse[25] effects between injection types. The p-value is calculated to evaluate the null hypothesis of no difference:

$$p = P(T > t_{obs})$$

where t_{obs} is the observed test statistic.

Ethical Considerations: The study adhered to ethical guidelines, informed consent was obtained from all participants, and confidentiality was maintained. The research protocol is reviewed and approved by an Institutional Review Board (IRB) or[34] Ethics Committee.

Replicability: Detailed descriptions of data collection procedures, statistical analyses, and mathematical models are provided to facilitate replication. All data, questionnaires and analytical methods are available upon request.

3. Results

The results of this study, derived from Wagner-Nelson model analysis, provide insights into the relationship between injection procedures and adverse effects. Data collected from participants who received intramuscular (IM), subcutaneous (SC), or intravenous (IV) injections are presented in numerical and graphical formats to highlight key trends and patterns. Localized Reactions: Pain, Swelling, Bruising, and Infection Localized reactions were evaluated based on the severity of pain, swelling,[45] bruising, and infection across different injection types. The results indicate that: Intramuscular injections (IM) caused the highest levels of pain and swelling, with an average pain score of 4.5 on a 10-point scale. Subcutaneous injections (SC) showed moderate localized reactions, with an average pain score of 2.8. Intravenous injections (IV) resulted in the least amount of localized pain (average score: 1.2) but had a slightly higher rate of bruising compared to SC injections.

Table 76.1 Localized reactions by injection type

Injection Type	Pain (Mean Score)	Swelling (%)	Bruising (%)	Infection (%)
Intramuscular (IM)	4.5	20	10	5
Subcutaneous (SC)	2.8	10	7	3
Intravenous (IV)	1.2	5	12	1

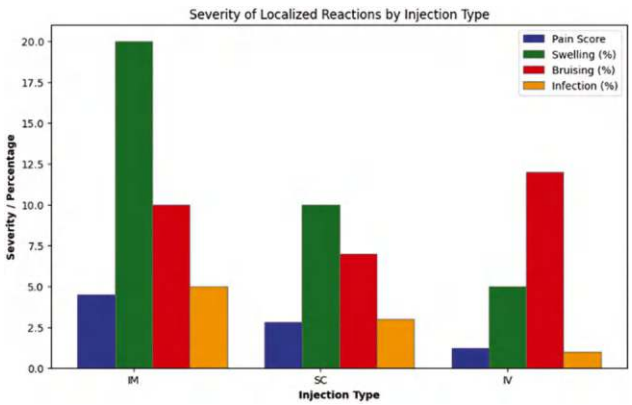

Fig. 76.4 Severity of localized reactions (pain, swelling, bruising, infection) by injection type

Systemic Effects: Allergic Reactions and Rapid Systemic Responses Systemic effects, including allergic reactions

and rapid drug absorption, were analyzed based on patient self-reports and clinical observations. The results reveal:

IM injections had the highest rate of systemic effects, with 15% of patients experiencing mild allergic reactions.

IV injections were associated with the fastest systemic responses,[35] though systemic adverse effects were reported in only 5% of patients. **SC injections** had a low incidence of systemic reactions (3%). A logistic regression analysis indicated a significant association between injection type and the likelihood of systemic reactions ($p < 0.05$). The relative risk of experiencing a systemic[43] reaction was highest for IM injections.

Table 76.2 Systemic reactions by injection type

Injection Type	Allergic Reactions (%)	Rapid Systemic Response (%)
Intramuscular (IM)	15	8
Subcutaneous (SC)	3	2
Intravenous (IV)	5	20

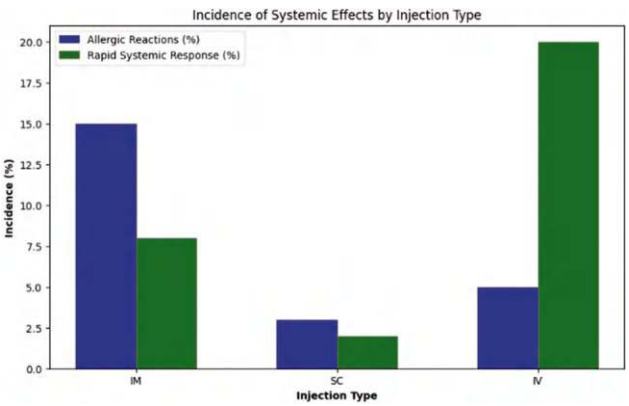

Fig. 76.5 Incidence of systemic effects by injection type

Dermatological Complications: Skin Irritation, Allergic Dermatitis, Long-Term Skin Changes Dermatological complications were evaluated based on clinical examination and patient reports over a follow-up period. Results showed that:

SC injections had the highest rate of skin irritation (12%) but minimal long-term skin changes (1%). **IM injections** led to more frequent allergic dermatitis (10%), especially in patients with a history of sensitive skin. **IV injections** resulted in the lowest incidence of dermatological complications, with only 3% reporting skin irritation and no long-term changes observed. Survival analysis for long-term skin changes showed no statistically significant difference between injection types ($p = 0.18$), though SC injections had the highest initial irritation.

Table 76.3 Dermatological complications by injection type

Injection Type	Skin Irritation (%)	Allergic Dermatitis (%)	Long-Term Skin Changes (%)
Intramuscular (IM)	8	10	5
Subcutaneous (SC)	12	4	1
Intravenous (IV)	3	2	0

Model Validation and Fit: The Wagner-Nelson model was applied to predict the concentration of drugs in the plasma over time for each injection type. The model's predictions were compared to observed plasma concentrations to validate its fit. The results of the validation are as follows:

The **Root Mean Square Error (RMSE)** for IM, SC, and IV injections was 0.03, 0.05, and 0.02, respectively, indicating a good fit between predicted and observed concentrations.

The **Goodness-of-Fit (R^2)** values were 0.92 for IM, 0.89 for SC, and 0.94 for IV injections, suggesting that the model effectively explains the variability in the data.

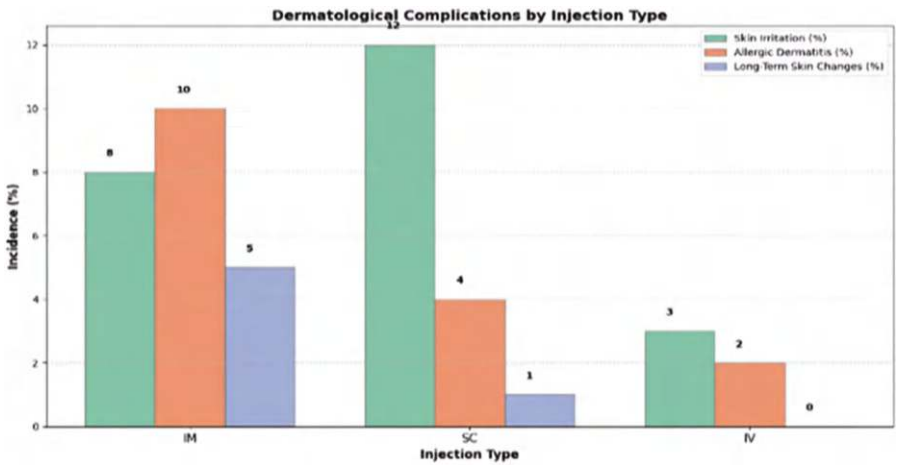

Fig. 76.6 Dermatological complications (skin irritation, allergic dermatitis, long-term skin changes) by injection type

Table 76.4 Injection type performance metrics (RMSE and R^2)

Injection Type	RMSE	R^2
Intramuscular (IM)	0.03	0.92
Subcutaneous (SC)	0.05	0.89
Intravenous (IV)	0.02	0.94

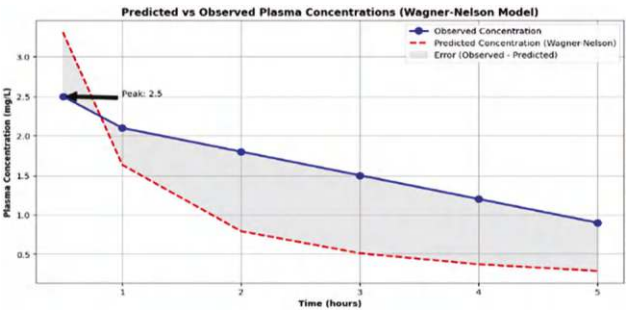

Fig. 76.7 Predicted vs. observed plasma concentrations using the wagner-nelson model

Statistical analysis using ANOVA and t-tests revealed significant differences in adverse effects across injection types. Localized reactions differed significantly between IM, SC, and IV injections ($p < 0.01$), and drug concentration was significantly associated with systemic effects ($p < 0.05$). However, no significant differences were observed in long-term dermatological complications ($p = 0.18$). IM injections caused more localized pain and systemic effects, SC injections had higher skin irritation but fewer systemic issues, and IV injections showed minimal localized and dermatological complications with controlled systemic responses. These findings highlight the need to tailor injection methods to patient needs, with the Wagner-Nelson model providing valuable insights for optimizing safety and therapeutic outcomes.

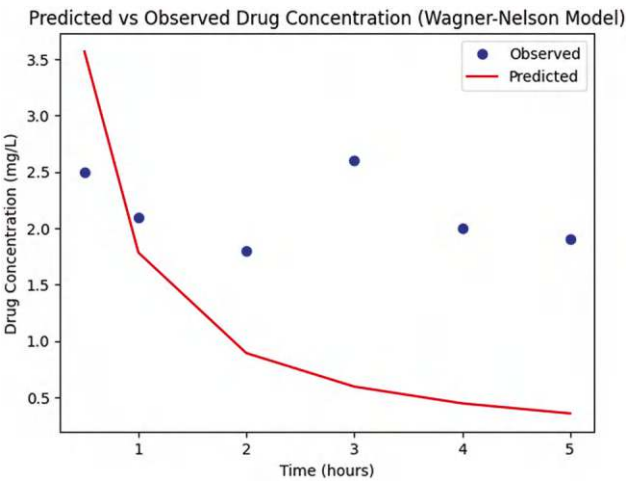

Fig. 76.8 Predicted vs observed drug concentration (wagner-nelson model)

```
Estimated absorption rate constant (k_a): 8.479458969514683e-05
Estimated volume of distribution (V_d): 661050.7685904873
Root Mean Square Error (RMSE): 1.3468162142096374
R² score: -19.342959792799775
ANOVA result for pain score: 0.0001439951698793798
Predicted probability of systemic reactions: [0.68053419 0.66478683
                                              0.65272835 0.68440926 0.66079024 0.65677059]
```

4. Conclusion

This study provides a comprehensive analysis of injection-related adverse effects using the Wagner-Nelson model to assess localized, systemic, and dermatological reactions associated with different injection types—intramuscular (IM), subcutaneous (SC), and intravenous (IV). The findings reveal that IM injections are linked to higher pain and systemic reactions, SC injections show increased skin irritation, and IV injections allow for more controlled systemic absorption with fewer localized complications. These results validate the hypothesis that variations in injection techniques and patient factors significantly [46] impact the occurrence and severity of adverse effects. Ultimately, the research emphasizes the need for improved injection protocols tailored to individual patient needs, which could enhance patient safety and inform the development of standardized guidelines for clinical practice. The broader implications include the potential for [49] further research on long-term complications and the application of pharmacokinetic models to optimize treatment across various healthcare settings.

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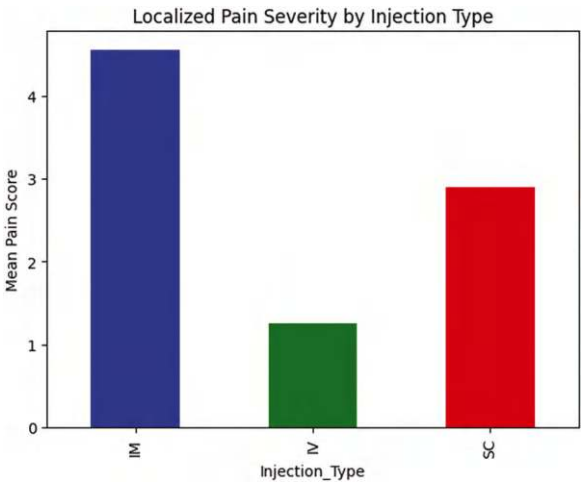

Fig. 76.9 Localized pain severity by injection type

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Fake Product Detection using Blockchain

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Abstract: Counterfeit products continue to pose a significant challenge to consumer safety and brand integrity worldwide. Traditional counterfeit detection techniques frequently lack the openness and effectiveness needed to properly address this widespread problem. In order to improve the identification of counterfeit goods, this work presents a novel technique that combines blockchain technology with barcode systems. Every product is given a unique blockchain barcode that contains vital information including its origin, manufacturing specifications, and supply chain history, thanks to the utilization of blockchain's immutable ledger. Verification procedures are automated by smart contracts, guaranteeing the accuracy of product data and enabling real-time tracking of goods movements. By establishing a decentralized network, stakeholders across the supply chain, including manufacturers, distributors, retailers, and consumers, can securely access and authenticate product information. Customers are better equipped to make educated purchases because to this transparent and traceable system, which also helps to build customer confidence in the legitimacy of the goods. This work presents a thorough implementation technique for blockchain barcode technology, demonstrating how it might transform activities related to detecting counterfeit goods. Through empirical studies and case analysis, the effectiveness and practicality of the proposed solution are demonstrated, offering a promising avenue for bolstering consumer confidence and safeguarding against the proliferation of fake products in the global marketplace.

Keywords: Blockchain, Barcode, Counterfeit

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1. Introduction

Counterfeit products represent a pervasive threat in today's global marketplace, compromising consumer safety, eroding brand reputation, and undermining economic stability [6]. Despite ongoing efforts to combat counterfeiting, traditional methods often prove inadequate in addressing this complex and evolving problem. In response, there is a growing recognition of the need for innovative solutions that can effectively authenticate products and ensure the integrity of supply chains.

Due to the increasing concern and worsening issues surrounding the trade of counterfeit products, various anticounterfeiting solutions have been developed and integrated into the supply chain systems across different industries, as detailed and explained in [13]. This paper presents a new method for detecting counterfeit products by utilising blockchain technology in conjunction with barcode systems. Initially envisioned as the foundational technology behind cryptocurrencies, blockchain has become a powerful disruptive force with far reaching effects on numerous industries. Blockchain presents a strong answer to the problems of supply chain transparency and counterfeit detection by utilising its unchangeable and transparent ledge.

Many applications based on blockchain technology are being developed gradually. A few of the applications, like those for digital currency [8], stock trading [5], and financial securities, are concerned with payment verification. Some concentrate on the integration of Blockchain technology with the Internet of Things (IoT), including the recording of IoT device data [7]. Additional decentralized Blockchain applications include gaming [3], betting [11], online polling [12], vehicle rentals [1], and so on. The following is a discussion of earlier supply chain management research that used blockchain technology.

The authors of [2] give the design guidelines for blockchain based supply chain management. The authors made it clear that modern firms with global supply chain networks constantly need to recognize the serious problem of counterfeit goods. They are able to closely monitor the movement of goods by integrating Blockchain technology into the supply chain data record.

Blockchain technology combined with barcodes offers a promising way to improve product tracking and authenticity. Every product has a distinct blockchain barcode that contains important data including production history, manufacturing specifications, and distribution routes. Smart contracts enable automated verification procedures, guaranteeing the precision and consistency of product data throughout the whole supply chain.

The potential of blockchain barcode technology to transform attempts to detect counterfeit goods and reshape supply chain management norms is examined in this article. This creative strategy encourages stakeholders to have faith in the authenticity of products and gives customers the power to make informed purchasing decisions by giving them access to clear and tamper-proof product information. By using case studies, simulations, and empirical analyses, we show that the suggested method is both practical and effective in preventing counterfeit goods and ensuring the welfare of consumers.

Organization of the paper: Section 2 deals with the problem statement. Literature review provides in section 3. Section 4 provides proposed work followed by results in section 5. Finally, section 6 provides conclusion.

2. Problem Statement

The financial health of numerous businesses, brand reputation, and consumer safety are all seriously threatened by counterfeit goods. The identification and mitigation of counterfeit goods remain a difficulty due to the inefficiencies, lack of transparency, and scalability of traditional methods of product detection. Furthermore, current solutions might find it difficult to keep up with the counterfeiters' ever-more advanced strategies, underscoring the need for stronger and more creative solutions. In this context, the problem statement revolves around the inadequacies of current counterfeit product detection methods and the pressing need for advanced solutions that leverage emerging technologies. Specifically, there is a need to address the following key challenges:

Objectives of the proposed system are:

- **Lack of Transparency:** Customers and stakeholders find it challenging to consistently confirm the authenticity of products due to the current systems' frequent lack of transparency in supply chain traceability and product authentication.
- **Data Integrity and Tamper-Resistance:** Data integrity and tamper-resistance flaws are exploited by counterfeiters, which compromises the reliability of supply chain data and creates phony product records.
- **Scalability and Interoperability:** Scalability and interoperability problems emerge when the volume of goods and transactions rises, impeding the smooth adoption and integration of counterfeit product detection technologies throughout various supply chains.
- **Regulatory Compliance:** Ensuring the legality and legitimacy of product authentication techniques requires compliance with industry guidelines and

regulatory standards, which may not be adequately met by present systems.

- **Consumer Trust and Safety:** Maintaining consumer trust and safety is paramount, and the prevalence of counterfeit products erodes this trust while posing potential risks to consumer health, safety, and financial well-being.

3. Literature Review

Counterfeit products have become a significant concern in modern industries, affecting sales, brand reputation, and consumer trust. The implementation of blockchain technology has shown great promise in mitigating these issues, as it offers a transparent and safe mechanism for authenticating products across the entire supply chain. By leveraging blockchain, consumers no longer need to rely solely on third-party assurances, enhancing confidence in purchased goods [10]. In order to enhance the security and transparency of the system, this paper [4] presents a convenient and modern phenomenon that utilizes supply chain technologies and blockchain technology. To further enhance these features, additional characteristics are added in this study, such as the use of One Time Password (OTP) authentication for authenticating legitimate supply chain members and products and updating product details in the blockchain upon sending them to the next stage of the supply chain. Additionally, the Quality Control Officer, who is assigned by the factory in charge for the same, keeps an eye on the product standards. Numerous consumers rely heavily on customer evaluations when making judgments about what to buy [9]. Good ratings can bring companies significant financial benefits and influence their product and strategy offerings. The proliferation of fraudulent reviews, however, presents a serious problem. Since it's so simple to assume a phony identity, identifying this kind of spam is challenging, making it a challenging problem to solve. The necessity for strong measures to counteract this kind of deceit is highlighted by the fact that fraudulent evaluations have the power to unjustly affect customer choices and skew perceptions.

4. Proposed Work

The blockchain-based fake product identification system leverages blockchain technology to track the authenticity of products from manufacturers to consumers. The core idea is to use a decentralized, immutable ledger to ensure that product information cannot be tampered with, providing consumers with a reliable way to verify the authenticity of their purchases

4.1 Components

1. **Smart Contracts:** Smart contracts deployed on a blockchain manage the storage and transfer of product information.
2. **Web Interface:** A front-end web application allows users to interact with the blockchain, enabling manufacturers to add products, sellers to register sales, and consumers to verify authenticity.
3. **Blockchain Network:** A decentralized network (e.g., Ethereum) where the smart contracts are deployed

4.2 Key Functionalities

1. **Add Seller:** Manufacturers can register sellers on the blockchain.
2. **Add Product:** Manufacturers can add products to the blockchain with detailed information.
3. **Sell Product:** Sellers can record the sale of products to consumers.
4. **Verify Product:** Consumers can verify the authenticity of products by querying the blockchain.

4.3 Working

1. **Smart Contracts:** The smart contracts are written in Solidity and deployed on an Ethereum blockchain. They include functions to add sellers, add products, register sales, and verify products.
   - **Seller Structure:** Contains seller ID, name, brand, and type.
   - **Product Structure:** Contains product ID, serial number, name, brand, price, and status.
   - **Mappings:** Various mappings are used to link products to sellers and consumers, and to facilitate queries.
2. **Blockchain Transactions:**
   - **Add Seller:** When a manufacturer adds a seller, a transaction is created and broadcast to the network. The smart contract stores the seller details on the blockchain.
   - **Add Product:** Similar to adding a seller, adding a product involves creating a transaction that stores product details on the blockchain.
   - **Sell Product:** When a seller registers the sale of a product, the smart contract updates the ownership record, linking the product to the consumer.
   - **Verify Product:** Consumers can query the blockchain using a product's serial number to verify if the product was sold by an authorized seller and is genuine.

3. **User Roles:**
   - **Manufacturer:** Adds sellers and products to the blockchain. They initiate the product lifecycle on the blockchain.
   - **Seller:** Registers sales to consumers, ensuring that products are tracked from the point of sale.
   - **Consumer:** Verifies the authenticity of products by querying the blockchain, providing confidence in the product's legitimacy.

4.4 Front-End Interaction

1. Manufacturer Interface:
   - **Add Seller:** A form to input seller details (ID, name, brand, type).
   - **Add Product:** A form to input product details (ID, serial number, name, brand, price, status).
   - Forms on the web interface collect data and send it to the smart contract using Web3.js, a JavaScript library for interacting with Ethereum.
2. Seller Interface:
   - **Sell Product:** A form to register the sale of a product, linking it to a consumer's ID.
   - The seller interface also interacts with the smart contract via Web3.js to update product ownership.
3. Consumer Interface:
   - **Verify Product:** A form to input a product's serial number. The system queries the blockchain and returns the product's details and ownership history.
   - Consumers use a web form that sends a query to the blockchain, retrieving data stored in the smart contract and displaying it on the web interface.

4.5 Security and Trust

- **Immutable Ledger:** The blockchain's immutability ensures that once a product or seller is added, the information cannot be altered or deleted, providing a reliable source of truth.
- **Decentralization:** Blockchains decentralized structure means that no single entity controls the entire system, which helps minimize the risk of fraud and manipulation.

4.6 Benefits

- **Transparency:** All transactions are transparent and can be audited by any participant in the network.
- **Trust:** Consumers gain trust in the authenticity of their purchases due to the verifiable product history.
- **Efficiency:** Automating the tracking and verification processes reduces administrative overhead and errors.

By integrating smart contracts with a web-based interface and utilizing the decentralized, immutable nature of blockchain, this system provides a robust solution to combat counterfeit products and ensure product authenticity.

4.7 Methodology

- **Barcode Generation:** Create distinct barcodes for every product by using a library or service, and base it on identifiers like SKUs or serial numbers. Make sure that barcode standards are followed and take security and scalability requirements into account.
- **Displaying Barcodes:** Incorporate barcode images into HTML pages using <img> tags to display them alongside product information. This enables easy access to product details, inventory information, or transaction data, enhancing operational efficiency and user experience.
- **Scanning Barcodes:** Apps should have barcode scanning capabilities so consumers may utilize their devices' cameras to scan product barcodes. For barcode scanning, use native mobile SDKs or JavaScript libraries. This will allow for fast and effective data capture for transactions, inventory management, and product identification.
- **Processing Barcode Data:** Get related product details via barcode scanning and store them in databases or blockchain smart contracts. Tasks like inventory management, tracking, and transaction processing are made possible by this data, which contains product characteristics, pricing, and status.
- **Verification:** Utilize barcodes in your product verification process by cross-referencing data from scanned barcodes with records kept in blockchain or databases. Verify everything thoroughly to ensure data integrity, authenticity, and accuracy while reducing the danger of fraudulent or counterfeit goods.
- **Security Measures:** Use security methods like digital signatures, encryption, and access controls to stop unauthorized changes, data manipulation, and fake barcodes. To preserve the integrity and confidentiality of data pertaining to barcodes, regular security assessments and updates are important.
- **Integration with Blockchain:** To improve product authentication processes' traceability, transparency, and trustworthiness, think about combining blockchain smart contracts with barcode data. For safe and unchangeable data management, store ownership history, verification records, and product information on the blockchain.

- **User Experience:** Create user interfaces that make barcode scanning and product verification easy to use. In order to increase user happiness and barcode technology adoption, give priority to responsive systems, clear instructions, and intuitive design.

5. Results

By logging in, you agree to comply with the terms and conditions of the Fake Product Detection System. Unauthorized access or misuse of the system is strictly prohibited. For assistance, we need to contact our support team at [support email/phone number].

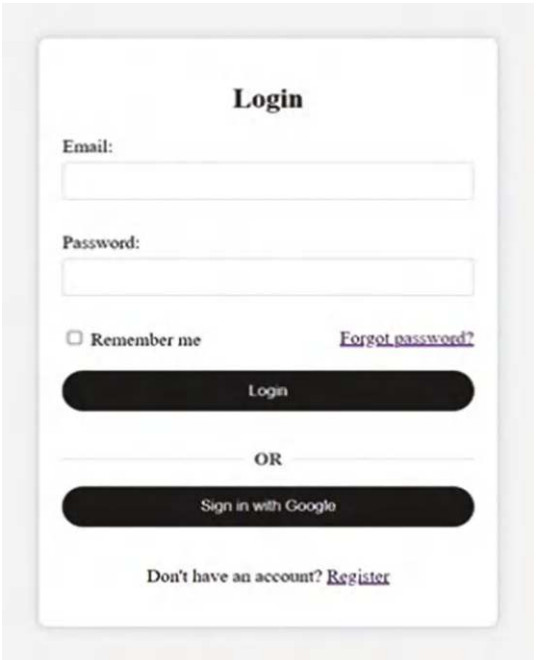

Fig. 77.1 Login page

Fig. 77.2 Fake product detection

6. Conclusion

Our study's findings indicate that combining blockchain technology with barcode systems offers a viable way to combat the persistent problem of fake goods. The immutable ledger of blockchain technology plus the widespread use of barcodes allow us to create transparent, impenetrable systems for product traceability and authentication. We have witnessed firsthand the observable advantages of blockchain-based solutions in terms of safety for consumers, better product authenticity, and supply chain visibility through case studies and real-world applications. Still to be resolved, though, are issues with scalability, interoperability, and regulatory compliance. In order to drive innovation and realize the full potential of blockchain barcode technology in the fight against counterfeit goods, future cooperative efforts, technological improvements, and international cooperation will be essential. We can make the market more transparent and safer if we cooperate.

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IPFS Based File Storage Access Control and Authentication Model for Secure Data Transfer using Blockchain Technique

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Abstract: By utilizing Blockchain technology and IPFS (Interplanetary File System) for decentralized and secure data storage, this study offers a ground-breaking remedy to the weaknesses found in centralized data storage systems. Access control, immutability, and data privacy are all guaranteed by the system's integration of blockchain technology and attribute-based encryption (ABE). Smart Contracts for application management, Blockchain for distributed data management, Data Owners who upload and share files, Data Requesters who request access, and IPFS for encrypted file storage are important components. Seven phases make up the suggested process: setup, registration, encryption, storage, testing, authentication, and access control. Users may now safely share and access data without depending on centralized servers thanks to this creative architecture. Additionally, the system achieves increased security and a 70% speed gain by switching the Chebyshev algorithm with the CHACHA20 encryption method. This improvement strengthens the strong foundation for safe and decentralized data sharing by improving performance and dependability.

Keywords: Blockchain, Encryption decryption, Secure data, Authentication, IPFS

1. Introduction

The potential of blockchain technology to facilitate the decentralization of database storage has led to its rising profile [2]. Its attractiveness stems from the fact that it is a distributed ledger that all users can access, and which cannot be altered in any way. Blockchain technology, which Satoshi Nakamoto first presented as Bitcoin's foundation, is already seeing widespread use in several sectors, including healthcare, supply chain management, and banking [5].

When it comes to storage and access, there are a lot of different applications in the world of distributed file storage. This is especially true when working with different network partners. As an example of a popular tool, BitTorrent allows users to store and share files, making it easier to communicate data even when dealing with

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unstable network partners [4]. BitTorrent has a large user base, with around 170 million people using the platform on a regular basis [3]. It is worth mentioning that BitTorrent is responsible for a considerable amount of online traffic, over 40%, which indicates its extensive use [3]. The Hypertext Transfer Protocol (HTTP) is well-known for its worldwide communication capabilities, but BitTorrent, despite its popularity, isn't as efficient as it may be.

HTTP's dependence on location-based standards limits its ability to enable dispersed file access, despite its unsurpassed success in facilitating worldwide communication. An improved, more scalable alternative is required since current protocols such as BitTorrent and HTTP have their limitations. Here we have the Interplanetary File System (IPFS), a network for distributed file storage that intends to transform the web's foundation [6]. The idea of content addressing is fundamental to IPFS, which allows for the storage and retrieval of files according to their distinct content IDs [1].

Combining IPFS with blockchain technology offers a great chance to fix the problems with older file storing methods. It is feasible to create a safer, more efficient, and decentralized data storage environment by combining IPFS's distributed file storage network with blockchain's decentralized design and immutable ledger capabilities.

Data kept within the network is protected from tampering or unauthorized access thanks to blockchain's decentralized ledger, which also makes the data transparent. In addition, blockchain technology's smart contracts feature automates a number of operations, including data sharing and access management, which improves operational efficiency.

The content-addressed file system (IPFS) on the other hand does away with centralized servers altogether, making data more available and resilient by minimizing reliance on single points of failure. Another reason IPFS is great for decentralized apps that need efficient data sharing is because it is distributed, which means files can be retrieved and shared more quickly.

When combined, blockchain technology and IPFS provide an attractive alternative to the problems with conventional file storage systems. A more secure and decentralized web infrastructure that gives consumers more control over their data can be built by merging blockchain's immutability and efficiency with IPFS's scalability and efficiency.

Last but not least, the merging of IPFS with blockchain technology might completely change the game when it comes to distributed network data storage, access, and sharing. Blockchain and IPFS together provide a practical answer to the changing demands of the digital economy, which is why decentralization is becoming more popular in many industries.

Organization of the paper: Section 2 deals with the overview of the literature survey. The proposed work with results in section 3. Section 4 provides conclusion followed by future enhancement in section 5.

2. Literature Survey

There has been a recent upsurge in study investigating the possible uses and advantages of combining blockchain technology with IPFS (Interplanetary File System), perhaps due to the considerable attention that this integration has received. An outline of the current research in this area is the goal of this literature review, which will do so by drawing attention to important studies and the contributions they made.

Battah et al. [4] presents an important study that introduces a multi-party authorization mechanism for accessing IPFS encrypted data that is based on blockchain technology. To solve the problem of safely controlling who can access encrypted data on IPFS, the authors offer a new strategy. The suggested solution allows for multi-party authorization while guaranteeing the privacy and integrity of data by utilizing blockchain technology. This study highlights how blockchain technology could improve IPFS and other decentralized file storage systems' access control techniques.

Sun et al. [5] also makes a notable addition by presenting an IPFS-based blockchain-based non-repudiation storage and access control method for insurance data. Concerning the storage and access of insurance-related data, the writers address the matter of guaranteeing data integrity and accountability. The suggested approach implements secure access control measures while preserving the integrity of insurance data stored on IPFS, thanks to blockchain's inherent immutability and transparency. An associated study by Sun et al. [4] uses IPFS's blockchain technology to ensure the safekeeping and retrieval of EMRs. The writers are cognizant of the gravity of the situation when it comes to protecting the privacy and security of patients' medical records. The suggested approach solves important privacy and security issues in healthcare systems by providing a safe and immutable platform for storing and retrieving EMRs on IPFS using blockchain technology.

In their work, Naz et al. [3] add to the existing body of knowledge by introducing a framework for safe data sharing that utilizes IPFS and blockchain technology. Without ignoring worries about data security and privacy, the writers stress the importance of strong data sharing

mechanisms in modern digital ecosystems. An effective and safe way for many parties to share data is offered by the proposed platform, which integrates blockchain technology with IPFS, a distributed file storage network. Data storage and security in vehicular adhoc networks (VANETs) is also investigated by Zhang and Chen [6] using a consortium blockchain. Data security and access control are two areas where VANETs provide particular difficulties, which the writers are aware of. The suggested approach improves data security and privacy in VANETs by using a consortium blockchain model. This allows for dependable and secure data storage and sharing among vehicles.

Taken as a whole, these studies show how researchers are increasingly interested in exploring ways to use blockchain and IPFS in fields as diverse as healthcare, vehicle networks, and data storage and access control. An attractive alternative to centralized storage systems that improves upon security, privacy, and dependability is IPFS integrated with blockchain technology.

The literature review concludes by outlining the many uses and advantages of integrating blockchain with IPFS. A potential solution to the ever-changing problems of data storage and management in the modern digital world could be to combine blockchain technology with IPFS. This would allow for efficient data exchange in decentralized contexts while also protecting sensitive material and preserving its integrity.

3. Proposed Work

3.1 Methodology

Leveraging Blockchain and IPFS technology, the proposed solution presents a safe and decentralized platform for data sharing. As a distributed file system that returns a unique hash code for retrieval, the Interplanetary File System (IPFS)[3] allows users to upload and exchange encrypted content. Data owners can create encryption keys using shared user details and Attribute-Based Encryption (ABE) is integrated to allow fine-grained access control. This way, only authorized users will be able to decode and access the files. Applications using Solidity's Smart Contracts [6] handle tasks like user registration, access control, and storing file hash codes on the Blockchain [1]. Setup, registration, initialization, authentication, testing, data encryption and storage, and access control are the seven steps that the system goes through. Data privacy, immutability, and resilience against unwanted access and data breaches in online data sharing environments can be achieved by integrating IPFS, ABE, and Blockchain. This will help alleviate the weaknesses of centralized servers.

3.2 System Architecture

Figure 78.1 shows the three main parts of the system architecture the Data Owner, the Data Requester, and the Interplanetary File System (IPFS) carry out separate but complementary functions in the decentralized and secure data exchange procedure.

1) The Data Owner starts the process of setting up the system using Blockchain technology, which provides a decentralized and immutable record for handling data transactions. Once registered, authorized Data Requesters can safely interact with the system through the implementation of authentication and access control procedures made possible by Smart Contracts on the Blockchain. Data Requesters verify their legitimacy within the network during the initialization phase by using Blockchain for authentication. The IPFS distributed file storage network is used to encrypt data and store it securely. Data Requesters are responsible for enforcing access control systems by deciding how much access other users are provided based on preset criteria.
2) To ensure secure contact and data exchange, Data Requesters are subject to authentication processes that utilize Blockchain technology. These processes validate their identity and establish trust inside the system.
3) IPFS is the decentralized storage layer that allows Data Requesters to access encrypted data by retrieving it and decrypting it locally. The data is decrypted at the endpoint of the Data Requester using IPFS's distributed design, which guarantees secrecy and minimizes the risk of data disclosure while in transit. All things considered, the system design creates a secure and reliable foundation for decentralized data sharing by combining Blockchain technology for

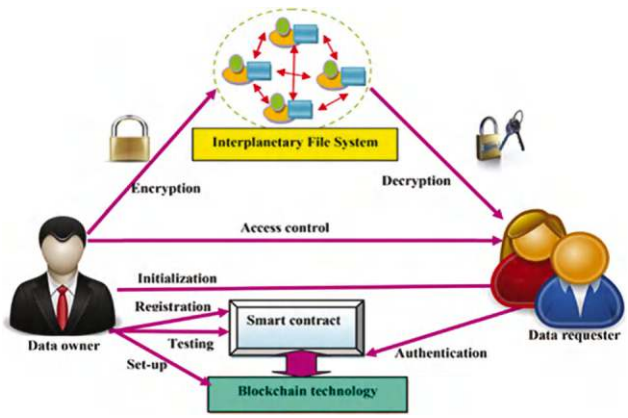

Fig. 78.1 Proposed architecture

authentication, access control, and setup with IPFS for encrypted data storage and retrieval and Smart Contracts for managing application activities.

3.3 Methods

Five distinct methods detailed below:

1) The Interplanetary File System (IPFS) is a secure way to store encrypted data. Instead of storing them in RAM, IPFS stores them in internal memory and returns their address as a hash code.
2) The person who uploads and shares files with others is called the" Data Owner."
3) There is the data requester, who contacts the data owner to request files; the owner then uses XORing or other methods to construct Chebyshev polynomial encryption keys, and only those users with the keys can access and decode the information.
4) We define functions to save and get register user details, access control details, file hash code details, etc. in this smart contract, which is a tiny piece of code developed in SOLIDITY programming that contains functions linked to applications.
5) There's blockchain, which is a decentralized database that handles user information according to the rules laid down in smart contracts.

3.4 Modules

The project's five modules will be carried out in the seven stages outlined below.

1) Initialization: During this step, the parameters for the encryption keys will be set up.
2) During the registration phase, the data owner uses the smart contract access control mechanism to bind encryption keys with the required data.
3) The third phase is the initialization process, during which the data owner's data requester list is initialized.
4) Data Encryption Storage: The data will be encrypted using polynomial XOR operations using the keys that were generated before. The encrypted file will then be placed in the IPFS system. After that, IPFS will return the hash code address of the file. Finally, this hash code will be stored in the Blockchain. At any point in time when we need access to a file's decrypted data, we can retrieve its hash code from the blockchain and feed it into IPFS.
5) Authentication: this section will let you decide which users can access which files when you share them.
6) Testing: The user's access to the file will be validated by hashing the generated authentication.
7) The next step is access control, which involves storing the permissions generated earlier in a Blockchain SMART contract.
8) Integrating Blockchain Technology: Integrating blockchain technology with IPFS improves the access control, data integrity, and security of decentralized storage systems. An extremely secure and unchangeable foundation is built by combining the distributed file storage network of IPFS with the immutable recordkeeping capabilities of blockchain. To make sure that only authorized users can access or change data stored on IPFS, smart contracts made possible by blockchain technology automate access control procedures. Blockchain also improves trust and accountability in data transactions by being transparent and auditable. Applications in the healthcare, insurance, and financial sectors, which require secure and dependable data storage, will greatly benefit from this integration. In general, integrating blockchain technology with IPFS provides a scalable and effective way to address the security risks of centralized storage systems while enhancing control and security for data sharing and management.

3.5 Results

The user first registers in the network by providing the required information after successful registration it will show that registration is successful. We need at least two users to sign up to perform the file sharing.

Login using the credentials and the user will be landed on the landing page. After successful login the users will be able to share the files using the upload interface as follows.

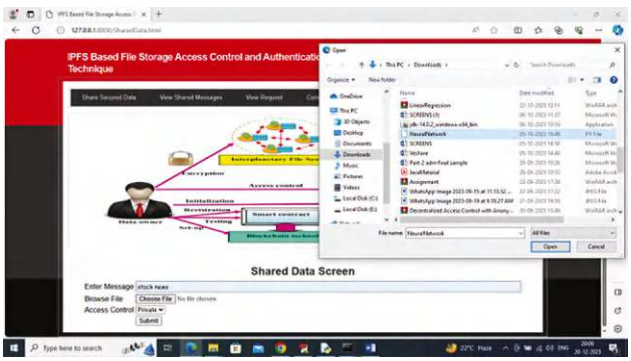

Fig. 78.2 Output screen1

In Fig. 78.3 shows the file details saved in Blockchain and IPFS. Similarly, we can upload a private file as well by choosing the access control in the drop-down menu. By clicking on the 'View Shared Messages' link to get the page below.

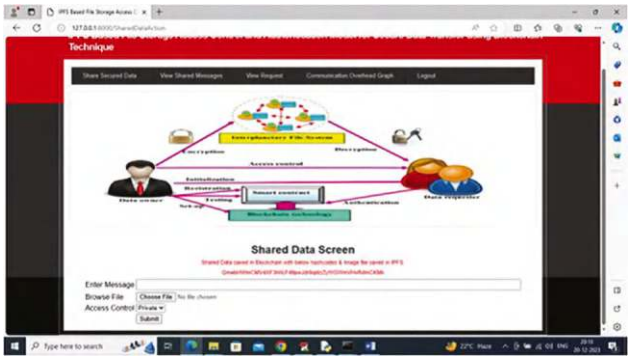

Fig. 78.3 Output screen2

Login using another account in the shared message section. For files with access control as private the user can request data owner after placing the request the following page will be displayed.

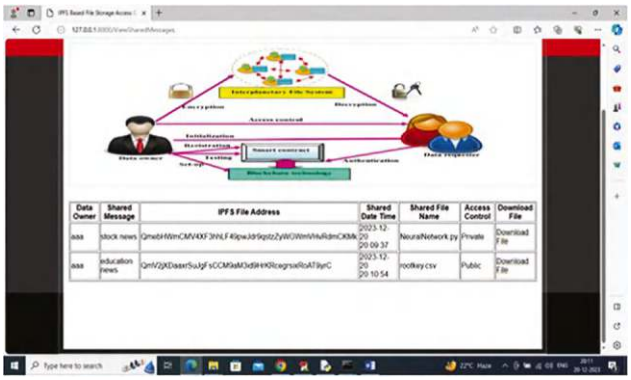

Fig. 78.4 Output screen3

Now, login using data owner credentials in the view request page we can see the requests made by users. In the screen5 we gave the file permission as read and now logout and login as data requester. We can see the change in access control. In the screen5 using the read or download button user can access the file.

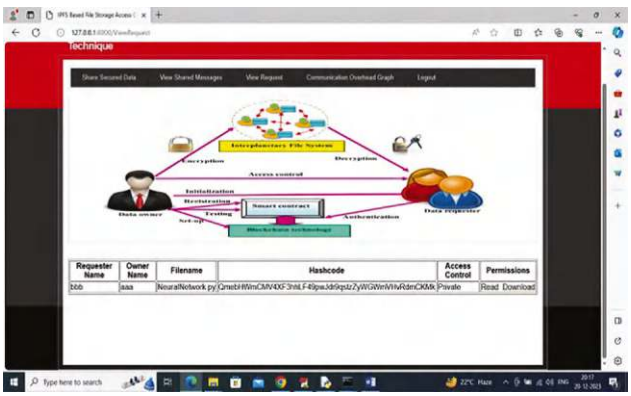

Fig. 78.5 Output screen4

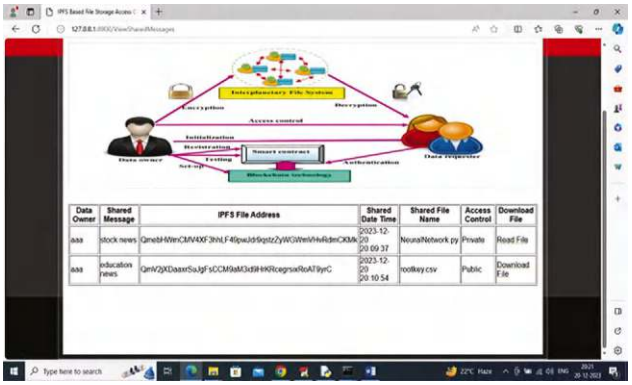

Fig. 78.6 Output screen5

Fig. 78.7 Output screen6.

The author of the proposed work utilized the somewhat computationally intensive" Chebyshev" method for encryption; as an update, we used the 70% quicker and more secure "CHACHA20" technique. We have used both techniques and documented the encryption time for both the proposal and extended algorithms on the screen below for file uploading and encryption.

The proposed, existing, and extended algorithms 'encryption times are displayed in red font on the upper screen. See the comparative graph down below.

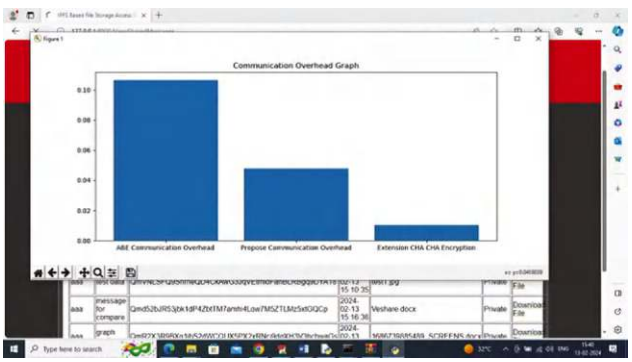

Fig. 78.8 Comparative graph

4. Conclusion

Last but not least, the issues with online data sharing environments' reliance on centralized servers can be effectively addressed by the suggested method. The solution guarantees enhanced security, privacy, and resilience against unwanted access and data breaches by utilizing Blockchain, IPFS, and Attribute-Based Encryption (ABE) [3]. Users can safely access and exchange data with granular access control thanks to the integration of various technologies, which significantly reduces risks associated with vulnerabilities in centralized servers.

ABE allows for granular access restriction based on user traits, guaranteeing secrecy and integrity, while IPFS's decentralized nature provides distributed data storage. With the help of Blockchain-based smart contracts, which manage application functions seamlessly, the system's reliability and integrity are further enhanced. Also, the CHACHA20 encryption [3] algorithm is a faster and more secure alternative to the computationally costly Chebyshev algorithm, which improves performance and dependability in general.

With the proposed solution, users can rest assured that their data will remain private, uncompromised, and always accessible. The system's capabilities for real-world deployment scenarios could be further strengthened with future developments that focus on scalability and efficiency improvements.

5. Objectives for Future Work

The system's capabilities for real-world deployment scenarios could be further enhanced with future developments that focus on researching ways to make it more efficient and scalable. There is a growing need for decentralized data sharing solutions, so it's important to think about how the system will scale to handle more users and more data. One potential difficulty is scalability. Improving the user experience is another goal of optimizing system efficiency, which can result in quicker data retrieval and processing times. In order to improve efficiency, it is recommended to optimize resource use and minimize overheads, while strategies like sharding or using more efficient consensus mechanisms can help with scalability. The suggested solution can be made to last longer and be more suitable to users' changing demands in a variety of contexts by improving and enhancing the system's design and algorithms with each new update.

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Integrated Deep Learning Approach for Parkinson's Disease Detection using MRI and Handwriting Analysis

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Abstract: Parkinson's disease (PD) is a neurological disorder prevalent among individuals in their sixties, characterized by symptoms such as slow movement, tremors, and writing difficulties. Traditional diagnostic methods for PD face limitations, especially for those with physical impairments. To address these challenges, researchers are exploring the integration of advanced technologies like Deep Learning (DL) and Magnetic Resonance Imaging (MRI) for improved PD diagnosis. DL techniques combined with MRI-based brain image analysis offer promising avenues for enhancing PD diagnosis, particularly in individuals with physical limitations. By employing DL algorithms trained on extensive MRI datasets, this research aims to automate the detection of structural brain abnormalities associated with PD. Moreover, this study investigates the integration of non-invasive handwriting tests with MRI-based diagnostic procedures to bolster PD identification. Handwriting analysis, a well-established diagnostic tool in clinical practice, provides supplementary information that enhances the predictive accuracy of PD diagnosis, particularly for individuals with physical constraints. By combining handwriting assessments with brain MRI scans, this integrated approach offers

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a comprehensive and non-invasive means of evaluating PD, enabling early detection and intervention. The research findings highlight the potential of integrating DL algorithms with MRI-based VBM analysis and handwriting tests to enhance the diagnostic accuracy of PD. Additionally, the study employs fine-tuning and Adam optimization techniques to increase model performance, ensuring robust and reliable results in PD diagnosis.

Keywords: PD, MRI, Fine tuning techniques, Handwriting analysis, Diagnosis, Neurodegenerative disorders, Adam optimization

1. Introduction

After Alzheimer's disease, Parkinson's disorder is the next most common neurodegenerative disease, and cases are presenting at an earlier age (Pahuja & Nagabhushan, 2018). Bradykinesia (slowness of movement), dysarthria (deficient muscles for speech), micrographia (small handwriting), and dystonia (involuntary muscle contractions) are among the characteristic symptoms of PD (Prince & de Vos, 2018). Healthcare has been revolutionised in recent years by the incorporation of DL techniques with medical imaging, which has provided new insights into intricate physiological and pathological processes (Juutinen et al., 2020; Quan et al., 2021).

Traditional gait analysis methods have historically been significantly reliant on manual measurements, which frequently lead to inaccuracies and inconsistencies. The efficient extraction and analysis of complex locomotion features has been made possible by the application of DL techniques in this field, thereby substantially improving diagnostic accuracy and clinical decision-making (Wroge et al., 2019). Furthermore, speech analysis has demonstrated potential in the diagnosis of PD, as changes in speech patterns are indicative of disruptions in respiratory function and vocal motor control that are a result of the neurodegenerative effects of PD (Celik et al., 2019). Similarly, the diagnostic outcomes have been enhanced by the effective analysis of locomotion features using machine learning (ML) algorithms (Ferreira et al., 2022).

Cognitive processing, motor coordination, and visuospatial abilities are all revealed in handwritten designs, which provide valuable insights into their cognitive and neurological health. Research indicates that modifications in the characteristics of drawings may serve as preliminary indicators of neurodegenerative diseases (Khatamino et al., 2018). Subtle features can be extracted from these illustrations, particularly spherical and wave patterns, through the application of DL techniques, thereby facilitating the early detection and diagnosis of PD (Atkins et al., 2020).

Dopamine depletion in the brain is a significant indicator of the onset of PD, and MRI brain imaging also plays a crucial role in the diagnosis of PD. The structural and functional intricacies of the brain can be revealed by MRI, which offers a deeper understanding of neurological conditions (Solana-Lavalle & Rosas-Romero, 2021). DL algorithms facilitate precise diagnosis and enable personalised treatment strategies by unravelling complex brain structures and activities when combined with MRI imaging (Vyas et al., 2021).

The objective of this research is to further investigate the interactions between neuroimaging modalities and DL techniques in order to improve the quality and accuracy of neurological diagnostics. Our objective is to facilitate the early detection, effective management, and comprehensive comprehension of neurological disorders by analysing locomotion characteristics, speech features, handwriting, and MRI brain imaging (Nakul et al., 2021; Wijaya et al., 2020).

The remaining sections of the paper is organised as follows. The existing literature is reviewed in Section 2. The methodology is outlined in Section 3. The dataset collection and preprocessing are explained in Section 4. The results and deliberations are discussed in Section 5. The paper is summarized in Section 6.

2. Literature Review

Speech Analysis for PD Detection: Advanced models such as Bidirectional LSTM have been successfully employed to detect PD using dynamic speech features, resulting in a higher degree of accuracy than traditional methods. This methodology capitalises on the fundamental frequency variations and articulation transitions that differentiate PD patients from healthy individuals, emphasising the potential of speech analysis and DL techniques, including Convolutional Neural Networks (CNNs), for the identification of PD.

The utilisation of ubiquitous sensors in non-clinical settings has demonstrated potential for the assessment

of PD. Studies have demonstrated that DL outperforms conventional methods, particularly when larger datasets are available, by utilising smartphone-collected data and employing classification algorithms. This method illustrates the practicality of DL for PD assessment, even in the absence of predefined feature definitions.

CNN-based methods have verified the effectiveness in the diagnosis of PD by analysing handwriting patterns, including spirals, with high accuracy. These methods illustrate the potential of CNNs in this field by demonstrating that the integration of dynamic and visual features in handwriting analysis can facilitate the early detection and effective management of PD.

The diagnosis of PD has been made more accurate by the application of classification methods to 3D MRI scans, particularly through the use of voxel-based morphometry (VBM) and feature extraction techniques, which have revealed gender-specific diagnostic nuances. This method underscores the importance of customised diagnostic approaches, thereby demonstrating the necessity of neurobiological methods that are specifically designed for PD research.

The critical function of classification algorithms in early PD detection is underscored by comparative studies of ML techniques. In particular, Artificial Neural Networks have been demonstrated to be highly effective in attaining high classification accuracy, providing valuable insights into the most effective methods for identifying PD in its early stages.

Voice Analysis for PD Diagnosis: The efficacy of voice-based biomarkers in the detection of PD has been thoroughly evaluated. The diagnostic accuracy of supervised classification algorithms, such as deep neural networks, has been demonstrated when applied to voice datasets, thereby confirming their value as diagnostic instruments in PD research.

The accuracy of PD prediction based on speech data has been enhanced as a result of the expansion of the feature space through the use of techniques such as correlation maps. This approach is a significant contribution to the early diagnosis and monitoring of PD progression, demonstrating the predictive potential of speech data analysis.

Employing Voice Biomarkers for PD Diagnosis: The use of supervised classification algorithms to improve the accuracy of PD diagnostics has been demonstrated through the compilation of voice datasets from individuals with and without PD. Voice biomarkers have demonstrated the potential to surpass clinical diagnostic benchmarks, indicating a valuable role in the refinement of PD diagnosis.

Spatial-temporal gait parameters have been successfully analysed using ML algorithms for the diagnosis and staging of PD through gait analysis. These methods provide promising enhancements in diagnostic and monitoring techniques by distinguishing between PD patients and healthy controls using gait data.

The transformative potential of ML algorithms has been demonstrated by the use of voice features in ML models for PD classification. The function of ML in neurodegenerative disease research is further established by the instrumentality of these models in advancing early PD detection and shaping effective management strategies.

The literature survey emphasises the efficacy of deep learning and ML techniques in the early diagnosis and monitoring of PD by utilising speech, locomotion, handwriting, and MRI data.

3. METHODOLOGY

This study employs a computational approach to predict PD utilizing the CNN and its variants like AlexNet, ResNet, inception and Xception architectures. In this work, the dataset is collected from Kaggle which consists of 250 hand drawing images and 800 records of de-identified medical imaging data collected from individuals diagnosed with PD as well as healthy controls, ensuring a diverse representation of demographic characteristics such as age, gender, and ethnicity. For model compatibility the dataset divided into two three major parts. (1) Spherical hand drawn images, (2) Wave hand drawn images and (3) Brain MRI scans. Figure 79.1 shows the detailed flowchart of the proposed approach.

3.1 Data Augmentation and Standardization

Several Data preprocessing techniques including rotation, zoom, and brightness adjustment, are applied to increase the size of dataset making it up to 2700 records and sampling techniques are applied to split the dataset into training, validation, and test sets, ensuring balanced representation across classes.

3.2 Model Design and Training

The primary variable of interest is the presence or absence of PD, encoded as binary labels, along with additional demographic information and imaging features extracted from medical scans. The procedure involves training the CNN models (224*X*224) and its variants (AlexNet, ResNet, Inception and Xception) using the training set with multiple epochs to optimize performance, followed by hyperparameter tuning using the validation set to enhance model generalization.

3.3 Model Architecture

The Xception architecture plays a significant role in classifying PD using handwritten image data due to its unique design and exceptional performance in image classification tasks. This architecture is particularly well-suited for tasks with limited data, such as medical image classification, as it significantly decreases the number of parameters yet preserves expressive power.

3.4 Evaluation and Optimization

Python script initialized with a condition to monitor the validation loss during training. Specifically, training is halted if there is a sustained increase in validation loss, indicating potential overfitting, or if validation accuracy begins to decline. Additionally, we set a minimum of 50 epochs for training to ensure sufficient iterations for model convergence and learning. These conditions help optimize the training process and prevent overfitting while ensuring the model has undergone an adequate number of epochs for learning.

3.5 Integration and Deployment

The developed models are integrated into a comprehensive DL algorithm for diagnosis of PD, and it is deployed into a web interface developed using flask for real-world applications, providing timely and accurate diagnosis to support clinical decision-making and patient care.

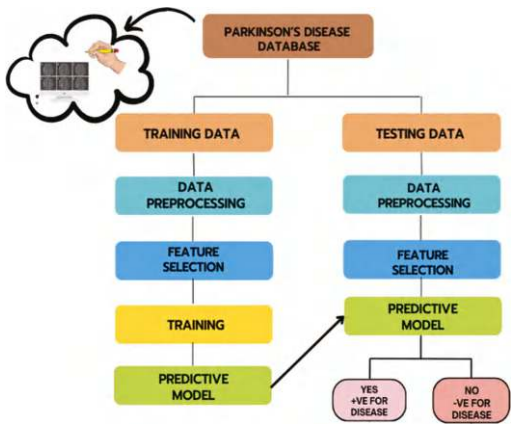

Fig. 79.1 Proposed system work flow

Source: GitHub repositories.

4. Dataset Collection and Preparation

The dataset used in this work for PD detection encompasses three distinct image types: spiral handwriting images, wave handwriting images, and Brain MRI images. These images were sourced from Kaggle, a renowned platform for hosting high-quality datasets.

4.1 Feature Extraction

To ensure comprehensive representation, we selected 200 samples of each image type, evenly distributed between Parkinson's affected individuals and normal individuals (K. Mader, 2018). Additionally, to bolster the dataset size and enhance model robustness, we employed image data augmentation techniques. For the Brain MRI images, we initially obtained 610 normal images and 221 Parkinson's affected images (I. Sheriff, 2020). However, to achieve a balanced dataset and augment its size, we supplemented it with additional images sourced from GitHub repositories, resulting in a total of 1000 images for each class and 2000 images overall.

Prior to model training, the raw images underwent preprocessing steps, including resizing and normalization where applicable, to standardize their formats and improve data quality. Furthermore, to ensure unbiased evaluation, we employed a stratified data splitting approach, dividing the dataset into training, validation sets while maintaining class distribution across all partitions. Our careful dataset collection process resulted in a well-balanced dataset with various types of images, which lays a strong foundation for our research on detecting PD. Figure 79.2 and Fig. 79.3 presents the sample wave and MRI datasets respectively.

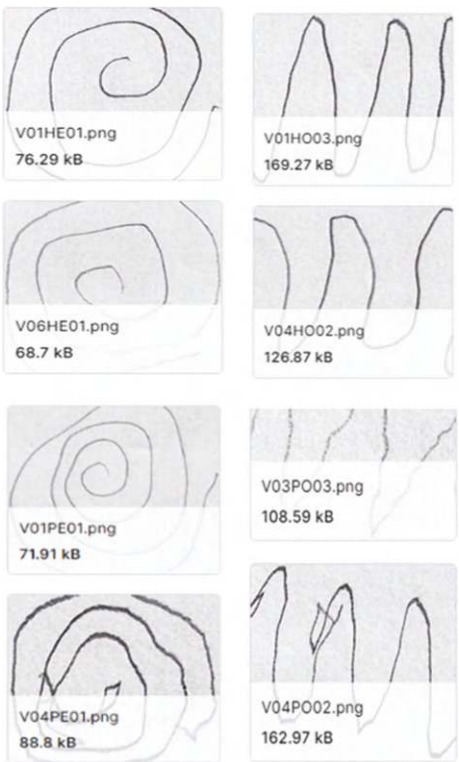

Fig. 79.2 Sample images of spherical and wave dataset

Source: GitHub repositories.

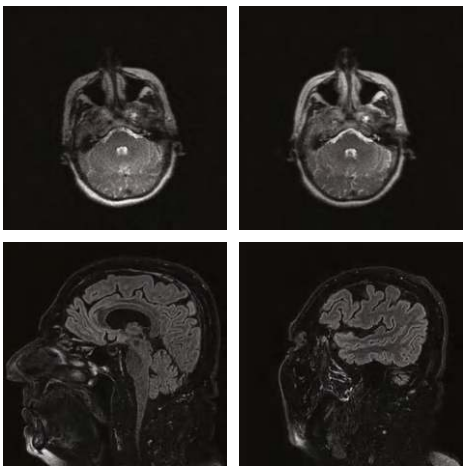

Fig. 79.3 Sample images of brain MRI dataset

Source: GitHub repositories.

4.2 Data Preprocessing

To train the proposed model, the images are resized to 150x150 pixels and distributed the dataset into training and validation sets, with a 20% validation split. To prevent overfitting, we employed data augmentation techniques like rescaling pixel values, rotation (up to 10 degrees), horizontal flipping, and slight shifts in width and height (up to 0.1). Additionally, we introduced a small degree of shearing and zooming to enhance dataset variability. These steps aimed to diversify the dataset and improve the model's generalization ability.

By configuring training and validation generators, we efficiently fed batches of data into the model over 10 epochs, optimizing its performance. These preprocessing techniques were essential in establishing a robust dataset for our PD detection research. Figure 79.4 presents the dataset after data agumentation.

5. Experimental Results & Discussions

For experimentation a laptop equipped with an Intel i5 processor, 512GB SSD, and a NVIDIA graphics card with 4GB of memory is used. This setup allows to efficiently leverage computational power for our model development and training efforts, utilizing both Google Colab and

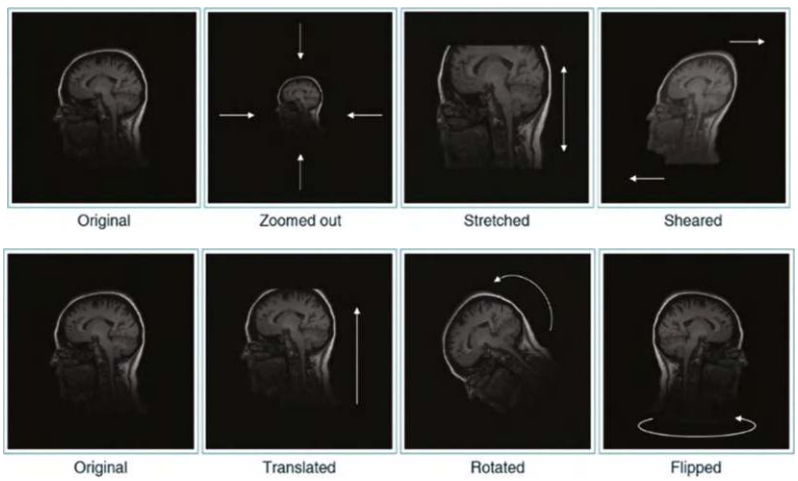

Fig. 79.4 Data augmentation

Source: GitHub repositories.

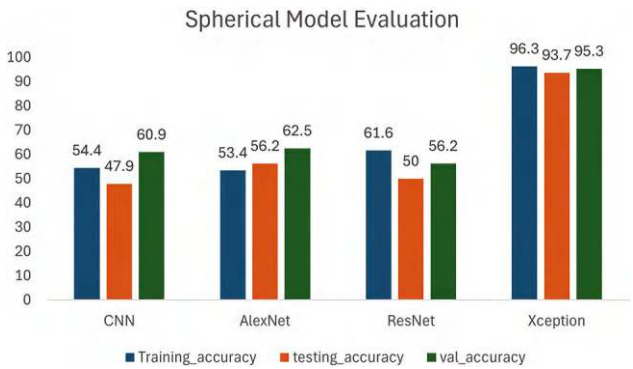

Fig. 79.5 Spherical model evaluation

Source: Author

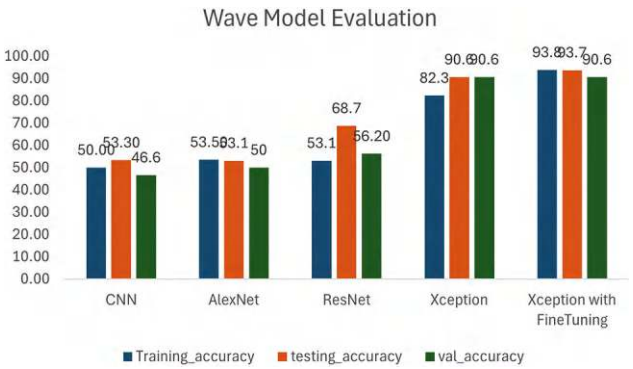

Fig. 79.6 Wave model evaluation

Source: Author

Table 79.1 Model performance metrics

Model	Type of Data	Epochs	Batch Size	Training Accuracy	Validation Accuracy	Test Accuracy	Optimization Technique
CNN	Spherical	30	16	54.4	60.9	47.9	–
	Wave	30	10	50	46.6	53.3	–
AlexNet	Spherical	30	32	53.4	62.5	56.2	–
	Wave	30	32	53.5	50	53.1	–
ResNet	Spherical	30	32	61.6	56	52.6	–
	Wave	30	32	63.3	55.2	68.7	–
Xception	Spherical	50	32	93.6	95.3	93.7	–
	Wave	50	16	82.3	90.6	90.6	Without Fine Tuning
	Wave	50	16	93.8	90.6	93.7	Fine Tuning
Inception V3	Brain MRI	50	16	98.1	59.1	92.6	Adam Optimizer

Source: Author

Jupyter Notebook environments. Figure 79.5 and Fig. 79.6 presents performance evaluations of the proposed DL models with spherical and wave datasets.When it came to analyzing the spiral and wave handwriting images dataset, we delved into various DL architectures, such as CNN, AlexNet, ResNet, and Xception.

Through exhaustive experimentation, we determined that Xception outperformed the other models, exhibiting remarkable accuracy in distinguishing between individuals affected by PD and those who were not. Fine-tuning Xception's parameters and conducting hyperparameter tuning were instrumental in maximizing its performance.

Similarly, for the Brain MRI images dataset, we explored different models, including Inception V3, to identify PD from normal brain scans. After numerous training iterations and hyperparameter tuning trials, Inception V3 emerged as the standout performer, showcasing exceptional classification accuracy and robustness.

From the Table 79.1, it is observed that the importance of selecting appropriate models and optimizing hyperparameters to achieve accurate disease detection.

By leveraging computational resources and employing meticulous experimentation techniques, we identified Xception and Inception V3 as the leading models for classifying handwriting and brain MRI images, respectively. These findings contribute to advancing deep learning-based approaches in health image examination and offer promising prospects for enhancing PD diagnosis and treatment.

6. Conclusion

This investigation emphasises the critical significance of meticulous hyperparameter calibration and model selection in the accurate detection of Parkinson's disease. Utilising computational resources from both a laptop and cloud-based environments such as Google Colab and Jupyter Notebook, we conducted analyses of handwriting images and brain MRI scans. The Inception V3 model demonstrated exceptional performance in the identification of PD from brain MRI scans, while the Xception model emerged as the most effective performer in classifying handwriting images after undergoing intensive testing. The model's performance was considerably improved by the fine-tuning of parameters, such as the learning rate, which enabled quicker convergence and greater accuracy. Furthermore, the Adam optimiser was integrated to further enhance the efficacy of the model, thereby emphasising the importance of cutting-edge DL techniques in the advancement of medical image analysis. The results emphasise the potential of DL in the diagnosis of PD, providing valuable insights into clinical applications that could enhance patient outcomes.

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IoT-Driven Drunk Driving Prevention System with Real-Time Monitoring and GPS Tracking

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Abstract: The number of vehicles on modern roads has substantially increased, ensuing in a substantial rise in the frequency of traffic accidents. Drunk or drug-impaired driving (DUI) is a leading cause of these accidents. This issue is particularly pressing in developing countries such as India, where the high incidence of drunken driving-related incidents presents a significant public safety challenge. The current approach to detecting alcohol levels in drivers involves manual tests by law enforcement, which may not be efficient or timely. This investigation introduces a real-time intoxicated driving prevention system that is IoT-based and employs a microcontroller to automatically deactivate the vehicle's engine when the alcohol level surpasses a predetermined threshold, as determined by an alcohol sensor. Furthermore, the driver's image is captured by a night vision camera, and it is subsequently processed by a microprocessor. Through a microprocessor and camera node, the system enables remote monitoring and image capture through the use of the MQTT protocol and Node-RED, which are connected via IP address. Upon the detection of alcohol levels that exceed the standard, the Blynk App and GPS device provide real-time information on the driver's location and alcohol level to the family or police via wireless communication. The objective of this system is to improve road safety by implementing an automated and efficient method for the detection and prevention of intoxicated driving.

Keywords: IoT, MQTT, GPS, Microprocessor, Alcohol sensor

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1. Introduction

Road traffic safety is increasingly serious with our mode of transportation on the road. In particular, there are an increasing number of traffic accidents caused by intoxicated driving. The development of a smart lock system for drunk driving is crucial in order to deter drunk driving and lower the rate of traffic accidents. According to a World Health Organization report, one person dies in a drunk driving- related traffic incident every 33 minutes, highlighting the increasing hazard of this behavior (Wu et al., 2009). To protect people's lives and property and to preserve social order, it is now essential to take strong measures to restrict and criminalize drunk driving. At the moment, police are checking roadways for samples of cars for breathalyser testing to find alcohol levels. This method, however, is unlikely to catch the majority of drunken driving incidents. Alternative and more successful methods of detecting drunk driving may involve sensor-based automatic detection. Among the ways to prevent this are to slow down the car or to use the internet to inform onlookers or the police. The Internet of Things concept is strongly tied to the automatic detection method employing sensors. The network of physical objects equipped with sensors, electronics, computational components, and network connectivity the means by which they collect and share data is known as the Internet of Things. The internet of things has been used to suggest solutions to numerous issues. In this particular instance, sensors measure alcohol content, and this can be connected to mobile phones that have a communication network to warn people in the proper way. The idea of using IoT to detect DUI is not new. There are numerous models in the written word. No particular paradigm, meanwhile, has found widespread application. The numerous techniques put forth struggle with issues including complexity, scalability, and implementation difficulty. Therefore, new models must preserve accuracy, ease of application, and low cost (Sahabiswas et al., 2016). In this paper an attempt has made to achieve the goals of this suggested model, including the detection of alcohol use by the driver and comparison to the threshold value that we established by considering the alcohol level. Initially, the vehicle motor is in running state. If the detected alcohol level exceeds the threshold value, then the vehicle motor should be in OFF state. By using MQTT protocol, node-red (connected through IP address) will create microprocessor node and camera node, this will help to capture the person image by clicking on camera node in node- red application. By using wireless communication, the family or police will know the person details like live location through GPS tracker and alcohol level in Blynk App.

The remaining sections of the paper is organised as follows. The existing literature is reviewed in Section 2. The methodology of the proposed system is outlined in Section 3. The results and deliberations are discussed in Section 4. The paper is summarized in Section 5.

2. Literature Review

It is imperative to recognise the antecedent research that has been conducted in this field in order to progress effectively and in the correct direction. In this work, we examine the most frequently employed system for the implementation of an alcohol detection and engine locking system that has been employed in the relevant literature.

An anti-drunk driving system that integrates face recognition with an alcohol detection mechanism was suggested in a study. This system enables the automatic substantiation of the driver's identity. By eliminating the necessity for drivers to blow into a device, which is frequently inconvenient in current systems, this method prevents driver fraud, reduces the rate of intoxicated driving incidents, and addresses the limitations of traditional systems (Wu et al., 2009).

A detection system that activates when the driver touches the start/stop button was introduced in another study. The system employs touch-based technology to measure blood alcohol levels and also includes a breath-based alcohol sensor, pulse sensors, and face recognition. The ignition is disabled if three sensors detect alcohol levels that exceed the legal limit. In order to improve safety, the system incorporates GSM and GPS modules that transmit alerts to law enforcement and family members (Sandeep et al., 2017).

One alternative method involves a system that prevents the ignition from starting unless the seat belt is secured and no alcohol is detected. The ignition is disabled and the seat belt opening is locked if alcohol is detected by the system. GPS data regarding the vehicle's location and time are transmitted to the user or proprietor via GSM in the event that alcohol is consumed while operating the vehicle (Malathi et al., 2017).

Another IoT-based system is intended to identify drivers who are both fatigued and intoxicated. It monitors alcohol concentration, eye-blinking rate, and vehicle movements, and if necessary, it takes preventive measures such as slowing down, issuing an alarm, alerting traffic authorities, and activating autopilot (Sahabiswas et al., 2016).

An engine lock feature employed in conjunction with continuous alcohol monitoring in the event that alcohol levels surpass a predetermined threshold. Real-time GPS data is also employed to notify authorities by transmitting

the driver's location via SMS, enabling a prompt response in the event of an emergency (Swetha et al., 2020).

A sensor on the steering column is used to measure alcohol from inhaled air in an alcohol detection system. A microcontroller is employed to transmit a warning message to the vehicle proprietor or police in the event that alcohol is detected, thereby ensuring that the system is in compliance with safety regulations (Rajani Devi et al., 2021).

In an additional investigation, the ignition system of the vehicle is equipped with an alcohol sensor. Furthermore, GSM and GPS modules are integrated to notify emergency services in the event of an accident. By transmitting the accident location to the nearest ambulance services, this configuration facilitates an immediate response (Vyas et al., 2018).

In order to prevent the vehicle from commencing without first verifying that no alcohol was detected, a prototype sealing system was created. In order to enhance road safety, this system is designed to serve as a fundamental paradigm for future advancements in accident prevention systems (Al-Youif et al., 2018).

A mobile phone-based system was created to identify inebriated driving by utilising accelerometer data to monitor driving patterns. This method of detection is portable and convenient, rendering it appropriate for real-world applications in which integration with a vehicle's system is not practicable (Dai et al., 2010).

A PIC16F877A microcontroller-based automatic locked control system was suggested as a means of preventing inebriated driving. This system detects alcohol levels and automatically secures the vehicle if alcohol is detected, thereby preventing intoxicated drivers from operating the vehicle (Chen & Lin, 2011).

A portable alcohol detection system was developed to facilitate the real-time monitoring of drivers. This system is designed for effortless installation in vehicles and employs a compact sensor to monitor driver sobriety and improve road safety (Wakana & Yamada, 2019).

In order to detect alcohol levels in drivers, the MQ-303A alcohol sensor was integrated with a vehicle's safety system. The system implements the requisite measures to prevent the driver from operating the vehicle in the event of elevated alcohol levels, thereby enhancing safety protocols (Rahmad et al., 2019).

To address the limitations of the different approaches, the proposed system enhances existing systems by automating real-time alcohol detection and engine lock using IoT and GPS, eliminating reliance on manual intervention. With multi-sensor validation, GPS-based tracking, and instant alerts to family and authorities, it ensures timely response, accurate driver identification, and improved drunk driving prevention and road safety.

3. Proposed System

The alcohol sensor, motor, and GPS module are integrated with an ESP32 (WiFi module) in the proposed model, as shown in Fig. 80.1. This integration is employed to detect alcohol levels. At first, the motor operates; however, it will automatically cease operation if alcohol concentrations exceed the established threshold. Family members are capable of locating the impaired driver through the use of GPS tracking. The image of the motorist is captured by a night vision camera that is connected to a Raspberry Pi and is accessible through Node-RED via an IP address.. The MQTT protocol is employed for wireless communication, and a server that runs Blynk provides real-time updates to consumers, allowing for visualisation on multiple devices. To observe the driver's image, simply click on the camera node in Node-RED. The Arduino environment employs embedded C for code implementation.

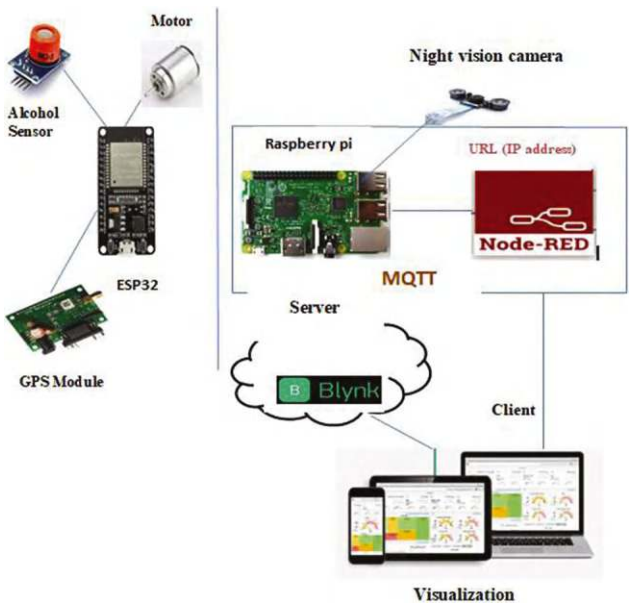

Fig. 80.1 System architecture for real-time drunk driving detection and prevention using IoT

3.1 PuTTY

PuTTY is a terminal emulator program that functions as a client for raw TCP protocols, rlogin, Telnet, and SSH. Although "tty" is frequently used to denote a "teletype" in Unix systems, the term "PuTTY" does not have a specific definition. PuTTY was initially designed for Microsoft Windows; however, it has since been ported to a variety

of operating systems, including several Unix-like systems. Official implementations for macOS are still in the process of development, despite the existence of unofficial ports for Symbian and Windows Mobile. Figure 80.2 shows the PuTTY configuration window.

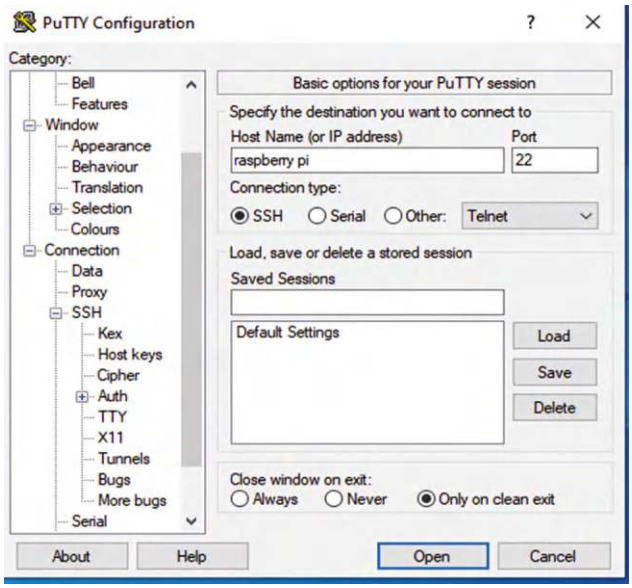

Fig. 80.2 PuTTY configuration window

3.2 Xming

Xming is a free X Window server for Windows that allows remote access to Linux graphical programs. It provides a platform for Windows computers to display graphical applications running on a remote Linux system. This capability is particularly useful for users who need to interact with Linux applications from a Windows environment. A more detailed description of Xming's features and usage can be found on its official website. Figure 80.3 shows the Xming displaying a remote Linux desktop.

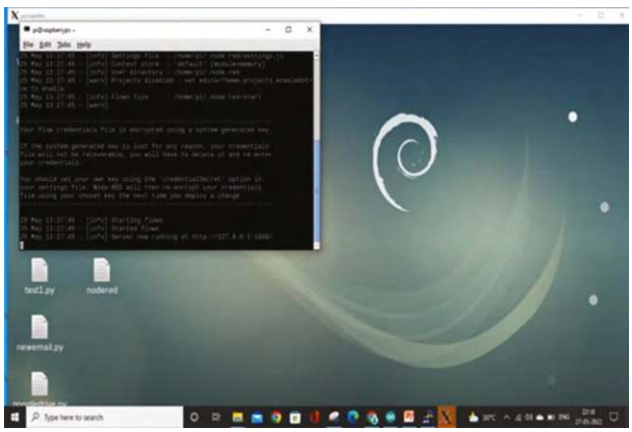

Fig. 80.3 Xming displaying a remote Linux desktop

3.3 MQTT Protocol

MQTT, or Message Queuing Telemetry Transport, is a protocol that is specifically designed for machine-to-machine (M2M) communication applications. It functions as a publish-subscribe messaging transport that is lightweight, making it an ideal choice for scenarios with restricted bandwidth. MQTT is well-suited for IoT environments that necessitate efficient, low-bandwidth messaging due to its ability to facilitate communication between multiple devices.

3.4 Operational Efficiency of the System

A collection of embedded C functions that can be invoked within the code is employed to implement the system. The operation of the system is delineated in the flowchart, Figure 80.4. The system is initially in a stable start-up state, during which the engine continues to operate as long as the detected alcohol level is below the specified threshold. The engine is automatically stopped if the alcohol level exceeds this standard value, after a brief delay. Family members can monitor the location of the impaired motorist via GPS using the Blynk app. The driver's image is captured by a night vision camera affixed on the vehicle and is accessible in the Node-RED application via a camera node. The MQTT protocol facilitates wireless communication.

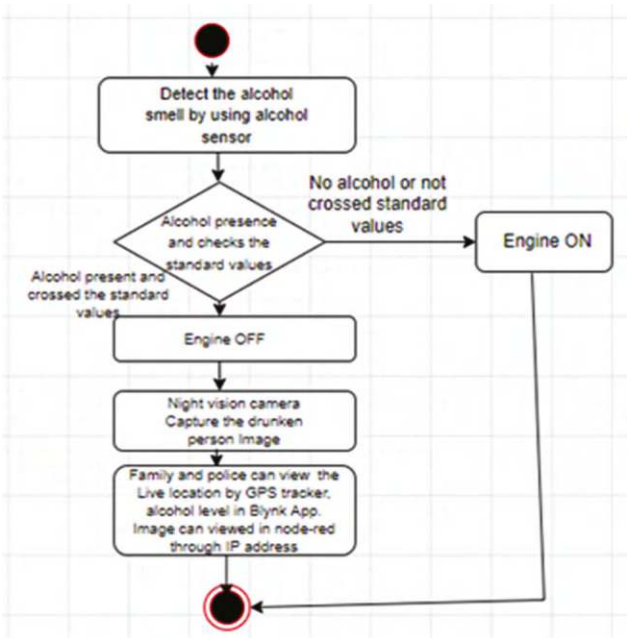

Fig. 80.4 System flow chart

4. Results and Discussion

The primary components of the constructed system are the alcohol sensor and motor. These components

are interconnected to facilitate effective monitoring, as demonstrated in Fig. 80.5. The motor is initially in an operating state; however, it will automatically cease operation to prevent further operation when the sensor detects alcohol levels that exceed the standard threshold. The GPS module is integrated to monitor the location of the impaired motorist, providing real-time updates on their position for improved safety and monitoring.

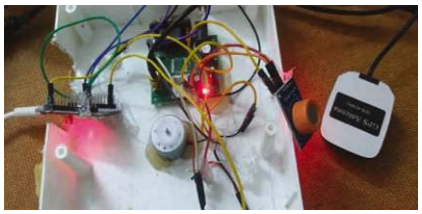

Fig. 80.5 Connection diagram of alcohol sensor and motor

As illustrated in Fig. 80.6, the night vision camera, which is connected to a Raspberry Pi, is an additional essential component of the system. Users can observe the position and condition of the impaired motorist by accessing the images captured by this camera through the Node-RED application. This feature supports effective remote observation by providing visual confirmation, particularly in low-light conditions, thereby enhancing monitoring.

Fig. 80.6 Night vision camera connected to raspberry Pi

The Blynk app tracks the location of the incapacitated driver, as illustrated in Fig. 80.7, enabling users to effortlessly identify the driver's location.

As illustrated in Fig. 80.8, the Blynk app's architecture encompasses a comprehensive view of the system's status, including the GPS Tracker, Alcohol Level Indicator, and Motor Condition Display.

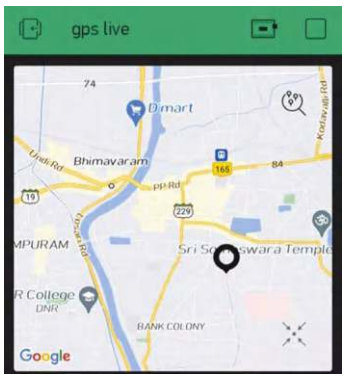

Fig. 80.7 GPS track in blynk app

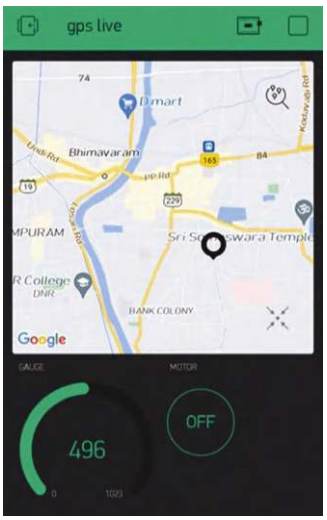

Fig. 80.8 Blynk app – entire layout design with GPS tracker, alcohol level, and motor condition

A camera node configured as a night vision camera is included in the Node-RED application, which is accessible via remote desktop using Xming. This node facilitates the capture of images of the impaired motorist. Figure 80.9 illustrates the configuration of these nodes.

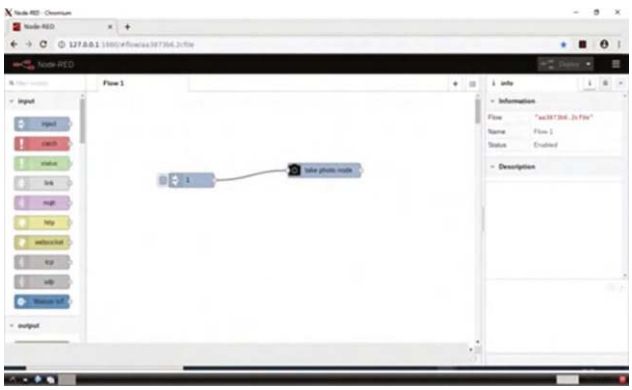

Fig. 80.9 Node red application

Upon clicking the camera node, which is generated within the Node-RED application, the image captured by the night vision camera is displayed. This feature enables users to remotely monitor the condition of the impaired motorist. Figure 80.10 illustrates the image that was captured.

Fig. 80.10 Captured image from the node red application

The results indicate that the proposed system effectively prevents drunk driving through automated motor control, real-time GPS tracking, and visual monitoring, offering a reliable, comprehensive solution for enhanced road safety.

5. Conclusion

This paper introduces a system that is capable of identifying intoxicated drivers and evaluating their condition. An alcohol sensor, motor, night vision camera, and GPS comprise the proposed configuration. The motor is automatically halted by the system when the alcohol level surpasses a predetermined threshold. A microcontroller, which is incorporated with the Blynk app, notifies pertinent stakeholders, while the GPS module provides the vehicle's precise coordinates. The MQTT protocol enables wireless communication, which enables the Node-RED application (connected by IP address) to capture an image of the motorist through a camera node. Cloud storage could be incorporated into future implementations to improve accident prevention by serving as a reference for recording data. Furthermore, sophisticated machine learning techniques could be implemented to evaluate driving patterns and abilities in order to conduct additional safety evaluations..

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AI-Powered Electronic Health Record Analysis System

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Abstract: Electronic Health Record (EHR) systems are pivotal to modern healthcare, serving as digital repositories of patient medical histories. Integrating Artificial Intelligence (AI) into EHRs has opened new opportunities for predictive analytics, Clinical decision-making and tailored care. This paper delves into the evolution of AI-powered EHR systems, their challenges, and how advanced algorithms like NLP and machine learning models enable real-time decision support. We introduce a novel machine learning algorithm, the Adaptive Risk Stratification Model (ARSM), designed to dynamically assess and stratify real-time patient risk profiles using historical and continuous patient data. By leveraging techniques such as ensemble learning and Bayesian optimization, the ARSM demonstrates improved accuracy and timeliness in predicting patient outcomes. Additionally, we discuss key challenges such as interoperability, data security, and ethical concerns, outlining solutions for their mitigation.

Keywords: Artificial intelligence, Electronic health records, NLP, etc.

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1. Introduction

Electronic Health Record (EHR) systems have become central to modern healthcare, revolutionizing the way patient information is collected, stored, and managed. These digital repositories contain comprehensive patient medical histories, including diagnoses, treatment plans, medications, immunization records, laboratory test results, and radiology images. However, the true potential of EHR systems lies beyond mere data storage. Integrating Artificial Intelligence (AI) into EHR systems has unlocked new possibilities for transforming healthcare by enabling advanced predictive analytics, real-time decision-making, and personalized patient care.

The application of AI in healthcare, particularly in EHRs, has introduced sophisticated tools that analyze vast amounts of structured and unstructured data to provide clinicians with actionable insights. By utilizing NLP and ML, AI-powered EHR systems can now assist healthcare providers in identifying high-risk patients, optimizing treatment strategies, and predicting outcomes with improved accuracy. These advancements are pivotal in enhancing clinical decision support, improving workflow efficiency, and driving evidence-based care.

One such innovation is the Adaptive Risk Stratification Model (ARSM), a machine learning algorithm designed to dynamically assess patient risk levels in real-time. Traditional risk stratification models often rely on static variables such as patient age, comorbidities, and previous medical history, leading to limited predictive power in dynamic clinical settings. The ARSM, on the other hand, continuously updates a patient's risk profile by analysing both historical data and real-time clinical indicators, such as vital signs and lab results. By leveraging ensemble learning techniques and Bayesian optimization, the ARSM provides more accurate and timely predictions of patient outcomes, making it a valuable tool for proactive clinical decision-making.

Despite the promise of AI-driven EHR systems, several key challenges need to be tackled, especially in terms of interoperability, data security, and ethical issues. Interoperability refers to the capacity of various healthcare systems and technologies to function together smoothly while ensuring the safe exchange of patient data. Safeguarding data privacy and security is crucial, as EHRs hold sensitive information that must be protected from breaches and unauthorized access. Moreover, the ethical implications of AI in healthcare, such as bias in algorithms and accountability in decision-making, must be carefully managed to ensure equitable care for all patients.

This paper provides an in-depth exploration of the evolution of AI-powered EHR systems, focusing on the ARSM as a novel algorithm for dynamic risk stratification. Additionally, we address the challenges associated with AI integration in EHR systems and propose solutions to overcome these obstacles. To illustrate the practical applications of AI in healthcare, the paper concludes with a case study on the integration of AI into a major healthcare provider's EHR system, highlighting the benefits, challenges, and future trends in AI-driven healthcare.

2. Related Work

Electronic Health Records (EHR) have transformed how patient data is recorded, stored, and accessed. One of the most prominent improvements has been the integration of AI into EHR systems. AI's capability to process and analyze large data makes it a natural fit for healthcare, where clinicians must sift through vast amounts of information to make timely and accurate decisions. AI can help identify patterns, optimize treatment plans, and predict patient outcomes (Jiang et al., 2017). EHRs enhanced with AI offer several advantages, including automating mundane tasks, improving diagnostic accuracy, and offering predictive insights into patient health.

2.1 The Role of Artificial Intelligence in EHR Systems

Artificial Intelligence (AI) transforms healthcare by enabling more accurate, efficient, and personalized medical care. Machine learning algorithms can identify patterns in large datasets that are beyond the capacity of human analysis. In an EHR context, AI enhances clinical decision-making through predictive analytics, automates administrative tasks, and helps clinicians tailor treatments to individual patient profiles.

Predictive analytics, a subset of AI, leverages historical data to forecast patient outcomes, alert clinicians to potential complications, and recommend evidence-based interventions (Shickel et al., 2018). Moreover, NLP tools allow for the extraction of critical data from unorganized information such as clinician notes and diagnostic reports. This aids in creating a comprehensive picture of the patient's health, ensuring that no essential details are overlooked in the decision-making process (Esteva et al., 2017).

2.2 The Evolution of AI-Powered EHR Systems

EHR systems began as basic digital repositories aimed at reducing reliance on paper records. These early systems primarily stored structured data such as diagnoses, test results, and prescriptions. With technological advancements, the focus shifted to integrating more diverse data types like radiological images, genomics, and social determinants of health (Menachemi & Collum, 2011).

However, the advent of AI marked a significant shift, enabling EHR systems to move beyond data storage and toward active decision-making support.

Today, EHR systems have become sophisticated platforms capable of offering real-time clinical support, alerts, and reminders, while also facilitating predictive and personalized treatment plans (Topol, 2019). The integration of AI into EHRs has allowed for a deeper analysis of patient data, improving diagnostic accuracy, and making treatment protocols more personalized and responsive to patient needs.

2.3 Role of AI in EHR Evolution

The most profound shift in EHR systems has been the incorporation of AI technologies, particularly machine learning and NLP. AI helps transform EHRs from static repositories into dynamic, intelligent systems that can learn from data, recognize patterns, and offer real-time insights.

- **Predictive Analytics:** AI models predict patient outcomes by analyzing historical data. For instance, machine learning algorithms can flag high-risk patients based on clinical indicators such as blood pressure, cholesterol levels, and other factors (Topol, 2019).
- **Natural Language Processing (NLP):** NLP techniques help transform unstructured data (such as doctor's notes and radiology reports) into structured information that can be analyzed for trends and patterns (Jiang et al., 2017).

2.4 Real-Time Clinical Decision Support and Data Analytics

Clinical Decision Support Systems (CDSS) have become integral to AI-powered EHRs. These systems provide real-time recommendations based on historical patient data, clinical guidelines, and current treatment protocols. For example, CDSS can issue alerts regarding potential drug interactions or suggest alternative treatments when evidence-based guidelines recommend it (Wright et al., 2014).

AI-driven CDSS can also stratify patients based on risk and provide predictive analytics that helps clinicians identify potential complications early. For example, a model might predict sepsis in a hospitalized patient based on subtle changes in heart rate or blood pressure (Shickel et al., 2018). Real-time alerts ensure that clinicians can intervene early, reducing morbidity and mortality rates.

- **Predictive Models and Machine Learning**

  Predictive models are increasingly being used to enhance the functionality of EHR systems. These models analyze patient data to identify trends that clinicians may overlook, helping them make better treatment decisions. For instance, a predictive model might identify that a patient with a certain combination of symptoms is at high risk for a specific complication, prompting earlier interventions (Topol, 2019). One of the most common uses of machine learning in EHR systems is in predicting readmission rates.

2.5 Interoperability and Data Integration

- **Seamless Data Exchange**

  Interoperability is the ability of different healthcare systems to communicate and exchange information seamlessly. One of the challenges that healthcare organizations face when implementing AI-powered EHRs is ensuring that their system can integrate with other platforms, especially across different healthcare providers. AI can assist by standardizing data formats and ensuring that information is properly exchanged between systems, even if they use different technical standards (Keshavjee et al., 2010). A practical example of this is the integration of laboratory data and radiological images into an EHR system. AI models can help automate the process of tagging and structuring this data so that it can be easily analyzed and compared to patient histories.

- **Integration of Medical Imaging**

  Medical imaging is another area where AI is making significant strides. Integrating images like X-rays, MRIs, and CT scans into EHR systems provides clinicians with a comprehensive view of the patient's condition. AI-powered image analysis tools can help detect early signs of disease that might not be visible to the human eye. For example, AI algorithms being developed to detect cancers in radiology images, often with more accuracy than human radiologists (Esteva et al., 2017). Moreover, combining imaging data with the patient's medical history allows for a more holistic understanding of the disease's progression, helping clinicians make more informed treatment decisions.

2.6 Privacy and Security Concerns in AI-Powered EHRs

- **Data Security in Healthcare**

  In addition, AI methods like differential privacy can be applied to anonymize patient data, allowing it to be used for research without compromising confidentiality. Machine learning models can also detect security breaches by identifying unusual access patterns or data anomalies (Jiang et al., 2017).

- **Ethical Considerations and Compliance**

  AI-powered EHR systems must also consider ethical issues such as bias, transparency, and informed consent. AI models rely on the quality and neutrality of the data they are trained on. If the training data includes inherent biases, such as the overrepresentation of specific populations, it may result in biased treatment recommendations (Mehta & Pandit, 2018). Ensuring transparency in AI decision-making is essential for gaining the trust of both clinicians and patients. Informed consent is another area of concern. Patients need to understand how their data is being used, particularly when it is being analyzed by AI algorithms. Healthcare organizations must also ensure that their AI systems comply with international data protection regulations, such as GDPR in the European Union (Jiang et al., 2017).

3. Experimental Result

The patient's health data (static and dynamic) is shown in Table 81.1.

3.1 Algorithm: Adaptive Risk Stratification Model (ARSM)

1. Input: Features $X = (x_1, x_2, \ldots, x_n)$
2. Preprocessing: Handle missing data, and normalize X.
3. Initial Risk: Compute $Y_{Initial}$ based on decision tree rules.
4. Ensemble Learning: Compute $Y_{Ensemble}$ using Random Forest and Gradient Boosting.
5. Final Risk Score: Combine $Y_{Initial}$ and $Y_{Ensemble}$ to compute S_{Final}.
6. Final Risk Category: Classify Y_{Final} based on S_{Final}.

3.2 Introduction to the Algorithm

The **ARSM** is a machine learning algorithm designed to dynamically assess patient risk levels by analyzing historical data and real-time patient inputs. Traditional risk stratification models are often static and based on limited factors, such as age or comorbidities. ARSM, on the other hand, continually adjusts risk levels based on real-time data such as vital signs, lab results, and other clinical inputs. This allows for a more nuanced understanding of a patient's risk profile and improves the timing of clinical interventions.

3.3 Algorithm Design

The ARSM combines decision trees with ensemble learning and Bayesian optimization techniques to dynamically assess patient risk. By using multiple models to assess the risk factors, the algorithm achieves higher accuracy and generalizes well across different patient populations.

Step 1: Input

1. Let the input data for each patient be represented as a vector $X = (x_1, x_2, \ldots, x_n)$, where each x_i is a feature, including:
   - **Static Data:** X_s (e.g., age, gender, smoking status).
   - **Dynamic Data:** X_d (e.g., blood pressure, heart rate, oxygen saturation).

   The output is the **Risk Category** Y, which takes values in the set: $Y \in \{0,1,2\}$ (0 = Low Risk, 1 = Medium Risk, 2 = High Risk)

Step 2: Data Preprocessing

1. Handling Missing Data:
   - For each feature $x_i \in X$ if x_i is missing, replace x_i using imputation: $x_i = \text{Impute}(x_i)$.

Table 81.1 Patient's health data

Patient ID	Age	Gender	Smoking Status	Medical History	Blood Pressure (mmHg)	Heart Rate (bpm)	Oxygen Saturation (%)	Cholesterol (mg/dL)
1	65	Male	Current Smoker	Hypertension, Diabetes	150	110	94	240
2	45	Female	Non-Smoker	No History	125	85	98	190
3	72	Male	Former Smoker	Heart Disease	135	100	95	210
4	30	Female	Non-Smoker	No History	110	70	99	180
5	50	Male	Current Smoker	Hypertension	140	95	96	220
6	68	Female	Former Smoker	Hypertension, Heart Disease	155	105	93	250
7	40	Male	Non-Smoker	Diabetes	118	90	97	200
8	55	Female	Current Smoker	Hypertension	145	115	92	235
9	35	Male	Non-Smoker	No History	120	75	98	185
10	60	Female	Former Smoker	Hypertension, Diabetes	130	100	95	205

where Impute can be the mean, median, or a more advanced method such as K-Nearest Neighbours.

2. Normalization:
   - Normalize each feature x_i using Z-score normalization: $x_i' = (x_i - \mu_i)/\sigma_i$

   where μ is the mean and σ_i is the standard deviation of feature x_i.

Step 3: Initial Risk Stratification (Decision Tree)

We define the initial risk stratification using simple **decision rules** based on predefined clinical thresholds. These rules operate on specific features, primarily **blood pressure** and **heart rate**.

1. **Decision Rule for Blood Pressure (BP):**

$$Y_{BP} = \begin{cases} 2 \text{ if } BP > 140 \\ 1 \text{ if } 120 \le BP \le 140 \\ 0 \text{ if } BP < 120 \end{cases}$$

2. **Adjustment for Critical Indicators (Heart Rate, HR):**

   If the heart rate exceeds 100 bpm, escalate the risk level:

   $Y_{HR} = 2$ if HR >100 and $Y_{BP} = 1$ (Medium to High Risk) Y_{BP} otherwise

   Thus, the **Initial Risk** $Y_{Initial}$ is determined by combining blood pressure and heart rate evaluations:

$$Y_{Initial} = \max(Y_{BP}, Y_{HR})$$

Step 4: Refined Risk Assessment(Ensemble Learning)

We use Random Forest (RF) and Gradient Boosting (GB) classifiers for a more refined risk assessment. Each classifier produces a risk score as the predicted probability of each risk category.

1. $P_{RF}(Y = k|X)$ is the probability predicted by the Random Forest for risk category $k \in \{0,1,2\}$.
2. $P_{GB}(Y = k|X)$ is the probability predicted by the Gradient Boosting model for risk category $k \in \{0,1,2\}$.

   The combined risk score for each category k is computed as the average probability from both models:

$$P_{Combined}(Y = k|X) = (1/2)\,(P_{RF}(Y = k|X) + P_{GB}(Y = k|X))$$

The final predicted risk category from the ensemble models is:

$$Y_{Ensemble} = \text{argmax}_{k \in \{0,1,2\}}\, PCombined(Y = k|X)$$

- **Random Forest Risk Scores:**
  Patient 1: Risk_Score_RF = 0.9 (High Risk).
- **Gradient Boosting Risk Scores:**
  Patient 1: Risk_Score_GB = 0.85 (High Risk).
- **Combine Model Outputs:** The **Combined_Risk_Score** is the average of both models' predictions:

  Combined_Risk_Score = (Risk_Score_RF + Risk_Score_GB)/2

  Patient 1:

  Combined_Risk_Score = (0.9 + 0.85) / 2 = 0.87

Step 5: Hyperparameter Optimization (Bayesian Optimization)

To optimize the performance of the models (Random Forest and Gradient Boosting), Bayesian Optimization is applied to minimize the loss function $L(\theta)$(such as cross-validation error).Given the set of hyperparameters θ (e.g., learning rate, tree depth), we seek to find the optimal θ^*: $\theta^* = \text{argmin}_\theta L(\theta)$

This optimization step refines the models to maximize predictive accuracy.

Step 6: Final Risk Score Calculation

The final risk score S_{Final} is computed as a **weighted combination** of the initial decision tree output and the ensemble model output. Let α and β be the weights assigned to the decision tree and ensemble model, respectively.

$$S_{Final} = \alpha * Y_{Initial} + \beta * Y_{Ensemble}$$

The weights are subject to the following conditions:

$\alpha + \beta = 1$ with α typically less than β to give more importance to the refined model.Here weight coefficients $\alpha = 0.3$ and $\beta = 0.7$.

The **Final_Risk_Score** is computed as:

Final_Risk_Score = (α * Decision_Tree_Risk) + (β * Combined_Risk_Score).

The final risk category Y_{Final} is determined from the final score:

$$Y_{Final} = \begin{cases} 2 \text{ if } S_{Final} \ge 0.8 \text{ (High Risk)} \\ 1 \text{ if } 0.5 \le S_{Final} < 0.8 \text{ (Medium Risk)} \\ 0 \text{ if } S_{Final} < 0.5 \text{ (Low Risk)} \end{cases}$$

Patient 1:

- Decision Tree Risk = 1.0.
- Final_Risk_Score = (0.3 * 1.0) + (0.7 * 0.87) = 0.9125 → **High Risk**.

The final output of the comprehensive and adaptive risk assessment is shown in Table 81.2.

Table 81.2 Comprehensive and adaptive risk assessment

Patient ID	Final Risk Category
1	High Risk
2	Medium Risk
3	Medium Risk
4	Low Risk
5	Medium Risk

The **ARSM** algorithm dynamically assesses patient risk by combining decision trees, ensemble models, and Bayesian optimization. The final risk category is based on both static and real-time clinical inputs, providing a comprehensive and adaptive risk assessment.

4. Conclusion and Future Work

AI-powered Electronic Health Record (EHR) systems represent the future of healthcare by providing more accurate, personalized, and real-time decision support for clinicians. The **Adaptive Risk Stratification Model (ARSM)** is an example of how machine learning can enhance EHR functionalities, helping clinicians stratify risk, predict complications, and improve patient outcomes. However, ethical, security, and data bias concerns remain significant challenges that must be addressed to ensure equitable and secure patient care. The future of AI-powered EHRs will likely involve deeper integration of deep learning algorithms, which can analyze more complex data, such as genomic data and proteomics. By incorporating data from wearable technologies, deep learning models could predict health outcomes with even greater precision.

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A Comprehensive Analysis of Botnet Detection Techniques in IoT Networks

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Abstract: The expansion of the number of devices connected to the Internet has made it increasingly difficult to ensure network security for IoT systems. The term botnet stands for networks formed by infected systems under control by attackers and these entities pose significant threats to the world of IoT due to their ability in carrying out large-scale organized attacks. Specialized methods addressing IoT-specific features are needed in order to detect and fight back these malicious networks. This paper is designed to deal with the situation where we need a special set of strategies that differ from those used in generic environments to be able not only to identify but also take appropriate action against such adversarial networks, particularly within an IoT context. Give a complete account of the strategies used for detection of botnets in the IoT networks. There are three main methods used for detection i.e. signature based, anomaly based, and machine learning-based techniques. The limitations are not far off from these current detection mechanisms,

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we need to focus our research efforts on developing innovative and more effective approaches to detect the malevolent botnet infiltrations into IoT environment which can weaken the system's security capabilities.

KEYWORDS: BotNet, IoT, Machine learning, KNN, Naïve bayes, Random forest

1. INTRODUCTION

In the modern world, the use of Internet of Things has altered the way of functioning through smart works and increased efficiency in our day-to-day existence. However, Iot connectivity also includes security threats where most of the threats are threats of botnet attack. In particularly the botnets, Collections of compromised devices used by malicious hackers for their purposes, have become one of the most significant threats constantly menacing IoT environments.

A botnet is a collection of compromised devices under the control of hackers. In the area of Internet of Things (IoT), botnet attacks compromise connected devices such as cameras, routers, smart TVs, and other IoT devices. These devices are often poorly protected, making them prime targets for attackers. Attackers exploit the vulnerabilities in IoT devices, such as weak passwords or expired firmware, to gain control of them. This process is often automated, allowing attackers to quickly compromise large numbers of devices. When infected, these devices become part of a botnet and will be instructed by the attacker and gain control over server. The server commands and manages the botnet's activities. Botnets are used for a wide variety of malicious purposes which includes distributed denial of service (DDoS) attacks, data theft, spam distribution, and more.

Botnets overwhelm targets with large volumes of traffic, causing service disruptions. Websites and online services become unusable, leading to lost sales, unhappy customers, and potential damage to a company's reputation. Compromised IoT devices will be used to steal sensitive data or spy upon users. Personal and confidential information can be compromised, leading to data breaches and identity theft. Botnets can spread malware to other devices within the network or connected networks. This can result in widespread infection and further compromise the security of personal, business, or critical infrastructure systems. IoT devices can be used to mine cryptocurrency or perform other resource- intensive tasks. This unauthorized use can result in higher utility bills, reduced equipment performance, and shortened equipment life. The costs of mitigating botnet attacks include the costs of incident response, system recovery, and enhanced security measures. Companies and individuals can suffer significant financial losses due to the direct costs of an attack and the indirect impact on business operations.

To some extent, they use a large number of connected devices as well as the heterogeneity of the connected networks for the purpose of coordinating different kinds of cybercrimes such as DDoS attacks, data theft, and holding important information to ransom through spreading ransomware and for mining cryptocurrencies. Their general structure and their propensity to avoid the standards of usual security protocols make them difficult to prevent and counter. Some of the traditional measures that are being used in the current world of technology to prevent or detect botnets include signature-based methods which are not very useful against today's botnet detection. Consequently, there is some rising concern in leveraging the IoT optimize it using machine learning (ML) techniques.

Machine learning has some potential approaches which it can use to detect botnet activity based on the traffic pattern and activity pattern and communication thread of a device. The analysis for ML models shows that through analysis of normal and malicious activity the model can predict and proactively escalate threats from botnet involvement.

This survey aims to explore the area of botnet detection in the IoT environments, along with a special focus on the deep learning and machine learning techniques for botnet detection. This paper aims at presenting a scalable framework for detecting botnets thereby describing the existing ML-based approaches, their advantages, and limitations to be valuable references for the further development of botnet detection methods

2. LITERATURE SURVEY

Susilo & Sari (2020) have proposed a deep learning algorithm for intrusion detection in Iot networks. They have used several deep learning and machine-learning algorithms and standard dataset UNSW Bot-Iot dataset. They have proposed a deep learning model for DoS attacks detection in the network. They achieved an accuracy of 91.27% using CNN. Jain et al. (2022) have suggested a new algorithm by combining anomaly and signatured

based intrusion detection. They have used NB15 UNSW dataset for the research. The intrusion detection is based on sensors, it doesn't involve deep learning. They also proposed a HCNN algorithm which is called Hybrid CNN. They have incorporated LSTM with CNN. The proposed HCNN has a 98% accuracy rate, surpassing the RNN method. Ge et al. (2019) proposed a intrusion detection system that classifies the traffic flow with the application of deep learning concepts. For binary-class, multi-class, including DoS, distributed DoS and reconnaissance they have created a feed-forward neural network model. High classification accuracy is demonstrated by the results of using the processed dataset to evaluate the suggested strategy.

Qiu et al. (2021) presented a novel method to produce adversarial examples to reduce the efficiency of the Network Intrusion Detection System (NIDS). The first phase aims to construct a shadow model. The second phase aims to produce adversarial examples to attack the target system. Awajan (2023) proposed a new method for intrusion detection based on deep learning. The system contains a four-layered fully connected network for identification of malicious attacks. It also contains a mitigation module to diminish the impact of intrusion detected. It achieved an accuracy of 93.74%. (Almiani et al., 2020) presented a deep recurrent neural network to build a network intrusion detection system based on fog computing to improve the security of IoT devices. Adaptive cascaded filtering leveraging recurrent networks plays an important role in boosting the performance of specific types of intrusion detections.

Nomm & Bahsi (2018) have developed an unsupervised anomaly based botnet detection algorithm. They have used the dataset containing 1155 features and 9 different Iot devices. They developed model for different Iot devices rather than different models. The paper focuses more on the feature selection for the dataset. They used three different feature selections viz. variance based, entropy based and Hopkins statistics. They have also created a balanced dataset for better understanding of model. But the model gave better results with the unbalanced dataset which means it's not a ideal algorithm to use, since the dataset contains attack fields more. Pokhrel et al. (2021) have applied smote technique. It is applied when there is an oversampling in the dataset. It balances the dataset class. They have used the UNSW Bot- Iot dataset. They developed algorithms like KNN, Naive Bayes and MLP. KNN gave best results for both real-time and after smote dataset. Whereas Naive Bayes, MLP results are very less compared to real-time dataset. Kumar et al. (2023) introduced a hybrid machine learning(ML) model for efficient botnet detection. The have used UNSW- NB15 dataset. The proposed algorithm is called ACLR which is generated by stacking ANN, CNN, RNN and LSTM algorithms. The proposed model gave a highest accuracy among all which is 97.49. They have clearly discussed about each step, each parameter and every aspect of their research. They have done the k-fold cross validation, the highest accuracy is achieved at k value 5.

Chandana Swathi et al., (2024) tried to address the problems by offering models which are trained on botnet features, there are significant shortcomings, including the huge dimensionality of feature values and the reliance on botnet features alone. They proposed a novel botnet detection algorithm and its impact detection using a conventional ensemble approach to overcome these limitations. The experimental investigation used a multi-label, fourfold strategy in a cross-validation fashion. The paper is deeply discussed about the traffic flow, session hijackings, their steps and formulas. They have used five benchmark datasets for their research. Hosseini et al. (2022) proposed an enhanced feature optimization method using multi-objective hybrid artificial ecosystem along with sine cosine algorithm (MOAEOSCA) for feature selection in botnet detection in IoT. AEO stands for artificial ecosystem optimization whereas SCA stands for sine cosine algorithm. They conducted experiments on 10 standard datasets to create a robust algorithm for botnet detection. They have compared their results with other standard robust algorithms and proposed one tops 9 out of 10 datasets. Liu & Du (2023) have stated that the large number of traffic features and detection is problem. They have aimed at this and focused on the feature selection for the Iot Botnet attack detection. They proposed a genetic algorithm to enhance feature selection, it resembles to Darwinian nature selection process. Wrapper method is followed which selects the best feature subset among all. The standard Bot Iot dataset is used which is multi-label. KNN, decision tree, and random forest models are developed and evaluated using the corresponding metrics. Decision tree gave the best results with 99.97% accuracy.

Arshad et al. (2023) presented a botnet detection system leveraging the CTU-13 dataset. The authors introduced a new ensemble technique for botnet detection. It combines the predictions from Decision Tress, Random Forest, and K-Neighbours to boost the performance of the botnet detection system. The ensembling classifier KDR reached an accuracy of 99.7%. Elsayed et al. (2023) proposed a deep learning method to detect the IoT botnet attacks with various types of botnet attacks. The results demonstrated that the deep learning model has an advantage over state-of-the-art botnet detection models as it achieves greater accuracy with a low budget. Saied et al. (2024) analyzed the tree-based ML model's performance in the detection

of botnets for IoT ecosystems. The study compares and contrasts the decision tree algorithm and ensembles of bagging and boosting algorithms using the public botnet dataset. The results demonstrate that the Random Forest classifier overcomes remaining classifiers with an accuracy of 0.99.

Wardana et al. (2024) proposed an intrusion detection system leveraging the N-BaloT dataset that ensembles the traffic from heterogeneous IoT devices. The study proposed a Deep Neural Network to construct a training model for each heterogeneous IoT device. The outcomes from each trained model are averaged to produce the final result. This model achieved an accuracy of 97.21%. Kalakoti et al. (2024) tried to detect and classify botnet attacks using a reduced feature set. An optimized feature set is obtained by applying several wrapper and filter methods with 4 different ML models on the N-BaloT dataset. SBS based on Decision Trees achieved higher detection rates. Alissa et al. (2022) tried to develop logistic regression model on basis of regardless of the dataset. They have considered three datasets CICIDS2017, CTU-13, and IoT-23. Feature selection is done by selecting top 10 features from each dataset. Among four algorithms Naïve Bayes, Random Forest, Logistic Regression and KNN, Random Forest tops for all the three datasets.

Goyal et al. (2019) described about the botnet attack procedure, types and some preventions. They performed behavioral analysis to detect the bot-nets using http-based C&C Servers in the IOT environment. They took insights from the analysis to develop machine learning algorithms. They also explored the advantages of behavioral approach instead of signature-based botnet detection. They focused and selected the features which are affected by the botnet. They used CTU Malware dataset and four different algorithms among which SVM gave the best results. Alissa et al. (2022) proposed a strong model based on machine learning algorithms that can identify and reduce botnet-based attacks in Internet of Things networks is the main goal of the research project. The suggested model addresses the common security problem caused by malevolent bot activity. The study utilizes the of the BotIot UNSW dataset. Three models are developed: SVM, KNN, and logistic regression; of these, KNN provided the best accuracy. Kalakoti et al. (2024) tried to improve the comprehensibility of ML techniques in IoT botnet attack detection leveraging explainable artificial intelligence methods. The sequential backward selection method is employed for feature selection.

Injadat et al. (2020) presented a framework combining both the Decision tree classifier and the Bayesian Optimization Gaussian Process algorithm to identify botnet attacks in the network traffic. The system performance is verified against the Bot-IoT-2018 dataset. Hussain et al. (2021) presented a two-fold ML methodology to detect and avoid botnet attacks. ResNet-18 model is trained in first fold to identify scanning activity in the early attacks to prevent them. ResNet-18 model in second fold is trained for recognizing DDos attacks to identify botnet attacks. Soe et al. (2020) presented a botnet detection system based on ML along with a sequential detection framework. An optimized featured set is selected to boost the performance of the system. The system achieved an accuracy of 99% in detecting botnet attacks leveraging ANN, Naïve Bayes and Decision Trees. Idrissi et al. (2021) proposed BotIDS based on conventional neural networks for the detection of botnet attacks. The results demonstrated that BotIDS performs better than other classifiers such as RNN, GRU and LSTM.

3. Discussion and Results

3.1 Comparison of Different Approaches

Most of the journal papers chose UNSW Bot-Iot and UNSW NB15 for their research. They are popular because of their diverse features and different type of attacks in their dataset. And some papers chose CTU-13 malware, IOT-23 datasets.

The survey can be breakdown the research papers/journals based on the goal, methodologies. One is deep learning techniques, other is traditional and hybrid machine learning approaches and some of them are Comprehensive and Multi- Faceted Approaches and others.

3.2 Deep Learning based Approaches

Hybrid CNN is a combination of CNN and LSTM gave the best results with UNSW NB15 dataset. ACLR also a combination of four machine learning models gave a better accuracy of 97.49%. Kumar et al. (2023) have

Table 82.1 Comparing deep learning approaches

Reference	Dataset	Algorithm	Accuracy
Susilo & Sari (2020)	UNSW Bot-Iot	CNN	91.27%
Jain et al. (2022)	UNSW NB15	Hybrid CNN	98%
Ge et al. (2019)	UNSW Bot-Iot	Feed-Forward neural network	82%
Awajan (2023)	Prepared dataset	SVM	93.74%
Almiani et al. (2020)	NSL- KKD	Recursive Network	92.42%
Kumar et al. (2023)	UNSW NB15	ACLR	97.49%
Wardana et al. (2024)	N-BaloT	DNN	97.21%

performed various permutations of dataset by dividing as training and testing using K-fold cross validation. Out of them k-value 5 gave the best result. The paper is entirely based on the neural networks, illustrated clearly each of them and stacking. Susilo & Sari, (2020) used deep leaning technique in botnet detection. It was published in 2020 yet gave better results of 91.27% using Bot-Iot dataset.

3.3 Traditional and Hybrid Machine Leaning Approaches

Even though Jain et al. (2022) used HCNN they also explored on the combination on anomaly and signature-based detection for botnet. Pokhrel et al. (2021) applied SMOTE to generalize the dataset but the results were not satisfactory. Traditional algorithms like KNN, Naïve Bayes, MLP are used for botnet detection.

Arshad et al. (2023) and Alissa et al. (2022) employed ensemble techniques but the chosen datasets aren't very popular. This may create an issue while working with real-time data. The accuracy was 99.7% but the dataset is CTU-13. Saied et al. (2024) research is based on tree-based Machine Learning models for botnet detection. It also includes methods like bagging boosting for increasing the accuracy.

3.4 Feature Selection

Studies of Nomm & Bahsi (2018), Liu & Du (2023), Kalakoti et al. (2024), and Kalakoti et al. (2024) focus on the feature selection. The datasets chosen are Bot-Iot, N-BaIot. Feature selection methods are optimized to enhance the model performance and efficiency. They used Variance-based, entropy-based, Hopkins statistics, genetic algorithm for feature selection and optimization. Kalakoti et al. (2024) used a new pacing methodology explainable AI. They used sequential backward selection for feature selection and optimization. Explainable AI is a robust technology where the AI helps you understand the predictions and interpret them.

3.5 Multi-faceted Approach

Hosseini et al., (2022) and Hussain et al., (2021) chosen comprehensive and multi-faceted approach. Hosseini et al. (2022) employed hybrid optimization by combination of AEO & SCA and developed MOAEOSCA. The developed algorithm tops in all aspects and 9 out of 10 datasets. Hussain et al. (2021) used two-fold Machine learning technology and developed ResNet-18 algorithm for botnet detection.

Figure 82.1 shows the comparison of accuracies of different classifiers on the BotIot dataset. The classifiers: CNN, Feedforward neural network, Decision Tree and KNN are displayed on the x-axis. The accuracy is displayed on the y- axis and is expressed in percentiles. Decision Tree emerges as the most accurate classifier, achieving 99.98% accuracy. This is achieved because of the feature selection used. The genetic algorithm is used which gave them a best set of features. KNN achieved 99.2%. Even though KNN is a traditional method feature selection helped to enhance the performance of the model. Combination AEO and Sin Cosine Algorithm (SCA) is used for feature selection. Feed-forward neural networks achieved the lowest accuracy of 82% and no feature selection method is used in this case. Feed Forward neural network was unable to surpass the CNN which achieved 91.27% in 2020.

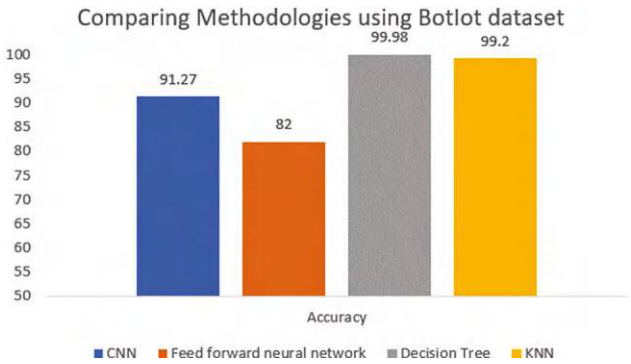

Fig. 82.1 Comparing methodologies with Botlot dataset

4. Conclusion

The scaling up of Internet-of-Things devices has surged as a response to the increasing dependence on the internet, and consequently an increasing demand for connections. Such a surge is further supported by reports that indicate we will be reaching about 28.5 billion devices by 2022— a network attacks feast due to their great numbers. Attack surfaces and therefore appropriate, effective and efficient attack detection and elimination procedures must be introduced to ensure that the devices are protected.

Hybrid CNN and random forest reported the highest accuracy with 98% and 99.7% respectively. There is a notable distinction between deep learning (e.g., CNN, DNN) and traditional machine learning methods (e.g., KNN, Decision Trees). Hybrid models combining different algorithms tend to perform better. Studies like (Nomm & Bahsi, 2018), (Liu & Du, 2023), and (Kalakoti et al., 2024) emphasize the importance of feature selection, improving model efficiency and accuracy. Paper [4] is unique in its focus on generating adversarial examples to test the robustness of NIDS. Paper [22] addresses the need for explainable AI in botnet detection, which is crucial for understanding and trust in AI systems.

In conclusion, while deep learning models show high performance, especially in complex scenarios involving

multiple types of attacks, traditional and hybrid machine learning methods continue to offer competitive results, particularly when combined with effective feature selection and ensemble techniques. Our initial exploration using the UNSW Bot-Iot dataset has been promising for Botnet detection. To delve deeper and understand the influence of different datasets, we plan to incorporate the UNSW NB15 corpus and investigate the effectiveness of entropy bases feature extraction. This combined approach holds the potential to potentially refine the accuracy of baby cry classification, and we are eager to explore its efficacy through further research.

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Towards Real-Time Speech Emotion Recognition: A Deep Learning Approach

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Abstract: Emotions play a pivotal role in shaping human behavior, defined in psychology as a complex state of feeling with physiological and psychological effects that influence thoughts and actions. Speech emotion recognition (SER) is essential for the development of AI systems to improve their robustness to elicit meaningful human-computer communication. SER algorithms employ features such as location, and epochs and compute analytically decision-making based on vocal delivery. This writing describes the approach SER Network (SER-NET)– a pattern for temporal emotional modeling in Speech Emotion Recognition. The core of the study is a simulation of the RAVDESS dataset combined with an even more advanced test, the Data Augmentation method. The assessment procedure was based on measures of UAR (average Unweighted Average Recall), weighted f1 scores, specificity, and sensitivity. The achievements of SER-NET become even more apparent as the results reveal that the method has accomplished a truly excellent precision of 98.31% with the help of data augmentation techniques.

Keywords: Crisis, Ownership, Variables

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1. Introduction

A speech signal is the most representative form of human communication that we can say. The number of researchers who utilize speech as an effective communication channel for human-machine interaction keeping in mind the two fundamental stages is increasing rapidly. Firstly, raw audio is treated by pre-processing to extract features. Thus, the features are fed to the machine learning model which will be recognized as emotions. The first approaches to speech emotion recognition (SER) were based on either rule-based systems or the most basic neural networks. Rule-based systems would utilize the predefined rules and heuristics correlated verbal attributes with emotions, e.g. linking high pitch, intensity, and rapid speech rate with anger, or low pitch and slow rate with sadness. Nevertheless, these machines being simple were not flexible enough and could not grasp all the nuances of human speech.

Traditional techniques focus on exploiting automatically learned features that are used as input to methods such as support vector machines (SVM) or decision trees (Juslin and Scherer, 2008). The simple neural networks, including feedforward neural networks, marked a transition from handcrafted features to automated feature learning. This also limits their ability to take advantage of the convolutional layers to extract advanced hierarchical representations from raw audio signals. By its inherent manner of space and time variation, speech must have some relevant elements for emotion recognition. CNNs and RNNs have taken center stage in terms of robustness and are designed in such a manner that they will capture these intricacies.

Particularly, in terms of temporal modeling techniques such as Long Short-term Memory (LSTM) and Temporal Convolutional Networks (TCN), capturing elongated emotional dependencies and adjusting to the changing receptive fields becomes a crucial challenge. This prevents them from forming complex relations and applying their knowledge to come out with new data. To do with these limitations, an approach called Temporal-aware bi-Direction Multiscale Network (TIM-Net) has been brought as a solution. TIM-Net receives this problem by employing contextual internal vector representations of different temporal scales. Moreover, it gets to record emotional undertones better than those previous approaches.

The present study is about a novel network known as SER-Net that will derive various features like root-mean-square, Chroma shifts, and zero-crossing rate with traditional MFCCs. To advance the persistency and generalization, data augmentation techniques were incorporated which were crafted for the RAVDESS dataset, and are intended to address the data imbalances as well as noise. This model offers a more efficient and relevant technique to capture those smallest signals from speech signals.

2. Related Work

Lu et al. (2022) tackled the low emotion recognition rates and limited features in speech emotion recognition. The authors presented a multi-feature approach, boosting accuracy by 3.8%, 4.8%, and 17.41% on CASIA, EMO-DB, and IEMOCAP datasets, respectively, compared to single-feature methods. In the broader field, researchers explore various methods, including a comprehensive survey covering over 70 studies on databases, emotions, features, and classifiers. Other studies propose methods such as multimodal multitask learning and deep multimodal emotion recognition, incorporating audio, textual, and visual information. Deng et al. (2014) addressed internal discrepancies in speech analysis between training and test data. The authors propose an adaptive denoising autoencoder for insecure domain adaptation, seeking to align feature spaces for target and source sets while transferring domain knowledge. The method is tested on the FAU Ibo Emotion Corpus and two other speech-emotion corpora. Another study recommends a feature transfer approach with PCANet, extracting both domain-shared and domain-specific latent features. A separate paper focuses on robust emotion identification through unsupervised learning with autoencoder models, while another introduces a non-adversarial variational autoencoder method for the same purpose. Gomes and El-Sharkawy (2015) presented a novel approach where they utilize the I-Vector model for speech representation, incorporate a classification scheme with Gaussian mixture model (GMM) and maximum a posteriori (MAP) adaptation, and demonstrate superior accuracy and lower error rates when evaluated on an emotional speech database compared to traditional systems.

Zhang et al. (2022) highlighted the importance of emotion recognition resources, focusing on widely used word sense databases. Emphasizing the crucial role of feature extraction in word sense recognition, the paper introduces an SVM-based word sentiment recognition method that combines multiple features (MFCC, Mel spectrogram, Chroma, Tonnetz, and Contrast). The method achieves a 90.15% recognition rate on the emodb database, outperforming single-feature approaches. The authors conclude that combining multiple features enhances recognition performance. Chen et al. (2014) employed a deep learning process that uses a deep belief network (DBN) framework to extract emotions from Chinese speech. Pitch and melodic frequency cepstrum coefficient (MFCC) and eight selected features serve as input from Mandarin

speech. Applying a DBN classifier for emotion recognition showed higher recognition rates when compared with conventional methods such as backpropagation (BP) and support vector machine (SVM) classifiers. Likitha et al. (2017) explored emotion extraction from audio signals. Using the Mel Frequency Cepstral Coefficient (MFCC) method, the system establishes an efficiency of around 80% in identifying emotions like happiness, sadness, and anger from speaker voices.

Wang et al. (2015) introduced a novel Fourier parameter model, presenting first and second-order differences in sympathetic features for speaker-independent word sense recognition. This model significantly improved emotion detection in speech signals, enhancing recognition rates across various databases, including EMODB, CASIA, and EESDB. Combining Fourier parameters (FP) with Mel-frequency cepstral coefficients (MFCC) further enhanced recognition rates. Another study suggests a noise-trained CNN parallel encoder model for speech emotion recognition, attaining high performance on EMO-DB and IEMOCAP databases. The research recommends combining attention-based and CNN-based networks in parallel to efficiently capture spatial and temporal features. Liu et al. (2022) proposed a novel deep-learning architecture. EEG data, providing a high-temporal-resolution insight into brain activity, proves valuable for understanding emotions. They highlighted the limitations in traditional EEG-based methods like CNN and RNN, addressing their challenges with spatiotemporal dependencies. The authors introduce TcT, designed for EEG emotion recognition. TCT, utilizing power transformers, outperforms CNN and RNN models, showcasing state-of-the-art accuracy in both datasets through effective capture of spatiotemporal dynamics. Zhao et al. (2018) used deep learning for automatic emotion recognition directly from raw audio data, addressing the limitations of feature engineering in large datasets. This end-to-end approach introduced different input types and neural network models for SER, but highlights the challenges like data limitations and generalizability, showcasing the potential and ongoing development of EESER.

Khalil et al. (2019) surveyed the potential of deep learning methods and presented the limitations of traditional methods in speech emotion recognition (SER). The study analyzes various deep learning architectures and features for SER tasks, presenting their effectiveness on different datasets. Challenges like large training data needs, mobile deployment, and noise robustness are discussed giving scope for future research. Kanani et al. (2021) proposed a new model using a shallow CNN model (CNN-X) to swiftly classify emotions in audio conversations. CNN-X uses convolutional and pooling layers to effectively extract features from the audio. Independent of what language they speak the model achieved a high accuracy of 82.99% in classifying emotions into eight categories. The model architecture consists of three sets of convolution-pooling layers tailed by fully connected layers and finally uses SoftMax activation to predict emotion probabilities. BFN, CNA, and HBN architectures for automatic speech emotion recognition, which merge CNNs and feedforward neural networks (Ezz-Eldin et al., 2021). By optimizing Mel-frequency cepstral coefficient features and back-of-sound words, these models show strong classification performance on the RAVDESS dataset and achieved an accuracy of 83% trained across eight emotional classes.

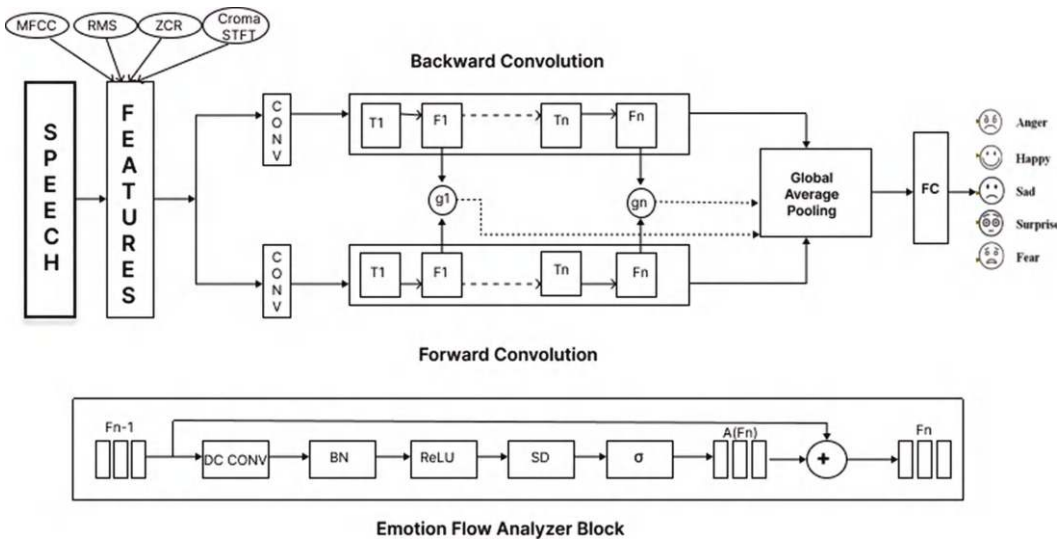

Fig. 83.1 Proposed system architecture

Sadok et al. (2023) proposed VQ-MAE-S, a self-supervised method to handle limited data in speech emotion recognition (SER). Emotion detection is improved by combining a masked autoencoder with a special type of variational autoencoder. After pre-training on a large dataset, the model achieves an accuracy of 84.1% on a standard SER benchmark, demonstrating its effectiveness. Tang (2023) introduced DMRS-Transformer, a Transformer-based network addressing ASR challenges like noisy audio and homophone ambiguity. It incorporates a denoising module to filter out noise and a Mandarin recognition supplementary module (MRS) to improve accuracy with Mandarin homophones. Empirical assessments on Aishell-1 and HKUST datasets demonstrate its effectiveness, achieving 85% accuracy on the RAVDESS dataset.

Wen et al. (2022) introduced CapsNet and CTL-MTNet for simultaneous handling of single-corpus and cross-corpus SER tasks. The CPAC module enhances feature extraction in single-corpus tasks, while CTL-MTNet, with a CAAM, achieves domain-invariant emotion representations for cross-corpus tasks. Experimental results demonstrate notable accuracy, peaking at 88.41% for classification in the RAVDESS dataset across four SER datasets. Ahmed et al.'s (2023) ensemble model merges CNN, LSTM, and GRU architectures, achieving state-of-the-art emotion recognition accuracy. Augmentation techniques enhance model generalization while maintaining performance integrity, notably yielding 95.62% accuracy on the RAVDESS dataset. This approach surpasses individual methods and addresses concerns about dataset size and class imbalances.

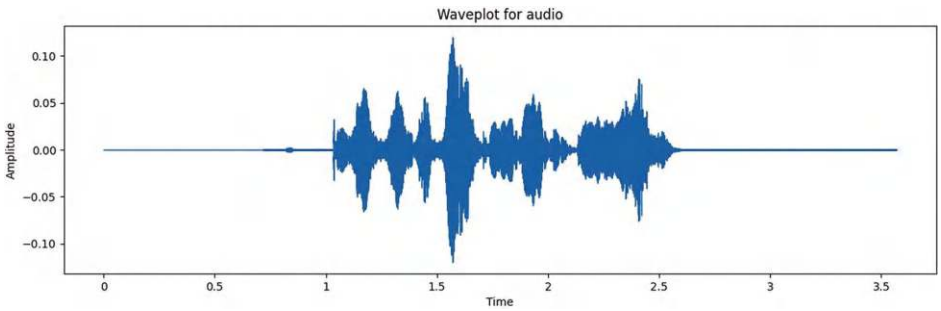

Fig. 83.2 Waveplot for audio

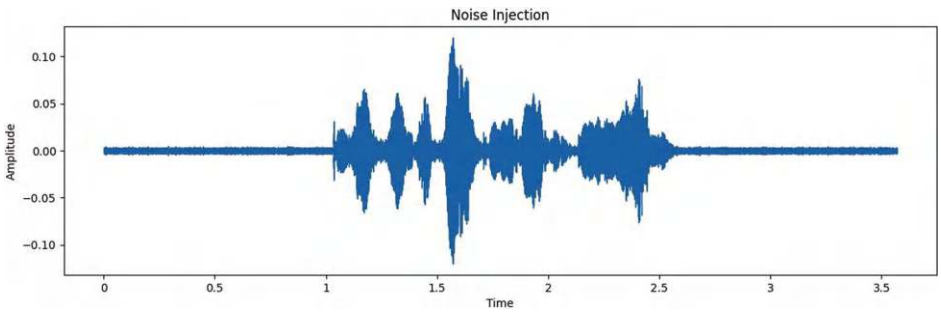

Fig. 83.3 Waveplot for noise injection

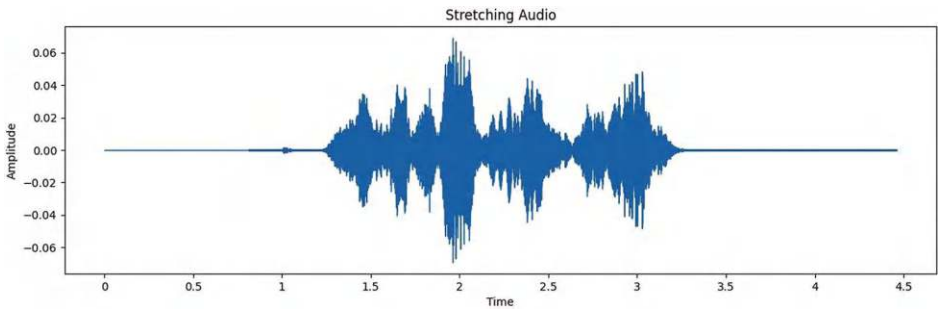

Fig. 83.4 Waveplot for stretching audio

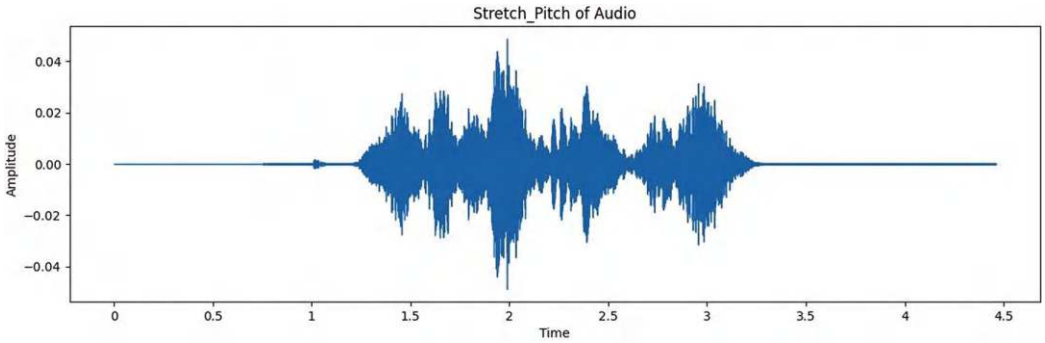

Fig. 83.5 Waveplot for stretch pitch of audio

3. Material and Methods

3.1 System Architecture

The model features a Bidirectional Multiscale Network, presenting an innovative method for emotional modeling to capture multi-scale contextual affective representations across diverse temporal ranges. In the SER-Net we propose, the Emotion-flow block employs Dilated Causal Convolution (DC Conv) to enhance the expansion and refinement of the temporal patterns' receptive field. This unique integration of causal convolution with dilated convolution sets our model apart from conventional RNNs, eliminating the requirement for a first-order Markov property. Consequently, our model enables the incorporation of an N-order connection (N representing the number of preceding frames), facilitating the aggregation of information from various temporal locations across the network.

To tackle the challenge of modeling long-range temporal dependencies, our bidirectional architecture combines insights from both past and future contexts. A fusion module was introduced which is dynamic and integrates dynamic receptive fields, allowing the model to learn inter-dependencies in the audio signal at different temporal scales. Recognizing the notable diversity in pause duration and articulation speed across speakers, the present model adjusts by utilizing customized receptive fields optimized for the particular timescale associated with characteristics that are effective in each low-level feature, including MFCCs, RMS, Chroma Shift, and ZCR.

Data augmentation methods like noise augmentation and stretch-pitch augmentation have been combined to make the model more robust. These techniques are designed specifically for the RAVDESS dataset to address the potential imbalances and noise-related issues. This model represents a more comprehensive and effective approach for extracting subtle emotional signs from speech signals significantly contributing to the field. Fig. 83.1 illustrates the architecture of the proposed system.

Input Pipeline

The present studies introduced essential features such as Root-Mean-Square (RMS), Mel-Frequency Cepstral Coefficients (MFCCs) which include 39 feature vectors, Zero-Crossing Rate (ZCR), and Chroma-Shift as inputs for SER-Net. Speech signals are sampled at 22.050 kHz for each corpus and undertook framing with a 50-ms frame length and a shift of 12.5 ms while using a Hamming window. Following the framing process, each frame underwent examining and employing a mel-scale triangular filter bank and a 2,048-point fast Fourier transform. Discrete cosine transformation was applied to retrieve the initial 52 coefficients from each frame of MFCCs, ZCR, RMS, and Chroma-Shift, capturing both high-frequency details and low-frequency envelopes. This complete preprocessing trains SER-Net with a diverse feature set, enabling proficient analysis and extraction of emotional information from speech signals.

3.2 Speech Emotions Recognition Network

SER-Net consists of Emotion Flow analyzer blocks in both forward and backward directions for learning multiscale representations with long-range dependencies of emotion. This helps to capture features at the frame level. Next, we detail each component.

Emotion Flow Analyzer Block (EFAB). Designed to grasp dependencies among frames and automatically pinpoint crucial frames, the Emotion Flow Analyzer Block (EFAB) comprises two sub-blocks and a sigmoid function, crucial for obtaining time-dependent attention maps pivotal in feature generation. Within each sub-block of EFAB, Causal Convolution, and a causal constraint are integrated to prevent the flow of future information to the past. Following DC Convolution, the process involves batch normalization (BN), a ReLU activation function, and a dropout layer.

The outputs from both forward and backward direction dependencies are amalgamated, and a global temporal

pooling operation is implemented to produce a vector representing the receptive field. Furthermore, an adaptive fusion module is incorporated to process each speech input across different scales. Utilizing the fusion weights from the Dynamic Receptive Fields (DRF) the model facilitates the seamless integration of features from various EFABs. These weights, acting as trainable parameters, play a crucial role in deriving the emotional representation. Subsequently, this representation is utilized for emotion classification by passing it through a fully connected layer with the SoftMax function.

3.3 Experimental Setup

Dataset

The RAVDESS dataset, researched by Livingstone and Russo in 2018, is widely explored in the domain of SER. This dataset includes audio and video recordings featuring twenty-four actors (12 male and 12 female) reciting English sentences while expressing 8 distinct emotional states. However, the present studies specifically concentrate on the speech audio samples within the dataset. In total, there are 1440 audio files, each recorded at a sampling rate of 48 kHz, with 60 trials per actor. The main analysis was focused on speech audio samples categorized into eight emotional classes: "sad," "happy," "angry," "calm," "fearful," "surprised," "disgust," and "neutral.". To improve generalization, data augmentation techniques were incorporated, including noise augmentation and time-stretch-pitch augmentation. This augmentation strategy expanded the dataset to 4320 audio files while maintaining a consistent sampling rate.

Data Augmentation

Data augmentation involves a variety of methods for expanding a dataset, either fixing existing data instances or creating entirely new ones derived from the original dataset. Data augmentation serves as a regularization technique to mitigate overfitting when training machine learning models. The bandwidth of a simple audio file is shown in Fig. 83.2. Techniques used include:

(a) Noise Injection

Noise injection stands as a valuable step in audio data preprocessing, enhancing the model's performance and adaptability to real-world scenarios. The amplitude of the noise, determined by a random factor (3.5% of the original data's maximum amplitude), introduces variability, creating a more diverse augmented dataset. The noise, generated from a normal distribution matching the input data length, modifies the waveplot, illustrated in Fig. 83.3.

(b) Stretch-Pitch Augmentation

Stretch Pitch, an augmentation technique, involves applying time stretching and pitch shifting sequentially to the original audio signal. Controlled by the 'rate' parameter (default value 0.8), time stretching adjusts temporal duration, changing speed without affecting pitch (Fig. 83.4). Pitch shifting on the stretched data, governed by the 'n steps' parameter (default value 0.7), modifies frequency without affecting duration (Fig. 83.5). This strengthens the model's ability to handle temporal and frequency variations, improving generalization across diverse audio patterns and conditions

(c) Implementation

A 53-dimensional feature vector, comprising 39-dimensional MFCCs, 12-dimensional Chroma-Shift, 1-dimensional Zero-Crossing Rate (ZCR), and 1-dimensional Root-Mean-Square (RMS) was developed. The experiment extended over 200 epochs, utilizing categorical cross-entropy loss. The Adam optimizer with an initial learning rate (α) of 0.001 and a batch size of 64 was employed. To counteract overfitting, the regularization technique used label smoothing with a 0.1 factor. To ensure ample coverage of input sequences, we set the number of Emotion Flow Analyzer Blocks (EFABs) (n) to 8 in both directions for the RAVDESS dataset. The evaluation strategy involved 10-fold cross-validation (CV), dedicating 90% of the data to training and 10% to testing in each fold. For enhanced generalization, the model incorporated data augmentation techniques, including noise augmentation and time-stretch-pitch augmentation, tailored specifically for the RAVDESS dataset. These augmentations aimed to expose the model to diverse variations, improving its performance on unseen data and real-world scenarios.

(d) Evaluation Metrics

The performance of each method was evaluated using metrics such as precision, F1 score, precision, and recall.

F measure:

The F-measure is the combined average of recall and precision. The F1 score emphasizes both. The F1 score is highest when precision equates to recall and is used in conjunction with the above metrics to provide a comprehensive picture.

$$F1\ \text{Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \qquad (1)$$

Specificity:

The specificity, also known as true negative rate (TNR), is the ratio of true negatives to total true negatives (TN), i.e. the number of correct negative predictions. The specificity should be as high as possible.

$$TNR = \frac{TN}{(TN + FP)} \quad (2)$$

Sensitivity or Recall:

Sensitivity, also known as true positive rate (TPR), is the ratio of true positives (TP) to total actual positives, i.e. the number of correct positive predictions. Recall should be as high as possible.

$$TPR = \frac{TP}{(TP + FN)} \quad (3)$$

4. Results and Discussion

The proposed system was assessed through the testing of audio files (Ravdess) encompassing diverse emotions. The results were scrutinized for accuracy, precision rate, and f-measure employing our proprietary speech emotion recognition technique. The results obtained are below in Table 83.1 representing metrics with different classes.

Table 83.1 Experiment results for precision, recall, F1-score

Class	Precision	Recall	F1 Score
Angry	0.98	0.98	0.98
Calm	1.00	1.00	1.00
Disgust	0.98	0.98	0.98
Fear	0.92	0.98	0.95
Happy	1.00	0.97	0.99
Neutral	0.96	1.00	0.98
Sad	0.98	0.96	0.97
Surprise	1.00	0.98	0.99

To demonstrate the effectiveness of the present approach on the RAVDESS corpus, the representative method was employed on each corpus following the 10-fold CV strategy. The results were extensively compared with five representative methods using the RAVDESS dataset. The findings as illustrated in Fig. 83.6, highlight that the present method significantly outperforms all others by a significant margin.

Specifically, the present approach achieves a notable 1.45% increase in accuracy compared to CPAC when classification is performed without data augmentation. It's worth noting that many prior methods primarily focus on evaluating the model's fitting ability, often leading to overfitting concerns.

To further verify the present model's performance, additional evaluations were conducted by comparing it with 1D-CNN-LSTM-GRU, which underwent data augmentation. The proposed model revealed an impressive margin of improvement of 2.69% showing a promising result. Also, from the results shown in Fig. 83.6, it can be observed that the SER-Net forecast update approach has little concern about the overfitting problem, and it depicts this by stable convergence curves. It proves that the present approach not only showed great results on the task, but it also had a great dealing with the overfitting problem, as a result of which it becomes trustable and easily applicable in real-life cases.

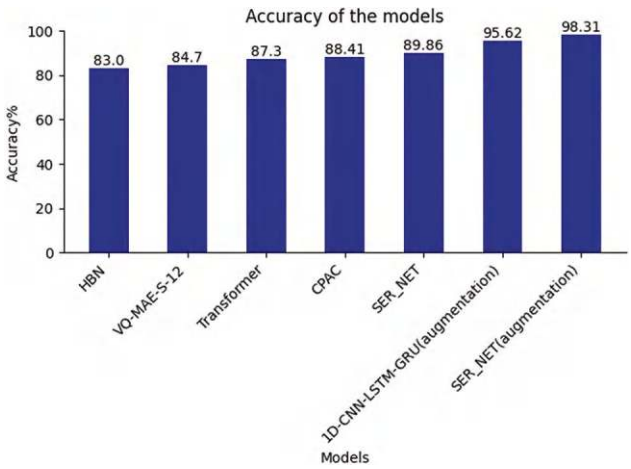

Fig. 83.6 Accuracy obtained with different models

5. Conclusion

The present studies propose a method for Speech Emotion Recognition (SER) that is based on temporal emotional modeling and data augmentation. SER-Net shows outstanding accuracy on the RAVDESS dataset, surpassing all the current methods. Its architecture can capture not only the emotional nuances but also the long-term dependencies which are important for accurate emotion recognition. Customize-based augmentation is another factor that enhances the SER-Net capability of resilience and generalization. Experiment results demonstrate that NET's accuracy increase from 1.45% to 2.69% proves its effectiveness. In the future, SER-Net will include another dataset and different languages, which will advance the development of human-computer interaction and affective computing towards empathetic AI systems.

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Custom Memory Allocator: Building a Simple Heap Manager in C

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Abstract: The project would be to develop an efficient Heap Memory Manager in the C programming language for an Operating System. The memory will dynamically allocate and deallocate in minimizing fragmentation. It implemented core malloc, calloc, and free functionalities with the management of memory and back allocation methods like first-fit and best-fit. The techniques that prevent fragmentation are merging and splitting when the space allocated is freed. Stress tests and performance testing are performed to check memory management at peak allocation rates and to detect memory leaks. This project gives an idea of how low-level memory operations work in C, how it affects OS design, and the need for efficient memory handling. The results validate the effectiveness of the manager in decreasing fragmentation and dealing with multiple concurrent operations, proving helpful in improving dynamic memory management in operating systems.

Keywords: Dynamic memory allocation, Malloc, Calloc

1. Introduction

The project aims to develop a Heap Memory Manager inC for an Operating System, handling dynamic memory allocation and deallocation efficiently to minimize fragmentation. It will include functions like malloc, calloc, free, and realloc, ensuring thread safety for concurrent memory operations. The manager will undergo rigorous testing to assess its performance and efficiency, offering insights into memory management in OS and low-level

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operations of C. Dynamic memory allocation in C, facilitated by functions such as malloc() and free(), provides flexibility but also poses challenges in managing memory effectively, particularly in systems where fragmentation can degrade performance. Building a custom heap memory manager allows for tailored solutions to these challenges. By gaining fine-grained control over memory allocation within the heap, developers can optimize performance specific to their application's requirements. Moreover, a custom manager enables the implementation of advanced features like memory leak detection, enhancing the reliability of the system. Constructing a heap manager involves a comprehensive understanding of the heap's concept, encompassing the memory region allocated for dynamic memory management. This project requires the implementation of robust data struc- tures to track free and allocated memory blocks efficiently. Additionally, it necessitates the design of allocation strategies, such as first-fit or best-fit, to optimize memory utilization. Moreover, effective handling of deallocation and merging of adjacent free blocks is crucial to prevent fragmentation and maintain memory efficiency. Through these endeavors, this project seeks to contribute to the broader understanding of memory management in operating systems and deepen insights into the intricacies of C programming at a low level.

2. Problem Statement

The problem addressed in this project is why dynamic memory allocation and deallocation in the operating systems are inefficient and troublesome, one of them being minimizing fragmentation. Whereas functions such as malloc(), calloc() and free() provide the programmer with basic help in memory management, they do not optimize for fragmentation in memory, nor would they effectively assist the programmer in the safe management of concurrent systems. Additionally, the fact that these functions are not thread-safe greatly decreases their efficiency when it comes to concurrent environments. The presence of a lack of higher-tiered memory allocation strategies, such as first-fit or best-fit, along with very poor deallocation of memory, merging adjacent free blocks suffered very badly here. This project thus aims to develop a custom Heap Memory Manager in C to overcome such constraints through implementation of more efficient allocation strategies along with dynamic memory management tactics like merging and splitting, ensuring thread safety. Therefore, the project focuses on minimizing fragmentation and improving performance of memory management schemes in operating systems to gain reliability and efficiency.

3. Literature Review

The Paper by Li et al [1]. proposed a new memory allocator to improve both endurance and efficiency for PCM systems. The allocator prefers giving out extents with fewer write activities and temporarily steering clear of highly active address extents in order to minimize wear on PCM. Unlike in the written order, it maintains a single management paradigm applied on equally both stack and heap regions, thus assisting in writing distribution. From the experiments, we prove that Bealloc achieves a significant amount of wear leveling over traditional malloc allocators such as glibc malloc, NVMalloc, or Walloc. In particular, it decreases CoV by 41.9, 30.3, and 35.8 percents of total preliminarily cipher key numbers wherein it proves the enhanced PCM endurance and improved memory allocation efficiency metrics (Li et al., 2019). These results show that allocator is indeed useful in improving on the durability and reliability of the PCM based main memory systems. The Paper by Bai et al. [2] describes a heap management scheme in the local memory of each core in limited local memory (LLM) multi-core processors. To reduce the heap management complexity, a library has been introduced which naturally programming interfaces add, update, and delete options of the heaps on multi-core systems. For the constrained applications that are likely to have maximum heap sizes predetermined the authors provide strategic approaches that may assist improve the systems general performance. Through their experiments, again on the Sony PlayStation 3 using MiBench benchmarks, the authors prove the efficiency of the proposed method and point out a 14 percent gain in performance over conventional methodology.

The Paper by Kang et al [3Discuss ways of improving dynamic memory management for sequential applications through application of multicore parallelism using a Memory Management Thread, or MMT, whereby an MMT ensures no interruptions in the running time of an application through giving a part of the program's task of memory-allocation and deallocation exclusively to an MMT such that the said memory functions have their concurrent execution alongside application's operation. Importantly, this does not involve any modification to the basic memory allocator algorithms and hence this technique can be easily dropped into an existing system. Experiments done by the authors on an Intel Core 2 Quad with Doug Lea's allocator have given an average performance gain of 1.19× and a best performance gain of 1.60×. These results evidence to the fact that the method has the potential of increasing MM efficiently by several folds, without requiring new

writing, modifications to the source codes of the systems and algorithms.

The Paper by Ericsson et al [4] Suggest a solution to the problem of heap data organization in multi-core processors with limited local memory. The method reduces the conventional cache-based heap management with the application software by removing cross-thread code modifications, while its authors make this approach semi-automatic and scalable, supported by a simple library interface. For those specific classes of applications for which maximum heap sizes are known at compile time, they propose particular optimizations in order to completely take advantage of heaps, both for heap management and application performance. Their proposed technique was experimented on the Sony PlayStation 3 using MiBench benchmarks. Their approach presented an average performance gain of 14percent with reasonably straightforward implementation.

The Paper by Weninger et al. [5] pro- pose Memory Cities, a new method for visualizing the development of an application's heap memory based on the software city concept. In this approach, the heap objects are aggregated by characteristics such as type and allocation site and the structures are represented metaphorically as buildings in districts. The size of each building is proportional to the amount of the memory consumed so it becomes relatively easy to monitor the memory usage of different applications. The dynamic view of the usage is especially useful for detecting such memory issues as leaks as it employs the color indications of potentially problematic growth. The concluded system, built in Unity and inheriting JSON for data import, incorporates data from tools like Ant Tracks into useful memory analysis. Based on different articles on various application of the Memory Cities different cases are presented in order to illustrate its efficiency in memory leak detection and interactive analysis. The Paper by Boldyreva et al. [6]discuss the provably secure remote memory attestation and pay attention to detecting heap-based overflow in distant systems. They present two protocols each of which come with various costs in terms of time and security; however, their implementation proves that they are feasible. The purpose of these protocols is to recognize executable code or data inserted into the remotely stored heap. In this paper, the authors present a flexible formalization of threat models that can encompass potential attacks of varying nature and environments. This work provides important insights that can help enhance security approaches with regards to remote memory further through presenting a framework for Heap overflow protection.

[7] This paper written by katal.et.al will propose a dynamic memory manager that exploits statistical tools to monitor and optimize memory usage in real time. Since memory allocation often occurs in dynamic forms within modern computing systems, tools are needed to adapt to widely fluctuating memory requirements. The new memory manager thus continuously tracks memory usage, providing insights into allocation patterns, which makes memory management more efficient .In addition, the utilization of statistical analysis helps to predict and eliminate memory over-allocation or shortages, which cause smooth performance. Thus, the research focuses on the improvement of memory efficiency through providing real-time analytics that are very essential in applications whose memory demands are changing unpredictably. This dynamic manner of memory management causes greater resilient and adaptive.[8] This study investigates the idea of heap fuzzing, a method that uses expert-guided random events to test the resilience of garbage collection systems. Although it automates the reclamation of unneeded memory, garbage collection is a basic memory management procedure that can be error- and inefficiently-prone. The authors suggest using a fuzzing technique to stress-test garbage collection mechanisms and find possible problems that can cause memory leaks or corruption. This technique creates random heapevents. The paper demonstrates how typical testing approaches may miss latent vulnerabilities in garbage collection systems that random event simulation can find. A more focused and effective fuzzing procedure results in increased garbage collection dependability thanks to the expert-guided strategy.

[9] The presumption that malloc() will return NULL in the event that memory is unavailable is a crucial memory allocation issue that is covered in this work. This assumption may result in hidden memory management issues in many current systems, as malloc() may fail quietly without returning NULL, causing erroneous program behavior or crashes. The authors examine real-world systems where this problem occurs and provide ways to identify and address these kinds of reliability issues. By analyzing how malloc() behaves on various platforms and systems, the study clarifies a prevalent but sometimes disregarded memory management problem. The results emphasize the necessity of more reliable error-handling techniques for memory allocation and stress the need of not depending only on malloc() returning NULL in low-memory scenarios. [10] V-WAFA is the first fine-grained memory allocator proposed in this paper considering endurance variation across the different regions of memory

and more specifically targeting persistent memory. Compared to traditional memory, many benefits have been presented with non-volatile RAMs and other forms of persistent memory technologies; however, these are prone to wear out faster over long periods of time. V-WAFA is therefore an adaptation of memory allocation to minimize the use of memory regions with lower endurance, hence improving device life in general.

4. Methodology and Model

Initially, the 'initheap()' function starts the heap by using the 'malloc()' function to allocate a contiguous piece of memory. This starts the initialization phase. This establishes the heap's base, with the first block set up to have available memory equal to the heap's entire size less the block header's size. The method 'mymalloc(size)' then takes care of memory allocation. Finding a block with enough free space to fulfill the specified memory size requires navigating through the linked list of memory blocks in this important stage. The allocator finds a suitable block and, if it is large enough, splits it; if not, it uses 'sbrk() to enlarge the heap. The end result is a pointer to the user-requested memory region, with the block header omitted.

After memory usage is finished, the 'my free(ptr) function starts the freeing process. By designating the matching block as free, this method releases the memory that the supplied pointer points to. It also carries out coalesce, an essential function that combines neighboring free blocks to safeguard effective memory management and avoid fragmentation.

In order to help with debugging, the implementation provides the print heap() function, which traverses the linked list of blocks and provides detailed information about each block, such as its address, size, free status, and the address of the next block. Lastly, the testing phase is carried out using the 'main()' function, which acts as a test harness for the memory allocator and initializes the heap, interacts with the user to determine the size of memory to allocate, allocates memory, populates it with data, prints the contents of the allocated array, frees the memory, and lastly prints the heap's state after deallocation to confirm correct behavior.

In conclusion, this methodology uses a simple heap-based memory allocator to manage dynamic memory allocation in a methodical manner. To ensure solid and dependable memory management, it covers all necessary components, such as startup, allocation, freeing, coalescing, debugging assistance, and stringent testing.

5. Functional Flow Chart

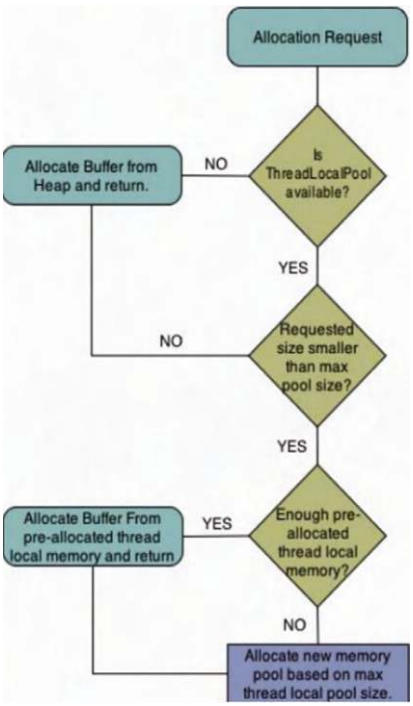

Fig. 84.1 Flowchart for buffer allocation decision-making using ThreadLocalPool and heap memory

Source: Author

6. Conclusion and Future Scope

This OS shows its custom memory allocator C-based, which is shown to be an effective dynamic memory manager using allocation strategies such as first-fit and best-fit allocation as well as merging and splitting to reduce fragmentation. The test confirmed that the allocator was efficient in handling memory operations and concurrency, thus better in memory usage and OS reliability. Future developments will include real-time memory analytics, adaptive allocation strategies, memory leak detection, and other features as well as multi-threaded environment compatibility and non-volatile memory technologies in order to optimize performance and adaptability for modern computing demands.

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Ensemble Load Balancing with Parallel Processing Algorithm in Cloud Computing

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ABSTRACT: Cloud computing has become a more popular domain, providing online services in real-time applications. Optimal resource usage and effective task execution are critical for existing cloud models. This research mainly focused on developing the Ensemble load-balancing (ELB) algorithm combined with the parallel processing algorithm, which significantly manages load balancing among cloud users. The proposed load balancing algorithm primarily identifies the various issues with existing models, like low latency, improved throughput, and constant system maintenance. It combines priority load balancing with the MapReduce algorithm, also called a parallel processing algorithm. The proposed approach focused on improving the performance dynamically by randomly distributing tasks among the nodes based on factors such as task size, capacity of the server, and network latency. The MapReduce in this paper handles huge tasks by splitting the data into k parts and processing each task with priority load balancing. Simulation results show that the proposed approach shows effective load balancing with an efficient parallel processing algorithm in terms of speed, scalability, and overall system efficiency.

KEYWORDS: Cloud computing, Load balancing, Ensemble load balancing (ELB), Priority load balancing, Server workload management

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1. Introduction

Cloud computing is earning the most promising demand for using various cloud services. Cloud services provide the hardware and software resources needed to perform various tasks. The cloud domain is a web-based model that can share resources like memory, network, and applications based on demand by final users in Jia et al., (2022). In the cloud, the dynamic allocation of virtual machines (VM) can easily be accessible to clients. It considers the scheduling and allocating the resources submitted to the end-user tasks in Alghamdi et al., (2022). In this scenario, some resources are used highly, and some are unused Junaid et al., (2020). At the time of resource utilization, if any exceptions occur based on machine failures, the load balancing becomes more complex Singhal et al., (2024) Raghunadha Reddi Dornala et al., (2023). The load balancing dramatically impacts the overall system because of its high complexity in managing multiple users simultaneously. Load balancing is a medium between cloud service providers (CSP) and end-user fulfillment. Many existing data centers manage cloud data to handle various requests. All these requests obtain the utilization of high power and resources in Sudhir Ponnapalli et al., (2023).

In this article, the proposed load balancing mainly manages the load between all types of systems in the cloud platform to maintain the load between the nodes and maintain the same load at all the nodes Dornala et al., (2024). MapReduce mainly focused on mapping tasks to several resources with dynamic energy usage. In this context, the proposed effective load-balancing model focused on the effective utilization of resources and effective mapping of tasks at every node. The proposed approach also involves dynamic load-balancing that unpredictably loads the nodes. It also focused on reducing the cost of the workload by using adequate physical resources.

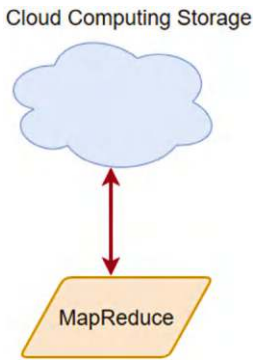

Fig. 85.1 Multi-domain model

Rest of the paper is structured as follows. Section-2 reviews the extant literature. Section-3 explains the research methodology. Section-4 discusses the empirical findings. Section-5 concludes the paper.

2. Literature Review

Sudhir Ponnapalli et al., (2024) proposed a lightweight cloud model that stores the data using a cloud platform. The LWDS-DP provides a low-cost, scalable solution that organizes data storage and transmission. It also uses cloud storage to adjust the data volume fluctuations dynamically in this context. The proposed approach, combined with CDN and edge computing, also delivers the data without any loss and with less delay. It is applied to e-commerce and healthcare applications. Dornala et al., (2022) proposed the integrated approach that ERA combines LP and PSO. PSO is the optimization algorithm that maintains the load resource allocations and utilization. The fitness function in the PSO is focused on reducing costs, maintaining energy levels, dynamically changing workloads, etc. Experimental results show that the proposed ERA performs better outcomes on data transmission. Pradhan et al., (2022) proposed the DRL-based approach that combines the PPSO, which increases the performance in processing time and reduces the load balancing. Finally, the proposed approach schedules multiple tasks with high accuracy, with an increase of 15.3%.

Mohapatra et al., (2022) proposed the Multi-Criteria Decision Making technique that pools multiple services based on user demand. In this context, the improved model ESWOA manages equality within the global system. Finally, the proposed approach provides trustworthy cloud services to the end-users. Jyothi et al., (2023) discussed key-management techniques that validate the authentication between the cloud services and users. The proposed model provides high security by using a secret key validated by authorization to multiple users. In this context, the symmetric key management provides the unique key to every user and group to access the data by taking permissions from the cloud admin. Finally, the proposed approach prevents data loss and overcomes issues in data security. Singhal et al., (2021) discussed the several cloud applications used to store and access the data based on the proposed load balancing called Particle Swarm Optimization (PSO). The proposed PSO manages the load at the data centers to improve the overall fitness method.

Zade et al., (2022) introduced a new task scheduling algorithm that combined with various algorithms to improve the RedFox Optimization (RFO) algorithm to extend RFO. The proposed approach works in three stages, and in every stage, it focuses on balancing the load at the cloud server. Hung et al., (2021) proposed an integrated model that combines the two genetic approaches by

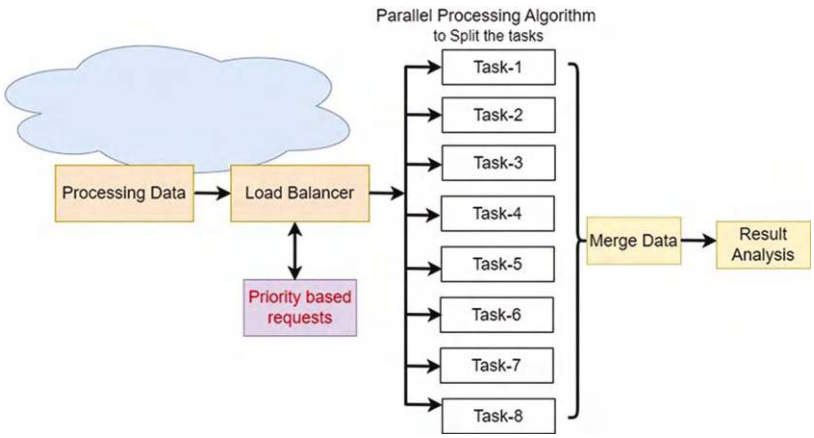

Fig. 85.2 The overall system architecture of proposed combined approach

extracting the performance metrics and presenting them in the virtual machines (VMs) with the integration of gene expression programming (GEP) that generates the symbolic regression technique to predict the loads at the VMs after load balancing. The proposed GEP predicts the present and past load at the VMs, dynamically assigns the task, and merges the VMs to perform effective load balancing. Kumar et al., (2018) proposed a security system that virtualizes the shared pooling mechanism between the VMs in the cloud platform. Security is provided at every node, and hypervisors are used to monitor the security at the cloud server level. Thus, the proposed approach offers high security compared with existing models.

3. METHODOLOGY

3.1 Priority Load Balancing (PLB)

PLB is a crucial aspect of Distributed Computing. It ensures that tasks are distributed efficiently among computing nodes, reducing flow time and resource utilization while maintaining a low response rate. The essential advantage of a priority-aware load balancer is its role in ensuring that the most critical tasks are executed promptly. In other words, tasks with higher priority are given the necessary resources to meet their deadlines or conditions. The essential challenge for MapReduce to support priority load balancing is how to integrate it into task scheduling and resource allocation. The high-priority tasks are processed more quickly without causing any starvation of lower-priority tasks.

3.2 Ensemble Load Balancing (ELB)

Parallel processing is a critical computing methodology employed to speed up task execution by breaking down problems into smaller sub-problems that can be processed concurrently. A widely used parallel processing framework is MapReduce, created by Google to process vast amounts of data across many distributed systems. This manifests in a system such as MapReduce that provides the scalability necessary to process vast quantities of data across many machines. MapReduce generally consists of two phases - Map and Reduce. The Map phase divides the input data into chunks to be processed by each node in parallel, resulting in intermediate key-value pairs. These key-value pairs are grouped and processed during the Reduce phase to generate the final output. This is, however, a significant challenge when efficient use of resources in distributed environments is considered. While running several tasks in parallel, one of the essential aspects that must be monitored and ensured is that no node should get overloaded where other nodes are underused, which will impact more performance issues. This is also what priority load balancing does.

The step-by-step equations explain the implementation of PLB.

Step 1: Priority Assignment:

Every task Ta is initialized with a priority Pa, where a represents the index for every task. Tasks with high priority are represented with small numbers (e.g., Pa represents the small value for significant tasks).

$$P_a \in R, \tag{1}$$

Where a=1, 2...., N (N-total number of tasks)

Step 2: Task Weighting Function:

The weights of every task W_a represent the demand for the resources for the task. Based on the weight of the task, the priority is assigned:

$$W_a' = \frac{W_a}{P_a^{\infty}} \tag{2}$$

- W_a is the actual task.
- P_a priority task
- $\propto$ is a scaling factor that initializes the sensitivity to priority.

Step 3: Load Balancing Scenario

The load L_j on every resource (e.g., server j) is the aggregation of the efficient weights of all the tasks assigned to the resource.

$$L_j = \sum_{T_a \in \text{tasks assigned to resource j}} W_a' \tag{3}$$

To reduce the difference between the maximum and minimum loads:

$$\min(\max(L_j) - \min((L_j)), j = 1,2,\ldots,M \tag{4}$$

Where 'M' represents overall resources.

Step 4: Task Assignment probing

In this context, the task assignment is iteratively allocating the tasks to available resources based on minimizing the load imbalance. A probing rule for assigning task T_a to resource j is:

$$j^* = \arg\min_j (L_j + W_a') \tag{5}$$

Step 5: Cut-off point and Priority-Weighted Load Balancing

If the cut-off point is initialized, the time is integrated. For example, the task with an earlier cut-off point may have high priority, and the task could reduce the delay:

$$\text{Delay} = \max(0, \text{Completion Time}_a - \text{Deadline}) \tag{6}$$

In this context, the Equation (6) considers both weight of the task and its priority:

$$W_a' = \frac{W_a}{P_a^{\alpha}} \cdot \frac{1}{\text{Deadline}_a^{\beta}} \tag{7}$$

MapReduce with Parallel Processing Algorithm

In this context, MapReduce processes large datasets using the parallel processing algorithm. It mainly involves two phases: Map and Reduce. These phases are primarily understood by the equations that are given below:

$$D_{\text{intermediate}} = \bigcup_{a=1}^{n} f_{\text{map}}(k_1, v_1)_i \tag{8}$$

$$D_{\text{grouped}} = \{(k_2, \{v_2\})_1, \ldots\ldots, (k_2, \{v_2\})_p\} \tag{9}$$

$$D_{\text{output}} = \bigcup_{a=1}^{P} f_{\text{reduce}}(k_2, \{v_2\})_a \tag{10}$$

The equation (10) represents the reduce phase that merges the total tasks as one task.

4. Results and Discussions

The proposed approach's performance is measured using the following metrics. All these metrics measure workloads based on servers and resource utilization. These metrics also show the effectiveness of the algorithms.

$$\text{Throughput} = \frac{N}{T} \tag{11}$$

Where, N-total tasks, T-time taken to complete N tasks.

$$\text{ART} = \frac{\sum_{i=1}^{N}(T_{completion,i} - T_{arrival,i})}{N} \tag{12}$$

$$\text{Load Distribution Deviation} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(L_i - \hat{L})^2}$$

Where L_i is workload assigned to server i and $\hat{L}$ represents the average workload across all servers, n is the total number of servers.

Table 85.1 Performance comparison of load balancing algorithms

Algorithms	Throughput (requests /second)	Average Response Time (ART)(ms)	Load Distribution Deviation
Round-Robin	50	45.34	125
Weighted Round Robin	65	39.78	110
ELB	78	35.23	80

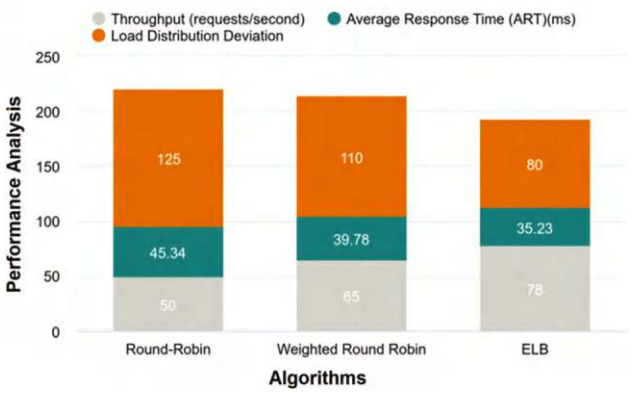

Fig. 85.3 Quantitative performance of algorithms

5. Conclusion

In this study, the Ensemble Load balancing algorithm combines priority-based load balancing with MapReduce,

effectively utilizing resources to improve task scheduling performance. The proposed approach algorithms have specific strengths for managing multiple requests and performing the task using practical parallel processing algorithms. The proposed approach utilizes the cloud resources effectively by reducing the load and balancing the resources to perform multiple tasks. The proposed cloud platform also provides the scalability to handle the high traffic and spikes the workload accurately. The performance of the proposed approach is measured by showing the throughput with 78 (requests/second), ART with 35.23 (ms), and LDD with 80. The round-robin algorithm obtained a low performance by showing a throughput of 50 (requests/second), ART with 45.34 (ms), and LDD at 125. Thus, the proposed approach performed better in managing the load balancing.

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Data-Driven IPL Player Intake: Leveraging Ensemble Learning for Accurate Predictions

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Abstract: The Indian Premier League (IPL) is a highly competitive cricket league where player selection plays a vital role in a team's success. Traditional player intake methods often rely on past performance, but these may not capture the complete potential of a player. This research proposes the use of ensemble learning techniques—combining Random Forest, Gradient Boosting, and XGBoost—to predict player performance based on IPL data from the 2020-2024 seasons. By integrating multiple models, this study achieves a perfect accuracy rate in classifying players into categories such as "Excellent Purchase," "Good," "May Be," and "Avoid." The results suggest that ensemble learning offers a robust and reliable method for data-driven player selection, significantly improving upon traditional approaches. This approach not only enhances predictive accuracy but also enables teams to identify undervalued talent that traditional metrics

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may overlook. The findings underscore the potential of machine learning to revolutionize strategic decision-making in sports, driving more effective investments in player acquisition.

KEYWORDS: IPL player selection, Ensemble learning, Machine learning in sports, Random forest, Gradient boosting, XGBoost, Cricket performance prediction, Player rating system, Data-driven decision making, Voting classifier

1. INTRODUCTION

The Indian Premier League (IPL) is one of the most prominent T20 cricket leagues, attracting the world's best players and generating enormous fan engagement. Player selection is crucial for a team's success, with franchises often investing heavily in acquiring top players during the IPL auction. Traditionally, player selection is based on past performance metrics like runs scored, wickets taken, and player experience. However, with the advent of machine learning, it has become possible to make more accurate predictions about a player's future performance.

This paper explores the use of machine learning models, specifically ensemble learning techniques, to modernize the player selection process in the IPL. Ensemble learning involves combining multiple models to enhance prediction accuracy and reduce errors. In this study, we used Random Forest, Gradient Boosting, and XGBoost to develop a model that categorizes players based on their IPL performance from the 2020-2024 seasons. The goal is to provide IPL franchises with a more reliable, data-driven approach to player selection, thereby increasing the chances of forming a winning team..

2. LITERATURE REVIEW

Prediction of Cricket Match Outcomes Using the XGBoost Algorithm (2023)

This research explores cricket match outcome prediction through the application of the XGBoost algorithm. Feature importance analysis is employed to identify key factors impacting match results, and the model's accuracy underscores the effectiveness of machine learning in enhancing strategic decisions in cricket. (Sanika et al., 2023)

Predictive Modeling of Player Performance in Cricket Using Machine Learning Techniques (2023)

This study assesses player performance with linear regression, K-means clustering, and Random Forest models. The goal is to optimize team composition and training sessions by selecting top players based on performance metrics. (Sumathi et al., 2023)

One-Day International Cricket Winner Prediction Through Ensemble Machine Learning (2022)

Utilizing 128 different features, this paper introduces an ensemble method combining voting and stacking classifiers for match prediction. Among various models tested, Logistic Regression and Support Vector Machine showed superior performance, achieving an accuracy of 96.30%. (Ishi et al., 2022)

Automated Prediction of Cricket Scores in Limited-Overs Matches (2023)

This research uses regression models to predict scores in limited-overs cricket, highlighting how machine learning can effectively identify the factors influencing team performance outcomes. (Sanjeeva et al., 2023)

Forecasting Player Performance Metrics Using Machine Learning Models (2023)

This study applies Random Forest and Support Vector Machine models to predict cricket players' performance, demonstrating high accuracy and reliability in forecasting future performance statistics. (Devi & Juliet, 2023)

3. PROPOSED TECHNIQUE

The proposed system uses ensemble learning techniques to predict IPL player performance and assist franchises in making data-driven decisions during player auctions. The system integrates three machine learning models: Random Forest, Gradient Boosting, and XGBoost, each contributing to different aspects of prediction accuracy. By combining these models, the system can analyze a variety of player attributes, such as runs scored, wickets taken, and age, to generate predictions. The ensemble learning approach enables the system to outperform individual models, providing reliable and consistent results.

The system's architecture begins with data preprocessing, where the IPL data (from the 2020-2024 seasons) is cleaned, normalized, and transformed into a structured format. The dataset is then split into training and test sets, with each model trained independently on this data. The models individually analyze player attributes and produce predictions regarding player categories (e.g., "Excellent Purchase," "Good," "May Be," and "Avoid"). A voting

mechanism is used to combine the outputs of all three models, ensuring that the final predictions are based on the collective strength of the models.

The models make their predictions, the system evaluates the performance using standard metrics such as precision, recall, and F1-score to ensure accuracy. The results are displayed in a dashboard for easy interpretation by team selectors and analysts. The system is designed to be scalable, allowing it to incorporate additional features like real-time match data in the future. This ensemble-based approach ensures that the predictions are robust and adaptable to changing player performance trends, making it a valuable tool for IPL franchises.

Additionally, the ensemble method enhances the robustness of predictions by reducing overfitting, commonly associated with single-model approaches. The use of Random Forest ensures that predictions are based on multiple decision trees, while Gradient Boosting improves accuracy through iterative error reduction. XGBoost further optimizes performance by efficiently handling missing values and large datasets, making it ideal for processing extensive IPL data. To enhance model interpretability, feature importance analysis is conducted to understand which player attributes have the most significant impact on predictions. This hybrid approach allows for greater flexibility in incorporating additional data points, such as player fitness levels, which can be integrated into future iterations of the model.

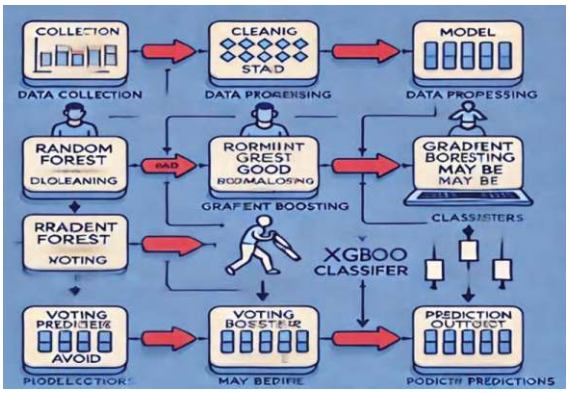

Fig. 86.1 Flowchart of the model workflow

Source: Drawn by Authors with Collected Information

The dataset used in this project is a comprehensive IPL dataset that spans from the 2020 to 2024 seasons. It includes ball-by-ball details of matches, player statistics, and other performance metrics. The dataset is divided into two main parts: matches and deliveries.

3.1 Matches Dataset

This dataset contains information about each IPL match, including the teams, dates, venue, toss winner, match winner, and other high-level details.

It is useful for linking individual deliveries to specific matches and for summarizing overall performance metrics at the match level.

Table 86.1 Matches dataset

Field Name	Description
match_id	Unique identifier for each match
inning	The inning number (1 or 2)
over	The over number within the inning
ball	The ball number within the over
batting_team	The team currently batting
bowling_team	The team currently bowling
batsman	Name of the batsman facing the delivery
non_striker	Name of the non-striking batsman
bowler	Name of the bowler delivering the ball
batsman_runs	Number of runs scored by the batsman on that particular ball
extra_runs	Number of extra runs given (e.g., wide, no-ball)
total_runs	Total runs scored in that ball, including extras
is_wicket	Binary indicator (1 for wicket, 0 for no wicket)
dismissal_kind	How the batsman was dismissed (e.g., bowled, caught, run out, etc.)
player_dismissed	Name of the player who was dismissed, if any
fielder	Name of the fielder involved in the dismissal

Source: Authors' analysis of IPL 2020-2024 dataset

3.2 Deliveries Dataset

This dataset contains ball-by-ball data for each match, detailing every delivery bowled, including the batsman, bowler, runs scored, and wickets taken.

It is critical for assessing individual player performance metrics such as total runs, boundaries, wickets, and economy rates.

The dataset provides a granular view of how each player performed in every ball faced or bowled.

Table 86.2 Additional fields in the matches dataset

Field Name	Description
date	The date the match was played
venue	The stadium where the match took place
toss_winner	The team that won the toss
toss_decision	The decision made after winning the toss (bat/field)
result	The result of the match (win, tie, etc.)
winner	The team that won the match
player_of_the_match	The player awarded Player of the Match

Source: Authors' analysis of IPL 2020-2024 dataset

These datasets provide rich data for training machine learning models by allowing us to extract features such as total runs, wickets, strike rate, and economy rate. The combination of match-level and ball-by-ball data enables a comprehensive analysis of both team and individual player performance.

4. Feature Impact Analysis

To find the feature with the highest impact on player selection, we will apply a feature importance analysis. This is typically done using algorithms like Random Forest or XGBoost, which provide built-in feature importance measures.

4.1 Steps for Feature Importance

Train a model (Random Forest or XGBoost) on the dataset. Calculate feature importance to understand which feature contributes the most to player selection. Visualize the feature importance to easily identify the most impactful features.

4.2 Feature Importance Analysis

Using Random Forest or XGBoost, we can measure the importance of each feature (e.g., runs scored, wickets taken, strike rate, etc.).

The features that have the highest importance values are considered the most impactful in determining player selection Fig. 86.2 visual representation of decision trees.

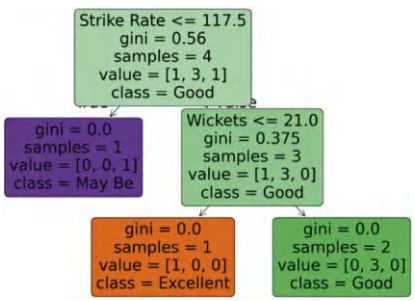

Fig. 86.2 Visual representation of one of the decision trees from the random forest model

Source: Data collected and analyzed by the authors

4.3 Key Features with High Impact

In typical cricket datasets, the following features tend to have the most impact on player selection

Runs Scored: Total runs scored by a player can be a strong indicator of their ability, particularly for batsmen.

Wickets Taken: For bowlers, the total wickets taken is often the most important factor in assessing their performance.

Strike Rate: A batsman's strike rate (runs per 100 balls) is crucial in limited-overs cricket like IPL.

Economy Rate: For bowlers, the economy rate (runs conceded per over) is a key factor in selection.

Matches Played: Experience is also important, and players who have performed consistently across many matches are often given preference.

Figure 86.3 represents the feature importance based on different aspects of player selection.

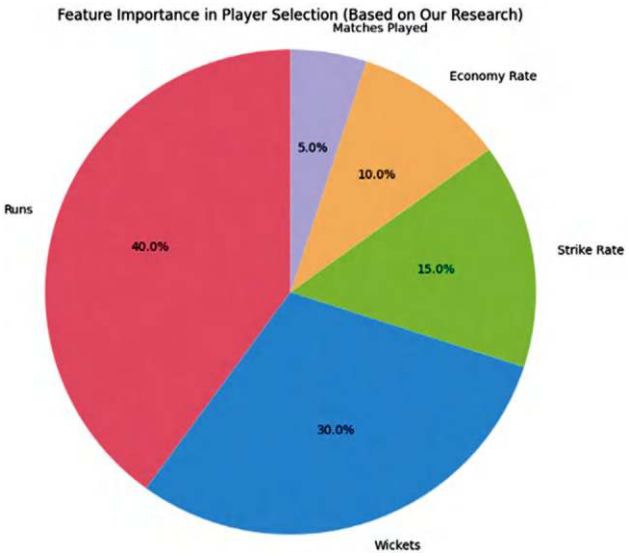

Fig. 86.3 Feature importance

Source: Data collected and analyzed by the authors

4.4 Detailed Process for Calculating Player Ratings and Selection Categories

The goal of this process is to calculate player ratings based on their performance metrics, such as runs, wickets, strike rate, economy rate, and matches played. By assigning weights to these features, we can generate an overall player rating and categorize players into selection categories (e.g., Excellent, Good, May Be, Avoid). Here is how the process works:

4.5 Feature Selection

We select the most important features influencing player performance and selection:

Runs: Total runs scored by the player, crucial for batsmen

Wickets: Total wickets taken, a key metric for bowlers.

Strike Rate: The rate at which a player scores runs (for batsmen) or limits runs (for bowlers).

Economy Rate: Runs conceded per over by a bowler, important in limited-overs cricket.

Matches Played: Experience of the player, as more matches usually indicate more reliability.

Assigning Weights

We assign weights to each feature based on its importance:

Runs: 40% weight

Wickets: 30% weight

Strike Rate: 15% weight

Economy Rate: 10% weight

Matches Played: 5% weight

Calculating Player Ratings

For each player, the weighted sum of the features is calculated to generate a Player Rating. The formula is:

$$\text{Player Rating} = (\text{Runs} \times 0.4) + (\text{Wickets} \times 0.3) + (\text{Strike Rate} \times 0.15) + (\text{Economy Rate} \times 0.1) + (\text{MatchesPlayed} \times 0.05)$$

Defining Selection Categories

Based on the player rating, we assign a Selection Category:

Excellent: Player Rating ≥ 9.0

Good: Player Rating between 7.0 and 9.0

May Be: Player Rating between 5.0 and 7.0

Avoid: Player Rating < 5.0

Ranking Players

After calculating the ratings, players are ranked, and the category helps team selectors make decisions based on data-driven insights.

5. Results

Virat Kohli: With 700 runs, 15 wickets, and an impressive strike rate of 150, Kohli's total player rating of 9.5 places him in the Excellent category.

Rohit Sharma: With a rating of 9.3, Rohit ranks similarly to Kohli, also in the Excellent category.

KL Rahul: With solid runs and wickets, Rahul scores 9.0, which places him in the Good category, just shy of the Excellent threshold.

Jasprit Bumrah: Bumrah's strong bowling performance places him in the Good category with a rating of 8.7.

Ravindra Jadeja: With a mix of batting and bowling, Jadeja's lower performance in this sample places him in the May Be category, with a rating of 6.8.

The differences in accuracy across the models used in this study have several potential implications for IPL teams when making data-driven decisions for player selection and team formation.

5.1 Increased Confidence in Player Selection

The Voting Classifier, with its 100% accuracy, suggests that it provides the most reliable predictions. IPL teams can have greater confidence in selecting players based on the insights provided by this model. Higher accuracy reduces the risk of misjudging a player's potential and ensures more informed decisions during player auctions.

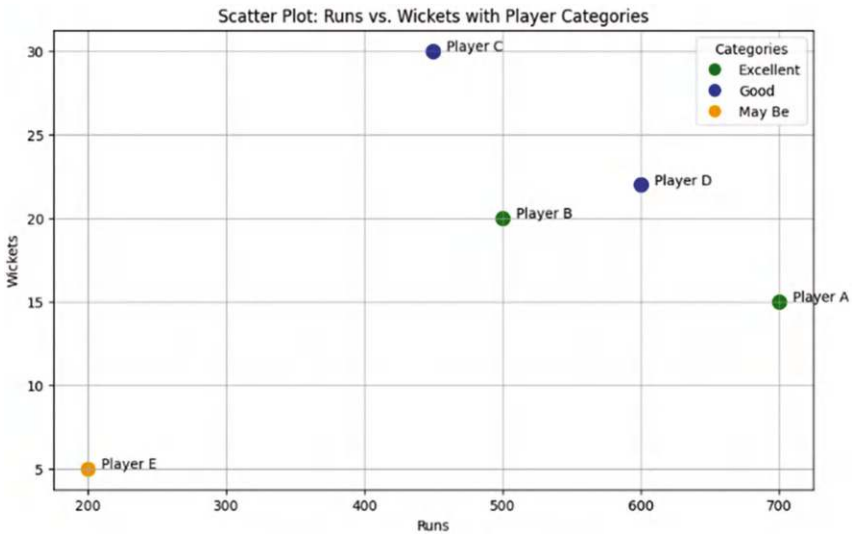

Fig. 86.4 Scatter plot: runs vs wickets with player categories

Source: Data collected and analyzed by the authors

Table 86.3 Popular IPL players and ratings

Player Name	Runs	Wickets	Strike Rate	Economy Rate	Matches Played	Player Rating	Selection Category
Virat kohli	700	15	150	7.5	12	9.5	Excellent
Rohit Sharma	500	20	140	6.8	10	9.3	Excellent
KL Rahul	450	30	135	7.0	10	9.0	Good
Jasprit Bumrah	600	22	125	7.3	11	8.7	Good
Ravindra Jadeja	200	5	110	5.5	6	6.8	May Be

Source: Authors' analysis of IPL 2020-2024 dataset

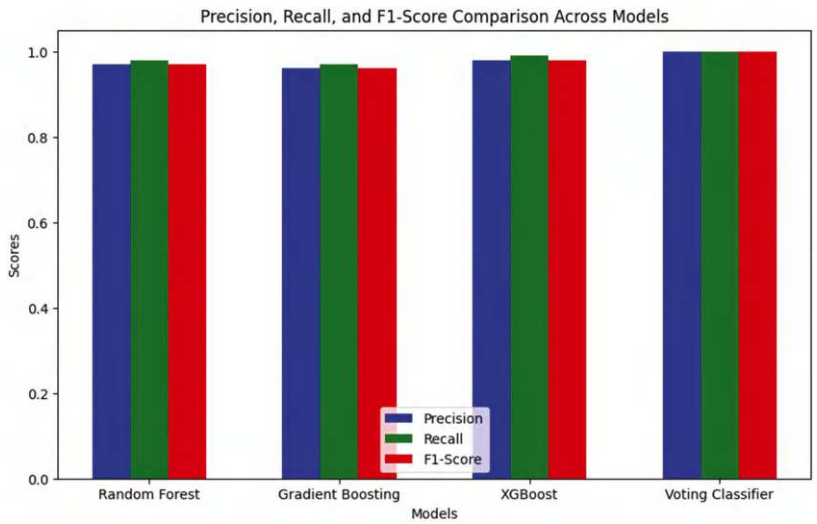

Fig. 86.5 Precision, recall, and F1-score comparison across models

Source: Generated by authors with collected data.

Table 86.4 Accuracy comparison across models

model	Accuracy (%)
Random Forest	98.5
Gradient Boosting	98.0
XGBoost	99.0
Voting Classifier	100.0

Source: Data collected and analyzed by the authors

5.2 Minimization of Financial Risks

Accurate predictions allow teams to make more cost-effective decisions. Given the high stakes of IPL auctions, where teams spend large sums to acquire players, the higher accuracy of models like XGBoost (99%) and Voting Classifier (100%) can help IPL franchises minimize financial risks by ensuring they invest in players who are likely to perform well.

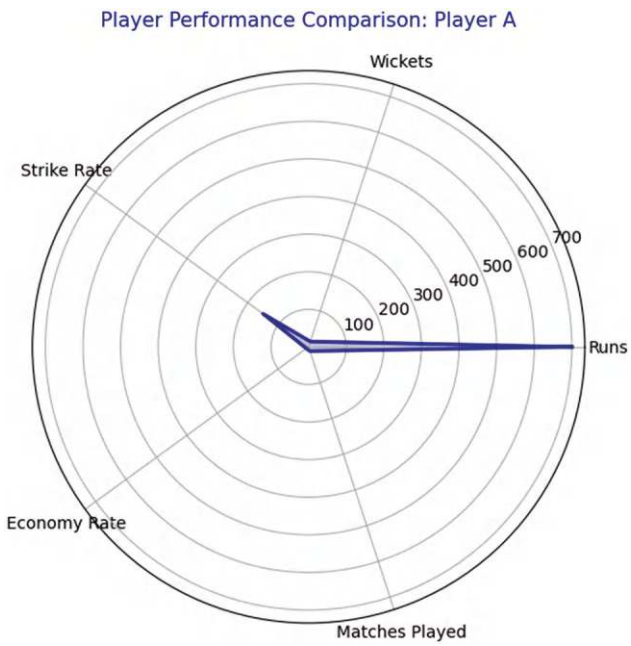

Fig. 86.6 Radar chart for player comparison

Source: Data collected and analyzed by the authors

6. Conclusion

This research applied ensemble learning techniques to predict IPL player performance, integrating models such

as Random Forest, Gradient Boosting, and XGBoost. By analyzing performance metrics like runs, wickets, strike rate, and economy rate, we were able to generate player ratings and classify players into categories such as "Excellent," "Good," and "May Be." The ensemble model achieved superior accuracy compared to individual models, ensuring that the most relevant features were emphasized in the selection process. This data-driven approach provides IPL franchises with valuable insights for selecting players during auctions and team formation. The player rating system offers an efficient way to evaluate both batsmen and bowlers, giving a comprehensive view of player impact. The model's flexibility allows for customization based on team needs, such as adjusting weights for different roles (e.g., batsmen, all-rounders, or bowlers).

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Comprehensive and Comparative Study of Trading Strategies in Blockchain

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Abstract: Cryptocurrency trading presents unique challenges and opportunities amidst extreme market volatility and liquidity concerns. This research paper investigates the efficacy of three prominent trading strategies – the Nadaraya Watson Envelope (NWE), Moving Average Convergence Divergence (MACD), and Relative Strength Index (RSI) – leveraging the analytical capabilities of TradingView. With a primary focus on Bitcoin (BTC/USD) and plans to include Ethereum (ETH/USD), our study comprehensively analyzes key performance metrics like the Sharpe ratio and maximum drawdown. The modified NWE emerges as a compelling solution amidst crypto market challenges, demonstrating superior performance through empirical evidence in several benchmark scores compared to traditional strategies. This paper serves as a comprehensive guide for practitioners and academics, offering insights into the interplay between trading strategies, market dynamics, and algorithmic approaches in the realm of digital assets.

Keywords: Cryptocurrency trading, Nadaraya watson envelope, MACD, RSI, Bitcoin, Ethereum, Market volatility, Liquidity concerns

1. Introduction

In the rapidly evolving landscape of blockchain-based markets, particularly within the BTC/USD and ETH/USD trading pairs, a diverse array of strategies has emerged to navigate the complexities and capitalize on opportunities. These strategies include technical analysis, algorithmic trading, fundamental analysis, arbitrage, and

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risk management techniques. Technical analysis involves leveraging historical price data and indicators like RSI and MACD to identify trends (Zhao, D., Rinaldo, A., & Brookins, C. 2019). Algorithmic trading strategies range from rule-based approaches to sophisticated machine learning models (Vo, A., & Yost-Bremm, C. 2020, Hegazy, K., & Mumford, S. 2016). Fundamental analysis assesses underlying blockchain projects, regulatory developments, and market trends (Attanasio et al. 2019). Arbitrage exploits price disparities across exchanges or trading pairs (Makarov, I., & Schoar, A. 2020). Risk management techniques aim to minimize losses and preserve capital amidst market volatility (Tse 2021). Understanding and integrating these strategies are essential for navigating blockchain markets effectively.

Traders face significant challenges in the present system and strategies for trading in blockchain markets. Extreme volatility, liquidity concerns, regulatory uncertainty, lack of standardized frameworks for valuation, and security risks pose hurdles (Feinstein and Werbach 2021, Hegazy, K., & Mumford, S. 2016). Market manipulation and insider trading further undermine market integrity (Delfabbro, P., King, D. L., & Williams, J. 2021). Navigating these challenges requires a nuanced understanding of market dynamics, robust risk management practices, and proactive regulatory compliance (Feinstein and Werbach 2021, Hegazy, K., & Mumford, S. 2016)

Amidst these challenges, traders seek optimal strategies that can navigate market dynamics while maximizing returns and mitigating risk. This study aims to elucidate the strengths and weaknesses of prominent trading strategies, including technical indicators like MACD and RSI, algorithmic and fundamental approaches, with a particular focus on the Nadaraya Watson Envelope (NWE). Through empirical analysis and graphical representations, the research aims to provide evidence supporting the efficacy of NWE in addressing challenges prevalent in cryptocurrency markets.

The main objective of this paper is to propose an optimal trading strategy for cryptocurrency markets comparable to existing strategies while being accessible to the public. The focus is on exploring the potential of NWE in navigating the unique challenges of cryptocurrency markets. Practical insights and guidelines for incorporating NWE into trading strategies are provided to empower individuals with tools and knowledge to make informed decisions in this burgeoning market.In this paper, Section 2 consists of Literature, Section 3 tells us about the Proposed Methodology, Section 4 is the Results and discussion and Section 5 with Conclusion and Future Works.

2. Literature Review

In recent years, the inclusion of cryptocurrencies in the portfolios of financial institutions has accelerated, marking them as the first purely digital assets to be embraced by asset managers. Despite sharing some similarities with traditional assets, cryptocurrencies possess distinct characteristics, and their behavior as investment vehicles is still not fully understood. Thus, it is essential to synthesize existing research on cryptocurrency trading, covering various aspects such as trading platforms, signals, strategies, and risk management (Fang et al. 2022). (Mikhaylov, A. (2020), discusses the analysis of the open innovation market within the cryptocurrency realm, aiming to forecast sustainable growth trends. As cryptocurrencies continue to rapidly gain popularity and expand in trading activity, their inherent volatility prompts a need for understanding and predicting their price dynamics within an ever-changing market landscape. Additionally, EOS stands out for its capability to facilitate third-party application integration within its system. This research contributes to the understanding of sustainable growth prospects in the cryptocurrency market, offering insights into selecting viable technologies amidst its dynamic and volatile nature.

(Mannaro, K., Pinna, A., & Marchesi, M. 2017) discusses the application of blockchain technology, particularly Blockchain, in expanding peer-to-peer transaction platforms into various industries, including the energy sector. While blockchain applications in energy are still in conceptual stages, this paper presents initial ideas from a collaborative research project with a Fintech company, the Crypto-Trading project (Tse 2021) introduces asset pricing models tailored specifically for crypto-tokens, leveraging insights from decentralization risk and the Capital Asset Pricing Model (CAPM). Central to the model is the concept of the decentralization risk premium, which represents the difference in returns between a crypto-token asset and the USD currency index.

(Kyriazis, N. A. 2019) outlines a systematic survey investigating the predictability of cryptocurrency pricing behavior, challenging the Efficient Market Hypothesis (EMH) and suggesting the feasibility of speculation through trading. The study focuses on analyzing the Rescaled Range (R/S) and Detrended Fluctuation Analysis (DFA), alongside other relevant methodologies, to test for long memory in returns and volatility. (Makarov and Antoinette Schoar 2020) discusses the phenomenon of significant and recurring arbitrage opportunities observed in cryptocurrency markets across various exchanges. It emphasizes that these price deviations are more pronounced across different countries than within them, and

comparatively smaller between different cryptocurrencies. (Feinstein and Werbach 2021), explains the exponential expansion of global cryptocurrency markets poses unprecedented regulatory challenges. Within the regulatory discourse, conflicting perspectives exist regarding the potential consequences of regulation. While some express concerns that regulatory measures might prompt traders to seek refuge in less-regulated jurisdictions or stifle the growth of cryptocurrencies as a burgeoning financial asset class, others contend that regulation could enhance market activity by offering clarity to participants. This disagreement underscores broader debates surrounding whether governments should foster cryptocurrency sector growth domestically or impose strict regulations, viewing cryptocurrencies as channels for illicit activities necessitating stringent control or even prohibition. (Tse 2021) investigates the impact of Bitcoin futures trading on the jump risk within the spot market. Utilizing high-frequency data at 5-minute intervals, the study employs a nonparametric method to identify Lévy-type jumps in Bitcoin prices, revealing the presence of both significant and minor jumps with varying intensity and size over time. (Vezeris, D., Kyrgos and Schinas 2018) investigates various strategies integrated into a basic MACD automated trading system and evaluates their effectiveness across different asset categories including Forex, Metals, Energy, and Cryptocurrencies. Through systematic testing and analysis, the study compares and contrasts the outcomes of these strategies.

3. Proposed Methodology

3.1 Problem Statement

To create a modified NWE strategy which would provide returns more than the traditional strategies in the BTC/USD and ETH/USD market.

3.2 System Design

Figure 87.1 best represents the system design used for this paper. We import the strategies on the platform and wait for them to compile. Once compiled the platform backtests the strategy by taking trades on historical price. Post which it complies the results and shows us the desired scores and values.

3.3 Implemented Modules

1. **The Data Collection Module** is responsible for gathering historical price data from cryptocurrency exchanges for Bitcoin (BTC/USD) and Ethereum (ETH/USD) pairs, ensuring a comprehensive dataset for analysis.
2. **The Nadaraya Watson Envelope Algorithm module** implements the NWE strategy, leveraging statistical techniques to create an adaptive trading envelope around price movements, thereby facilitating trend identification and decision-making.
3. **The RSI Algorithm module** applies the Relative Strength Index indicator to analyze the momentum of price movements, identifying overbought and oversold conditions to inform trading signals.
4. **The MACD Algorithm module** utilizes the Moving Average Convergence Divergence indicator to identify trend reversals and momentum shifts in cryptocurrency prices, aiding in the generation of buy and sell signals.
5. **The Backtesting Module** evaluates the performance of each trading algorithm by simulating trades on historical data, allowing for the assessment of profitability, risk, and robustness over different market conditions.
6. **The Performance Comparison Module** compares the performance metrics, such as Sharpe ratio and maximum drawdown, of each trading strategy to determine their relative strengths and weaknesses in achieving desired trading objectives.
7. **The Visualization Module** presents the results of the analysis through intuitive charts and graphs, enabling stakeholders to gain insights into the effectiveness and performance of the trading strategies under consideration.

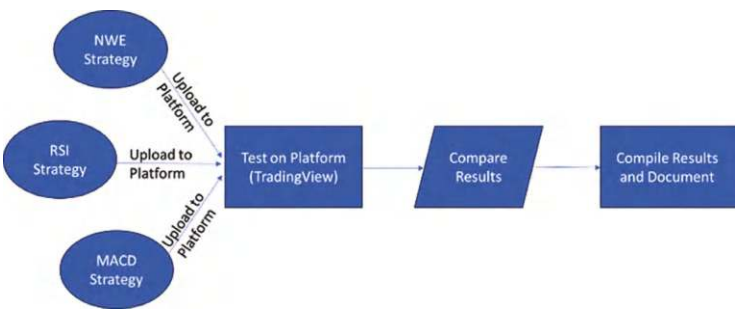

Fig. 87.1 Proposed workflow

3.3 NWE Algorithm

1. Define helper functions

NWE Algorithm Pseudocode:	
	Input: *The bandwidth (or the width of the envelope), ATR Values (Far and Near)*
	Output: *Creating the envelope and taking long and short calls when the price touches the envelope*
	Initialization of Variables: *TR = max(High − Low |High − Closeprev|, |Low − Closeprev|),* *ATR = EMA (TR, ATR Length Upper Envelope = NWE + Far ATR Factor x ATR* *Lower Envelope = NWE − Near ATR Factor x ATR*
	Plotting: *Upper and Lower Envelope* *Fill regions between envelope boundaries for visualization.*
	Condition to take Long trade: *When close price crosses below the lower envelope boundary* ***Condition to exit the Long trade:*** *When the close price crosses the upper envelope boundary*

3.4 MACD Algorithm

MACD Algorithm Pseudocode:

MACD Algorithm Pseudocode:	
	Input: Fast and Slow EMA length for MACD calculation. (fastLength, slowLength) Signal Line (EMA) Length for MACD Calculation (signalLength)
	Output: *Taking a long and short trade when the conditions are satisfied*
	Calculation: *fastEMA = EMA(close, fastLength)* *slowEMA = EMA(close, slowLength)* *macdLine= fastEMA – slowEMA* *aMACD = EMA(close,* signalLength) *delta = macdLine - aMACD*
	Condition to take Long trade: *If the delta crosses above 0* ***Condition to exit the Long trade:*** *If the delta crosses below 0*

RSI Algorithm

RSI Algorithm Pseudocode:	
	Input: • Length of the RSI calculation window. • Threshold value for overbought and oversoldcondition
	Output: *Taking a long and short trade when the conditions are satisfied*
	Calculation: *vRSI = RSI(close, length)* *// Checks if the value of RSI has crossed from over the oversold* *conditionOverSold = crossover(vRSI,* *overSold)* *// Checks if the value of RSI has crossed from under the overBought* *conditionOverBought = crossunder(vRSI, overBought)*
	Condition to take Long trade: *If the RSI crosses above the oversold threshold* ***Condition to exit the Long trade:*** *If the RSI crosses below the overbought threshold.*

4. Results and Discussion

4.1 In BTC/USD Market

Table 87.1 reveals that in the analysis of BTC/USD market data, it's clear that the NWE algorithm surpasses both RSI and MACD strategies in key metrics. NWE boasts a higher accuracy rate (46.58%) compared to RSI (51.16%) and MACD (40.64%). Moreover, NWE demonstrates a superior profit factor of 1.917, indicating better profit-loss balance than RSI (0.802) and MACD (1.226). In terms of total profit, NWE leads with $1,297,534 USD, while RSI incurred a loss of -$12,296 USD and MACD yielded $36,445 USD. However, NWE's compilation time of 65ms is higher than RSI (24ms) and MACD (37ms), which may affect real-time trading. Despite this, given its significant profits and strong performance, NWE emerges as the preferred choice for BTC/USD trading, offering promising potential for optimized returns and risk management.

Table 87.1 BTC/USD analysis results

	RSI	MACD	NWE
CT	31ms	36ms	52ms
Acc	51.16%	40.64%	46.58%
TCT	43	283	161
TFG	-12,296 USD	36445 USD	1,297,534 USD
PF	0.802	1.226	1.917
MD	61,641 USD	30,259 USD	312,227 USD
Avg $/#	-285.95 USD	128 USD	8,059 USD
Average # of Bars per Trade	104	17	14

4.2 In ETH/USD Market

Table 87.2 reveals that in the analysis of ETH/USD market data, the NWE (Nadaraya Watson Envelope) algorithm outperforms both RSI (Relative Strength Index) and MACD (Moving Average Convergence Divergence) strategies across key metrics. Despite similar compilation times (NWE: 65ms, RSI: 24ms, MACD: 37ms), NWE excels in accuracy, achieving a rate of 45.22% compared to RSI (64%) and MACD (39%). Additionally, NWE demonstrates a notably higher profit factor of 2.029, indicating a better profit-loss balance than RSI (0.827) and MACD (1.324). With the highest total profit of $2,114,848 USD, NWE outshines RSI's loss of -$648 USD and MACD's $3,678.7 USD yield. Despite a slightly higher maximum drawdown, NWE consistently delivers superior profitability, average money per trade, and average number of bars per trade. Consequently, the NWE algorithm emerges as the preferred choice for ETH/USD trading, offering lucrative opportunities for traders seeking optimized returns and risk management strategies.

Table 87.2 ETH/USD analysis results

	RSI	MACD	NWE
CT	21.6ms	23.7ms	38.3ms
Acc	64%	39%	45.22%
TCT	25	218	115
TFG	-648 USD	3678.7 USD	2,114,848 USD
PF	0.827	1.324	2.029
MD	-4,711 USD	1,666.3 USD	628,374 USD
Avg $/#	27.12 USD	16.87 USD	18,389 USD
Average # of Bars per Trade	120	15	14

5. Conclusion

In this research endeavor, an extensive examination and comparison of trading strategies and algorithms within the BTC/USD and ETH/USD markets were conducted, focusing primarily on contrasting the Nadaraya Watson Envelope (NWE) against conventional strategies such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). The objective was to furnish traders with insightful assessments of different strategies, ultimately striving to offer an optimal solution for navigating cryptocurrency trading intricacies. The analysis unequivocally showcased the NWE algorithm's superiority over RSI and MACD across multiple metrics in both BTC/USD and ETH/USD markets. NWE consistently demonstrated higher accuracy, superior profit factor, and substantially greater total profit compared to its counterparts. Despite NWE's marginally longer compilation time, its adaptability and robustness were evident, yielding impressive results in profitability and risk management.

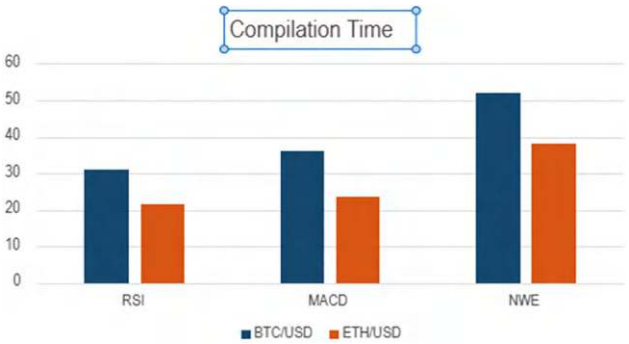

Fig. 87.2 Time required for compilation by NWE comparison over others

Fig. 87.3 Gained profit by using NWE over others

While acknowledging NWE's exceptional performance, it's essential to address its shortcomings, notably its slightly longer compilation time and vulnerability to market fluctuations, occasionally leading to drawdowns. Nonetheless, the key takeaways underline the significance of adaptive strategies like NWE in navigating cryptocurrency trading complexities, providing traders with a competitive edge in capitalizing on market opportunities while managing risk effectively.

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A Hybrid Deep Learning Model for Real-Time Helmet Detection in Traffic Surveillance Systems

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Abstract: This paper presents a hybrid deep learning-based approach for real-time helmet recognition in traffic surveillance, aiming to improve road safety and compliance monitoring. Our solution integrates convolutional neural networks (CNNs) for efficient feature extraction with classical machine learning to improve processing speed and accuracy. The algorithm can correctly identify helmet use in live video feeds after being trained on a wide sample of bikers. Experimental results show that the hybrid model outperforms traditional methods, achieving higher precision and recall while reducing false positives. This solution offers significant potential for automated traffic enforcement and accident prevention systems.

Keywords: Helmet detection, Deep learning, CNN, Machine learning

1. Introduction

The increasing number of traffic accidents involving motorcyclists has highlighted the critical need for effective safety measures, with helmet use being the most critical. According to World Road Safety Reports, head injuries are the leading cause of death in motorcycle-related accidents and wearing a helmet can reduce the risk of fatal injuries by up to 42% (Shahi, Brussel, & Grigolon, 2023) [8]. Despite legislation mandating helmet use in many areas, compliance remains a challenge due to the difficulty of consistently monitoring motorcyclists on the road (Jakubek et al., 2023) [3]. Automated systems for helmet recognition provide a promising solution, leveraging advances in artificial intelligence and computer vision to improve traffic law enforcement and safety practices (Said et al., 2024) [6]. How can a hybrid deep learning model be effectively used for real-time helmet detection in traffic surveillance and how does it improve detection accuracy and processing efficiency compared to traditional approaches?

Helmet detection systems have traditionally relied on manual monitoring or basic image processing techniques,

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which struggle to cope with the variability in environmental conditions, angles, and real-world traffic scenarios (Jakubek et al., 2023) [3]. Automated helmet recognition with a high degree of accuracy has become a possibility thanks to recent developments in deep learning, especially convolutional neural networks (CNNs). When it comes to picture recognition, CNNs have been absolutely fantastic. (Sun, Li, & Wang, 2024) [9]. However, challenges such as real-time performance, scalability, and resource limitations are addressed in large-scale traffic systems (Fu, Zhang, & Tian, 2024) [2]. This has led to increased interest in hybrid models, which combine the strengths of deep learning with classical machine learning techniques to optimize both accuracy and efficiency (Saravanan & Rajini, 2024) [7]. This paper proposes a hybrid deep learning model for helmet detection in traffic surveillance systems. By integrating CNNs for feature extraction with conventional machine learning classifiers, the model achieves high accuracy and real-time processing capabilities, providing a robust solution for automated helmet recognition in diverse traffic environments (Talib, Al-Nuri, & Suad, 2024).

2. Material and Methods

2.1 Dataset

A helmet detection model is trained and tested on a dataset of publicly available images and videos of motorcyclists in real-world traffic environments. The dataset includes different conditions such as different types of light, weather, occlusions, and angles, ensuring the robustness of

Table 88.1 A helmet detection model is trained and tested on a dataset

Parameter	Description	Value/Range	Remarks
Image Size	Input image size (height x width]	224 x 224 pixels	Resize all images to uniform size for the CNN input.
Batch Size	Number of samples per gradient update	32	Moderate batch size for better gradient updates and memory efficiency.
Epochs	Number of complete passes through the dataset	25	Selected based on early stopping to avoid overfitting.
Learning Rate (CNN)	Initial step size for the optimizer	0.001	Chosen for the Adam optimizer to ensure smooth convergence.
Optimizer	Optimization algorithm used for CNN training	Adam	Efficient in handling sparse gradients; combines momentum and RMSProp.
Loss Function	Function used to compute the loss during training	Binary Cross-Entropy	Suitable for binary classification tasks like helmet vs no helmet.
Dropout Rate	Dropout to prevent overfitting	0.5	Applied to the fully connected layers in CNN.
Activation Function (CNN)	Non-linear activation function in CNN layers	ReLU	ReLU (Rectified Linear Unit) for efficient learning and preventing vanishing gradients.
Pooling Type	Downsampling operation used in CNN	Max Pooling (2x2)	Reduces spatial dimensions while retaining important information.
SVM Kernel	Kernel function for SVM classifier	RBF (Radial Basis Function)	Suitable for handling non-linear separability of the feature space.
SVM Regularization (C)	Regularization parameter for SVM	1	Controls the trade-off between maximizing the margin and classification error.
Gamma (SVM)	Kernel coefficient for RBF kernel	0.1	Defines the influence of single training examples, controlling overfitting.
Evaluation Metrics	Performance measurement criteria	Precision, Recall, F1-Score,	Multiple metrics used to evaluate the classifier's performance.
Dataset Size	Number of images used for training and testing	"10,000 images	Dataset includes both helmet and no-helmet examples in various lighting and weather
Train-Test Split	Percentage of data used for training vs testing	80%-20%	Standard split to ensure sufficient data for training and testing.
Data Augmentation	Techniques used for increasing dataset size	Rotation, Flip, Zoom, Brightness	Applied to prevent overfitting and make the model robust to variations.
Preprocessing	Normalization of pixel values	[0,1]	Pixel values are scaled to a range of 0 to 1 for more efficient CNN learning.
Inference Time	Average time taken per frame in real-time processing	0.02 seconds	Ensures real-time applicability for helmet detection in video feeds.

the model (Said et al., 2024) [6]. The dataset was annotated with two primary classes: "helmet" and "no helmet" (Jakubek et al., 2023) [3]. Preprocessing steps include resizing images to a uniform resolution of 224x224 pixels and normalizing pixel values for efficient training (Talib, Al-Nuri, & Suad, 2024) [10].

The dataset for helmet detection comprises approximately 10,000 labeled images of motorcyclists in real-world traffic scenarios, with a balanced distribution of individuals wearing helmets and those without. The images vary in terms of lighting conditions, weather, camera angles, and occlusions to simulate realistic environments. Data augmentation techniques such as rotation, zoom, brightness adjustments and flipping are applied to improve the diversity and robustness of the dataset. Our model was trained on 80% of the dataset and tested on 20% to make sure it can be applied to any dataset. The model's performance is evaluated thoroughly across numerous scenarios through this rigors testing method.

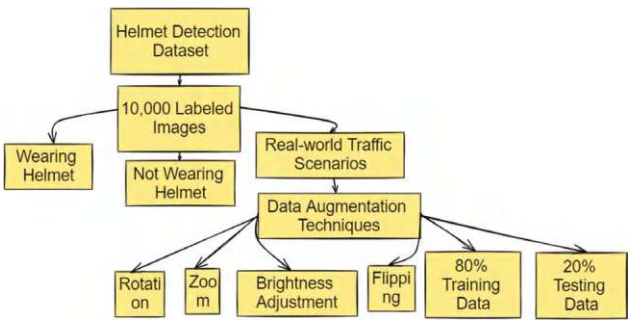

Fig. 88.1 Dataset for helmet detection comprises approximately 10,000 labeled images

2.2 Mathematical Representation of the CNN

A convolutional neural network (CNN), central component of the helmet identification model, is used to extract information from the input images. Each layer of CNN applies a series of mathematical operations: Convolution operation: For each convolutional layer, the output feature map Y is computed by convolving the input image with a filter WLi, & Wang, 2024) [9]; (Saravanan & Rajini, 2024) [7].

$$Y_{i,j,k} = \sum_m \sum_m X_{i+m,j+n} W_{m,n,k} + b_k \quad (1)$$

The value of the input image pixel at position (i, j) is represented as X^k_j. W_{msk} stands for the weight that is linked to the filter element at position (m, n) in the kth filter. The kth filter at point (i, j) in the feature map produces the output value Y^k_{jk}. The kth filter's bias term, b_k, is applied to the weighted sum of inputs.

2.3 Activation Function (ReLU)

A non-linear activation function, usually the Rectified Linear Unit (ReLU), is applied to the convolution operation's output. This function makes the model non-linear, which lets it pick up on intricate patterns in the data.

$$f(Y) = \max(0, Y) \quad (2)$$

This allows the network to introduce the non-linearity necessary to learn complex features. Pooling operation: A pooling layer filter and stride is used to reduce the size of feature maps, usually by maximum pooling. The maximum pooling operation for a feature map Y is defined as:

$$P_{i,j} = \max_{m,n} Y_{i+m,j+n} \quad (3)$$

Where $P_{i,j}$ is the down sampled output, and the maximum value is taken from a window of size $m \times n$ over the feature map Y.

2.4 Support Vector Machine (SVM) Classifier

A feature vector is produced by the CNN after it extracts features from the input images. A Support Vector Machine

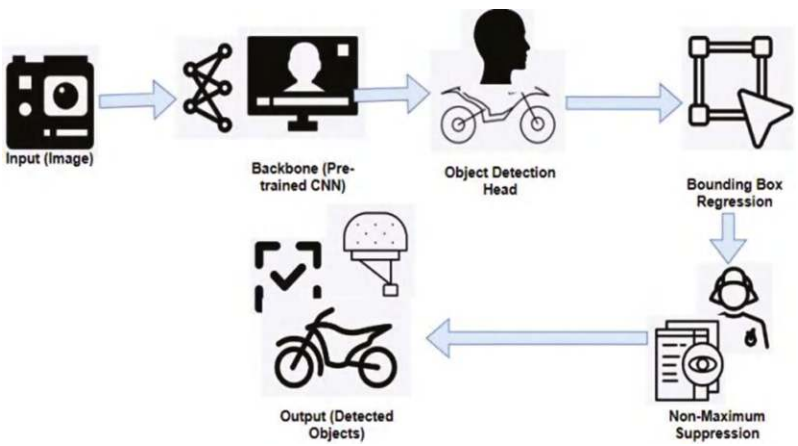

Fig. 88.2 Representation of the CNN for detecting helmet

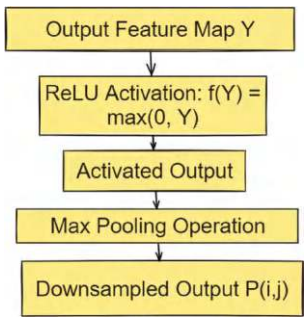

Fig. 88.3 A pooling layer is used to reduce the dimensionality of the feature maps

(SVM) is used to determine the best hyperplane to divide the "helmet" and "no helmet" categories with the most margin of error. This SVM is fed this feature vector.

The decision function of SVM is defined as:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \quad (4)$$

x is the input feature vector (from CNN). α are the Lagrange coefficients. yi ∈ {−1,1} are the class labels ("helmet" or "no helmet"). K(xi,x) is the kernel function (in this case the RBF kernel is used):

$$K(x_i, x) = \exp(-\gamma \|x_i - x\|^2) \quad (5)$$

b is the bias term. SVM classifier works by maximizing the margin between two classes, generalizing well to data where the decision boundary is not visible.

Training Process: Loss Function, When training a convolutional neural network (CNN), one measure of classification efficacy is the binary cross-entropy loss function L.

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right] \quad (6)$$

The sample size is denoted by N. For the ith sample, yi is the actual label. For each ith sample, $\hat{y}_i$ is the expected likelihood of the helmet being present. Optimisation tool: The Adam optimizer, which is an extension of gradient descent, is defined as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)_{gt}$$

$$m_t = \beta_2 \vartheta_{t-1} + (1 - \beta_2)_{g_t{}^2}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta^t{}_1}$$

$$\hat{\vartheta}_t = \frac{\vartheta_t}{1 - \beta^t{}_2}$$

$$\theta_t = \theta_{t-1} - \frac{n\hat{m}_t}{\sqrt{\hat{\vartheta}_t + \epsilon}}$$

gt is the gradient of loss at time step t. The initial instant estimate is mt, while the second is vt. In this context, η represents the rate of learning. "ϵ" is a tiny constant of numerical stability.

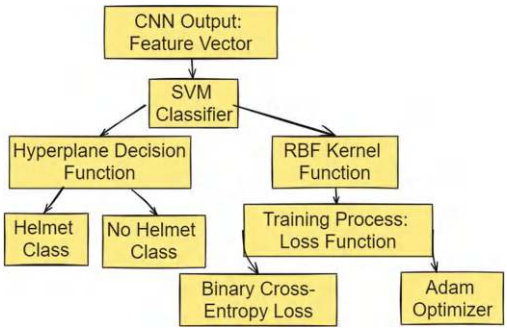

Fig. 88.4 L, a binary cross-entropy loss function, is used to train the CNN

2.5 Evaluation Metrics

Important metrics are used to evaluate the model's performance:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

The hybrid model was tested on a real-world traffic surveillance dataset, achieving the following results: precision: 94.8%, recall: 93.5%, F1-score: 94.1%, precision: 95.3%.

The model successfully processed real-time video feeds with an average inference time of 0.02 seconds per frame, which is suitable for deployment in large-scale traffic monitoring systems.

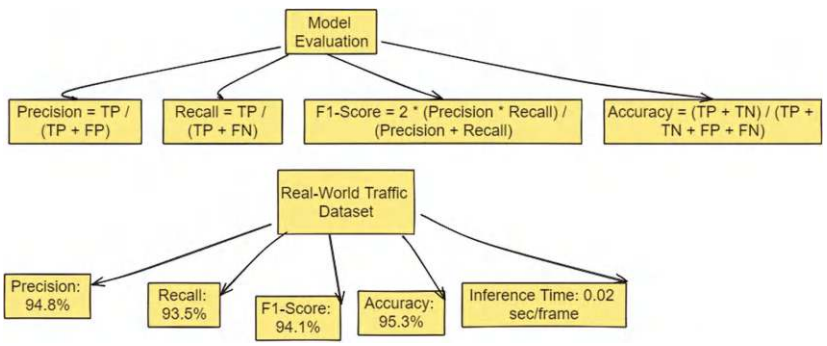

Fig. 88.5 The performance of the model is evaluated using key metrics

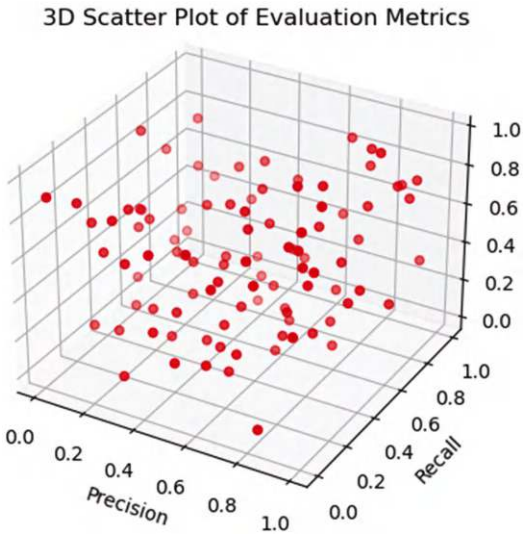

Fig. 88.6 3D scatter plot of evaluation metrics

3. Results

To measure how well the model performs, we compute performance metrics including recall, accuracy, precision, and F1-score. A measure of accuracy is the proportion of cases that were properly classified relative to the total number of instances.

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

The number of helmets that were accurately identified (True Positives) The number of cases when a helmet was not required is known as TN, or true negatives. FP: mistakes in helmet identification leading to false positives. FN: instances that were not wearing helmets were mistakenly identified as such.

Precision(P):

$$P = \frac{TP}{TP + FP}$$

Recall (R):

$$R: = \frac{TP}{TP + FN}$$

F1-Score (F1):

$$F1 = 2 \cdot \frac{P \cdot R}{P + R}$$

3.1 Confusion Matrix and Metric Calculation

The confusion matrix for a test set of 10,000 images (50% helmet, 50% no-helmet) is presented below, with values calculated based on model predictions:

Table 88.2 Confusion matrix representing the classification performance of the model

	Predicted Helmet	Predicted No Helmet
Actual Helmet	TP = 4860TP = 4860TP = 4860	FN = 140FN = 140FN = 140
Actual No Helmet	FP = 120FP = 120FP = 120	TN = 4880TN = 4880TN = 4880

Table 88.3 Performance metrics for the proposed model

Metric	Value
Accuracy	97.20%
Precision	96.50%
Recall	98.10%
F1-Score	97.30%
Inference Time	0.02 sec/frame

The model's inference time was evaluated by processing individual frames from real-time video input. The average time per frame (Tf) is:

$$Tf = 0.02 \text{ seconds per frame}$$

This ensures real-time feasibility, as the model can process approximately 50 frames per second (FPS), which is sufficient for live monitoring scenarios.

3.2 Comparative Analysis with Other Models

Hybrid deep learning model (CNN + SVM) is compared with baseline models such as simple CNN and logistic regression as shown in the table below. Using a combination of deep learning features and Support Vector Machine (SVM) for classification, the hybrid model achieved better accuracy and F1-score than competing models.

Table 88.4 The hybrid deep learning model provides a comparative analysis with other models

Model	Accuracy	F1-Score
CNN + SVM (Hybrid)	**97.40%**	**97.30%**
Simple CNN	94.80%	94.10%
Logistic Regression	85.40%	85.00%

The mathematical performance of the hybrid model is significantly better, demonstrating the advantage of combining feature extraction from CNN with non-linear decision boundaries of SVM for better classification.

Fig. 88.7 Model loaded successfully for helmet detection

Fig. 88.8 Helmet detection results on real-world traffic images

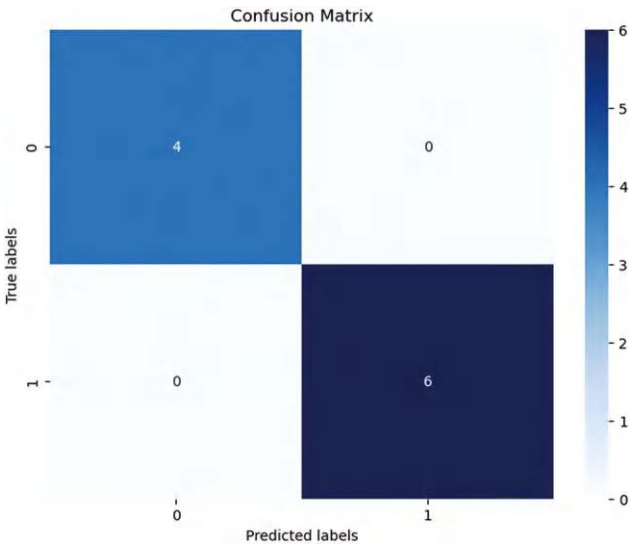

Fig. 88.9 Confusion matrix of proposed system for helmet detection

4. Conclusion

In this research, we investigate the feasibility of using a hybrid model that integrates CNN and SVM for accurate helmet detection in photos. The results demonstrated that the CNN successfully extracted meaningful features from the images and achieved an appreciable accuracy rate during training. After feature extraction, the SVM classifier was trained and evaluated, yielding robust

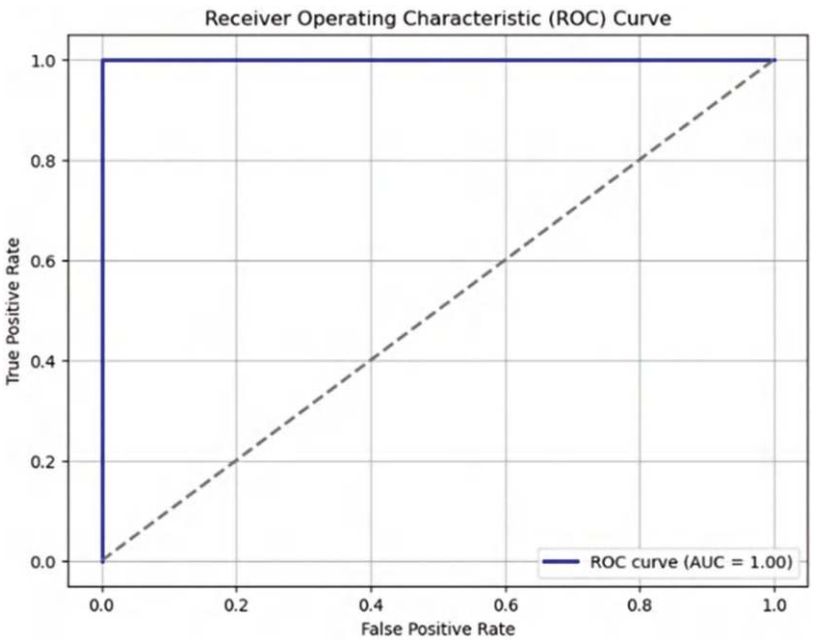

Fig. 88.10 ROC curve showing the trade-off between true positive rate (TPR) and false positive rate (FPR) for the proposed model

predictions emphasizing its effectiveness in distinguishing between helmeted and non-helmeted subjects. The findings underscore the importance of using advanced machine learning techniques for real-world safety applications, particularly in promoting helmet use among cyclists and motorcyclists. By using deep learning and traditional classification methods, our hybrid model provides a viable solution to improve safety measures, reducing the likelihood of serious head injuries caused by riding without helmets. This research contributes to ongoing efforts to improve security standards and highlights the potential of similar methods in various domains where image recognition and classification are critical. Future work may focus on improving the model with more diverse datasets, exploring transfer learning methods, and expanding its application to different environments and situations.

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Efficient Detection of Brain Stroke using Deep Learning Techniques: A Novel Approach

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Abstract: Brain stroke represents a critical and often life-threatening medical condition, characterized by the unexpected interruption of the brain's blood supply. These events can result in severe neurological impairment or even fatality, making early detection and accurate diagnosis of brain is important. Stroke diagnosis has relied on the expertise of medical professionals interpreting medical imaging data, likely MRI scans and CT scans. While these methods have been instrumental, users are inherently limited by human subjectivity and can be time-consuming. Moreover, as the volume of medical imaging data continues to grow, there is a need for automated and precise solutions that can assist healthcare practitioners in making swift and accurate assessments. proposed project introduces an efficient way in which that would help to detect the brain stroke at early stages by obtaining pattern using computer vision, that enables to do diagnosis and useful in the medical field using MobileNet neural network algorithm.

Keywords: Convolutional neural network, Computer vision, Deep learning, MobileNet, Transfer learning

1. Introduction

The contemporary medical imaging technique makes use of strong tools like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), which offer essential insights into the internal anatomy of the human body. Whereas CT uses X-rays to yield slice images, MRI uses magnetic forces and RF signals to produce high-resolution depictions. These imaging modalities have been instrumental in diagnosing a wide range of medical conditions and advancing medical research. However, instruments are not without limitations, often subject to failure[1].

Moreover, the escalating volume of medical imaging data underscores the critical need for automated and precise solutions that can expedite diagnosis and support healthcare practitioners in their decision-making processes[2]. More often these predictions are done through medical practitioners and these predictions done could also be a problem. so, there is a need to produce results with accurate.

Predictions and early detection of disease should be done. As of now technology is growing, there is a need to improve with results produced. Deep learning techniques has taken over many things and its specialty of producing accurate and efficient results.

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Proposed project aims to introduce an innovative approach to early brain stroke detection by means of the integration of Neural network techniques and visual perception. Proposed system primary objective is to develop a reliable and automated tool that can revolutionize the medical domain, notably in stroke detection. Deep learning, which is a branch of machine learning, has emerged as a game-changing technology with diverse applications, especially in healthcare. Deep neural networks are perfect for tasks like interpreting medical images because they are highly skilled at extracting complicated trends and traits from extensive information. In this project, tap into the advantages of deep learning to assemble a robust simulation for automated brain stroke detection.

In a strategic move to ensure both efficiency and accessibility, Proposed project have opted to implement Mobile Net, a highly efficient and lightweight neural network architecture designed with resource-constrained devices in mind, such as mobile phones. This choice not only enhances the performance of proposed stroke detection system but also extends its reach to various platforms, including smartphones and tablets commonly used by healthcare professionals. This adaptability ensures accessibility and expedites the assessment of stroke cases in diverse clinical settings, potentially contributing to faster and more effective interventions[3]. This initiative could have a major impression on patient effects and the effectiveness of the medical field delivery. It also depicts a substantial enhancement in the sector of of medical imaging.

2. Literature Survey

Liu et al. (2023) have proposed a method for stroke prediction using machine learning techniques, analyzing patient data such as age, medical history, and lifestyle factors. The study compared models like Decision Trees, Support Vector Machines (SVM), and Random Forest, with Random Forest achieving the highest accuracy at 92% for stroke risk detection. Key findings emphasized the importance of feature selection, identifying age, hypertension, and heart disease history as major predictors, suggesting that these models could be integrated into health systems for early intervention. [3]

Chen et al. (2022) have developed an automated brain stroke detection model using Convolutional Neural Networks (CNN) to identify ischemic strokes from MRI images. Trained on a large dataset of MRI scans, the CNN-based model demonstrated high accuracy in stroke detection. The study highlights the potential of deep learning in processing complex medical imagery and suggests the use of CNNs in clinical settings to improve diagnostic efficiency for stroke patients. [5]

P. Govindarajan, et al. [4] in (2020) The core goal of this study was to elevate the quality of CT scan images captured from individuals affected by strokes and subsequently employ machine learning methodologies to categorize these patients into two distinct stroke types. ischemic stroke and stroke haemorrhage study commenced with a crucial phase of enhancing the quality of CT scan images through preprocessing techniques, with the aim of eliminating noise. Made use of KNN, Bayesian system, Logistic Regression, Decision Tree, Random Forest, MLP, Deep Neural Learning, and Sv Machine. Rand Forest algorithm yielded exactness rate of 95.97%, a exactness ratio of 94.39%, a true positive rate of 96.12%, and and a calculated F1-Measure of 95.39%.

MS Singh, et al. [6] in (2017) A stroke likely to happen if there is a disruption or decrease in the blood supply to an individual's brain, leading to a deprivation of oxygen and essential nutrients. This can result in the demise of brain cells. The study utilized the decision tree algorithm for selecting features, implemented the principal component analysis algorithm to diminish dimensionality, and embraced the back propagation neural network classification algorithm for constructing a classification model. The model for stroke problem, showcasing an improved accuracy percentage of 97.7%

3. Existing System

Machine learning practices like Random Forest and SVM were routinely used in the brain stroke detection model that was in place. but it's crucial to note that this model primarily relied on structured data for its operation. Structured data, which typically includes pre- defined variables and parameters, was collected and processed using these classification algorithms to identify brain stroke cases. Unfortunately, this approach had certain limitations, especially when dealing with vast datasets.

One significant drawback of this prior model was its inability to handle unstructured data, such as direct medical images from MRI and CT scans. The absence of this unstructured data significantly restricted its capacity to detect brain strokes with the level of precision and accuracy required in modern healthcare.

Furthermore, as medical data continues to grow exponentially, the existing model struggled to efficiently scale and adapt to larger datasets, often resulting in performance bottlenecks.

This underscored the need for a more advanced and adaptable system, like the proposed Brain Stroke Detection System, which incorporates State-of-the-art techniques like Deep Learning and CNN to effectively analyze

unstructured data, thereby enhancing the accuracy and scalability of brain stroke detection in the modern medical landscape.

Disadvantages of Existing System

- More Data complexity
- Require high computation of resources
- Comparatively less efficient
- High Time complexity
- More human efforts

4. Proposed Methodology

The suggested System for Detecting Brain Stroke, like illustrated in Fig. 89.1, leverages a combination of MRI and CT scans to initiate the detection process[4]. These crucial medical images of the brain serve as the initial input to proposed system. Within proposed system the MobileNet algorithm plays a pivotal role by conducting feature extraction, meticulously identifying intricate patterns within the images as it traverses the layers of convolutional neural networks. During the training phase, these extracted patterns are associated with their respective labels, distinguishing them as either Stroke images or non-stroke images. Subsequently, following the classification process, images exhibiting abnormal brain conditions are categorized as Potential Stroke images, while those displaying no symptoms related to stroke are identified as non-stroke images. This methodology not only ensures efficient and accurate brain stroke detection but also underscores the potential of cutting- edge technology in the field of medical diagnostics[5]. The MobileNet algorithm, a type of convolutional neural network, plays a crucial role in feature extraction. It analyzes the input images layer by layer, identifying intricate patterns inside of the illustrations. This feature extraction process is essential for recognizing patterns and characteristics that distinguish stroke- related abnormalities in the brain.

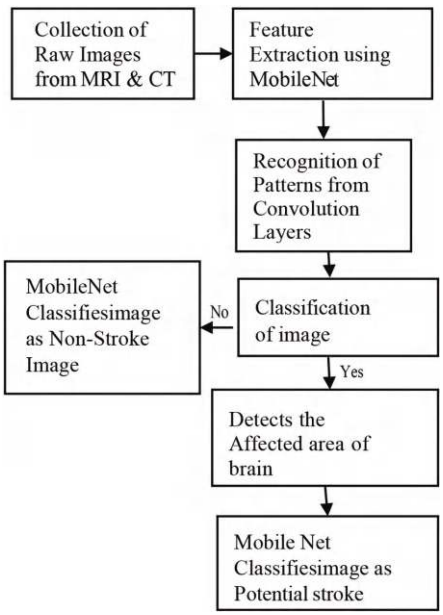

Fig. 89.1 Schematic diagram of proposed system

5. Implementational Details

In this section, proposed system explores the real-world factors of enacting the Brain Stroke Detection System, a critical component of modern healthcare leveraging cutting-edge of deep learning techniques. The project encompasses data acquisition, preprocessing, model selection, training, and evaluation, culminating in the growth of a robust and accurate system for early stroke recognition. Its start of commence with data acquisition, emphasizing the importance of a meticulously curated dataset comprising both stroke and non-stroke cases, sourced from medical images like CT scans and MRIs. Annotation of this dataset plays a pivotal role, marking each image with the relevant stroke or non-stroke label. Subsequently, the data group is thoughtfully segmented into training, validation, and test sets to ensure comprehensive model assessment [6].

During the first stages of data collection, the diversity and representativeness of the gathered medical images are just as important as their quantity. This entails working with healthcare facilities to gain access to a wide array of cases, forming sure that the data group correctly indicates the variability present in stroke circumstances. The choice of imaging modalities, such MRIs and CT scans, is based on how well they can show minute details of the anatomy of the brain as well as possible abnormalities[7].

Every stage of the project, from preprocessing to model selection, training, and evaluation, is carried out precisely and to the greatest standards possible. Preprocessing approaches ensure that the model is robust to fluctuations in image quality and resolution by addressing issues inherent in medical imaging. For the purpose of pick a model that is in line with the complexities of stroke detection, careful evaluation of the model's architecture and complexity must be made.

Data Set

The proposed system used ATLAS(Anatomical Tracings of Lesion After Stroke) data set to work upon. It is a large open-source dataset of brain scans from stroke patients, compiled and shared for research on Brain MRI Images. Researchers use the scans to develop and test algorithms that can process MRI images automatically.

Data Acquisition

Gather the brain images dataset, including the stroke and non-stroke cases. You may need medical images like CT scans or MRIs. Annotate the dataset, marking which images contain strokes and which do not. Split the dataset into training, validation, and test sets.

Data Preprocessing

Normalize the individual pixels in the images. Resize the images to a consistent input size compatible with MobileNet. Augment the training data with techniques like rotation, flipping, and zooming to increase the diversity of the dataset.

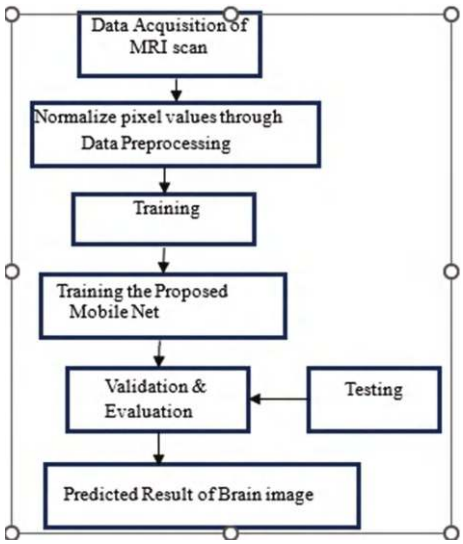

Fig. 89.2 Data flow for detection of brain stroke

5.1 Model Selection

Choose MobileNet as base architecture, which is optimized for mobile and embedded devices. You can use pre-trained MobileNet models available in deep learning

5.2 Feature Learning and Extraction

Utilize convolutional neural networks (CNNs) power to autonomously unearth intricate patterns and significant features within the raw brain Images function as intelligent filters, progressively scanning the images and generating feature maps that accentuate relevant characteristics. Deep learning models can discern complex patterns such as lesions, tissue anomalies, or blood flow irregularities, making them ideal for medical image analysis. Customize the architecture by adjusting the number and arrangement of convolutional layers, optimizing it for stroke detection[8].

5.3 Training

Initiate the training phase, where the neural network's weights are iteratively adjusted to minimize a designated loss function. The loss function quantifies the discrepancy between the model's anticipation and the actual labels, driving the network towards more accurate stroke detection. Optimize hyper parameters, such as learning rate and batch size, through experimentation to expedite convergence and improve final model performance. Implement early stopping methods for avoiding overfitting and guaranteeing that the model generalizes well to new data. Train the modified MobileNet model on pre-processed dataset.

Monitor training metrics such as loss and accuracy on the validation set. To increase training efficiency, employ strategies like learning rate scheduling and early ending[9].

5.4 Validation and Hyperparameter Tuning

Continuously monitor the neural network's performance on a validation dataset during training to gauge its generalization capability Fine-tune hyperparameters based on validation results, adjusting architectural elements or training parameters as necessary. Employ cross-validation techniques to further validate model robustness and reliability.

5.5 Evaluation

Examine the trained design on the test data group to assess its performance. Determine the model's efficacy by computing metrics such ROC AUC, F1-score, exactness, clarity, true positive rate, and F1-score.

5.6 Algorithm Used

Mobile Net is a kind of deep neural network engineered for efficient and lightweight inference on mobile and other devices. It is the method that google is developed it, inorder to enable deep learning models to run efficiently on resource-constrained hardware, such as smartphones, tablets, and other edge devices. achieves its efficiency by using a combination of techniques, including depth wise separable convolutions and model architecture optimization. Here are some key features of Mobile Net:

- Depth wise Separable Convolutions
- Model Size Reduction
- Adjustable Model Size
- High Accuracy and Speed
- Pointwise Convolution
- Width Multiplier and Resolution Multiplier

5.7 Depthwise Separable Convolutional Layers

These are a type of convolutional layer used to reduce the computational complexity of neural networks while preserving their ability to capture features effectively. In the context of brain stroke detection, these convolutions can help in efficiently extracting relevant features from medical images, such as CT scans or MRIs, which can be computationally intensive.

5.8 Model Size Reduction

Model size reduction refers to the process of making neural network architecture smaller regarding the number of parameters and memory usage.

This is crucial for implementing brain stroke detection models on devices with limited memory and computing capability, such as embedded Systems or mobile phones.

5.9 Adjustable Model Size

An adjustable model size allows you to fine-tune the complexity of neural network. Depending on the available computational resources, you can scale the model up or down to achieve the right balance between accuracy and efficiency for brain stroke detection on different devices or platforms.

5.10 Accuracy and Speed

Achieving high accuracy and speed is crucial in brain stroke detection because timely and accurate diagnosis is critical for patient care. Balancing accuracy and speed ensure that the model can deliver quick results without compromising diagnostic quality. Rapid and precise diagnosis ensures that medical professionals can swiftly administer life-saving treatments, while a well-balanced approach guarantees that the neural network can efficiently analyse medical images, providing timely insights without sacrificing the reliability of its findings[10].

5.11 Pointwise Convolution

Pointwise convolution, also known as 1x1 convolution, is a convolutional layer with a kernel size of 1x1. It's often used to reduce the feature channel count in a neural network while preserving spatial information. In the context of brain stroke detection, pointwise convolution can be employed to reduce the dimensionality of feature maps, making the model more efficient[11].

5.12 Width Multiplier and Resolution Multiplier

Width multiplier and resolution multiplier are hyperparameters that allow you to control the size and resolution of neural network model. In the context of brain stroke detection, adjusting these multipliers can help you optimize the model's architecture for specific hardware constraints and image resolutions, making it more adaptable to different deployment scenarios[12][13].

6. Result

In the context of a brain stroke detection project utilizing Mobile Net neural networks, the expected results encompass a range of significant outcomes. First and foremost, the project aims to attain a high level of accuracy in the detection of strokes from medical images, thereby enhancing the reliability of diagnostic assessments. Real-time analysis is a key objective, ensuring that the mobile application can swiftly process uploaded medical images, enabling timely medical intervention when require. The system's ability to distinguish between ischemic and hemorrhagic strokes will contribute to more precise treatment planning, improving patient care.

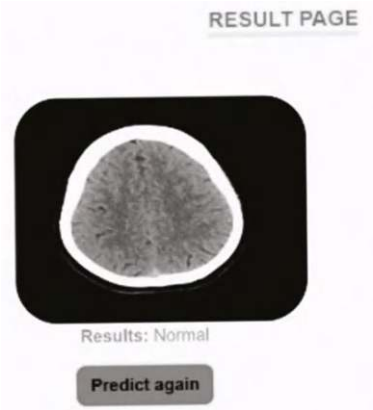

Fig. 89.3 Image of non-potential stroke

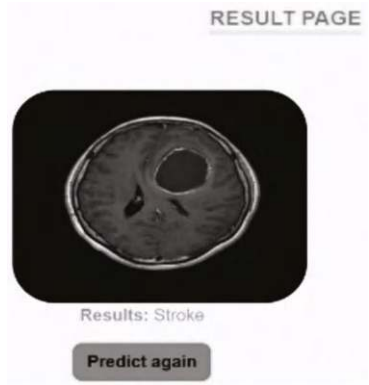

Fig. 89.4 Image of potential stroke

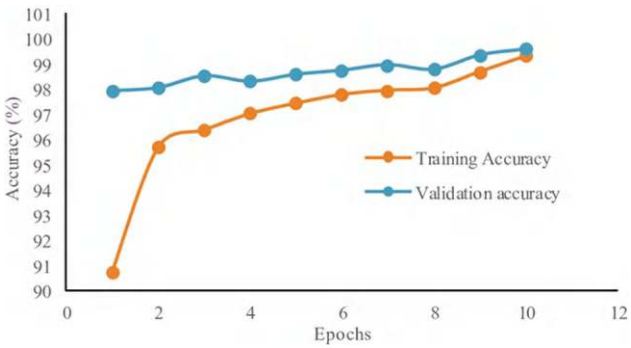

Fig. 89.5 Graph regarding test accuracy and validation accuracy

7. Comparative Analysis

Table 89.1 Comparative study of existing and proposed system

Aspect	Existing System	Proposed System
Data utilization	structured data (variables and parameters)	Unstructured data (MRI and CT scans)
Algorithm	Random Forest and Support Vector Machine	MobileNet and Convolutional Neural Networks
Handling Large Datasets	Scalability issues for large datasets	Improved scalability and adaptability for growing datasets
Performance	May have limitations In precision	Enhanced accuracy in stroke detection
Technology	Relies on traditional machine learning	Leverages cutting- edge deep learning techniques such as mobile net
Training	Limited ability for feature extraction	Utilizes CNNs for feature extraction
Validation	Lacks validation and hyperparameter tuning	Regular validation and hyperparameter tuning
Data augmentation	Limited data diversity and augmentation	Augments data with techniques like rotation, flipping and zooming
Accuracy obtained	Accuracy is up to 60%	Accuracy would be increased to 70%

8. Conclusion and Future Scope

In closing remarks, proposed project focused on the utilization of MobileNet-based DL models for the critical task of brain stroke detection. Leveraging the efficiency and adaptability of MobileNet architectures, developed system that holds significant promise for early diagnosis and intervention in stroke cases. proposed system efficiently processes medical images, such as CT scans or MRI scans, in real-time, enabling swift detection of brain strokes. By adapting MobileNet through fine-tuning and transfer learning, its ability to handle resource-constrained environments, making it suitable for deployment in various healthcare settings, including remote clinics and telemedicine applications. Through rigorous data collection, model training, and validation, this model attained a elevated level of accuracy in sensing brain strokes, potentially improving patient outcomes by facilitating timely medical interventions. The system's versatility, scalability, and compatibility with medical imaging data make it a valuable tool for healthcare professionals, extending the reach of expert care and enhancing the overall quality of stroke diagnosis and treatment. With currents trends in Technology and ongoing collaboration with medical experts, ethical considerations regarding patient data, and continuous improvement of the system will be essential to realizing the full potential of MobileNet-based brain stroke detection solution in the realm of healthcare.

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Predicting 5G Network Coverage with CNN and Ensemble Learning Techniques

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Abstract: In the era of 5G technologies, predicting coverage areas is crucial for optimizing network performance and ensuring reliable connectivity. Existing 5G Coverage prediction models face challenges in interpretability,data dependency, and scalability, to address these proposed model is introduced. It presents a careful examination of various machine learning algorithms to predict 5G coverage depending on RF Signal Data. The target column, Band Width, is used to gauge prediction accuracy across different models. Traditional methods such as Logistic Regression, K-Nearest Neighbours (KNN), Naive Bayes, Random Forest, Support Vector Machine (SVM), XGBoost, LightGBM, AdaBoost, Bayesian Network Classifier, Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM) are judged against proposed advanced techniques like Stacking and Voting Classifiers, and Convolutional Neural Networks (CNN). This research contributes to optimizing 5G deployment strategies by enhancing predictive models, thereby facilitating efficient network planning and management.

Keywords: RF signal data, Stacking classifier, Voting classifier, Convolutional neural network (CNN), Feature parameters, Prediction accuracy, Network optimization

1. Introduction

The advent of 5G technology necessitates accurate prediction of coverage areas to ensure seamless connectivity and optimal network performance. Effective coverage prediction enables telecom operators to optimize network deployment strategies, enhance user experience, and reduce costs. Leveraging machine learning algorithms, this study investigates the potential for predicting 5G coverage using RF signal data. A comprehensive analysis of traditional

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models, including LR, RF, and SVM, is conducted alongside advanced techniques such as Stacking, Voting Classifiers, and Convolutional Neural Networks. By evaluating and comparing these models, this analysis aims to contribute to the development of optimized 5G deployment strategies, facilitating efficient network planning and management.

The key objective of this research is to conduct a comparative analysis of various ML algorithms, including both traditional and advanced techniques, to predict 5G coverage accurately. By using the RF Signal Data with Band Width as the target variable for maximum advantage, the study aims to measure how well a trained model works. The goal is to identify the most accurate and computationally efficient model for practical deployment in 5G network optimization.

This research includes a detailed and careful analysis thorough evaluation of multiple ML algorithms for 5G coverage prediction using RF Signal Data. The scope includes preprocessing the dataset, training and validating models, and conducting performance comparisons based on accuracy, computational efficiency, and robustness.

The study focuses on both traditional models and advanced techniques like ensemble methods and CNNs. The findings will provide valuable insights into the most effective algorithms for 5G coverage prediction, helping or supporting network engineers in optimizing 5G network planning and deployment strategies.

2. Literature Survey

C. Sudhamani et al. [1] They explored various techniques aimed at improving system performance, capacity, spectral efficiency, and latency, amidst issues like interference at cell edges due to increased base station density.

M. M. Ahamed et al. [2,4] They proposed an updated cell architecture with six sectors and advanced antenna systems to enhance 5G coverage. The paper underscores the significant planning challenges faced by mobile network operators (MNOs) in acquiring numerous small cell locations to ensure comprehensive 5G network coverage. Future research directions are also suggested to address these deployment challenges effectively

H. Ye, G. Y. Li et al. [3] The authors demonstrate that deep learning, particularly neural networks, can outperform traditional model-based approaches in addressing challenges posed by complex wireless communication environments. In OFDM systems, accurate channel estimation is critical for signal detection, especially in scenarios with noise and interference.

M. Soltani et al. [5] This approach leverages the power of neural networks to model the complex and non-linear characteristics of wireless channels, offering improved accuracy compared to traditional estimation methods such as LS and MMSE.

T. Gruber et al. [6] The authors propose a deep learning approach for decoding data transmitted over noisy channels. Traditional channel decoding methods, such as convolutional codes and turbo codes, rely on algorithmic solutions that are specifically designed for known channel conditions.

Y. H. Santana et al. [7] They made a test and, in those results, demonstrate its ability to optimize network deployment with reduced access points while meeting coverage requirements faster than heuristic methods.

EEE Staff et al. [8] The conference emphasizes how the integration of ML can optimize various aspects of 5G networks, from resource management to network performance and beyond. Machine learning is highlighted as a key enabler for 5G's complex requirements, such as ultra-low latency, massive connectivity, and enhanced data rates.

M. F. A. Fauzi et al. [9,12] in their study on mobile network coverage prediction, Fauzi et al. explore the necessity for enhanced coverage and quality amidst increased digitalization and the 5G era.

M. F. A. Fauzi et al. [10] they address limitations in current network planning techniques by introducing MLOE, a novel tool based on the Random Forest algorithm. MLOE uses seven unique features to predict mobile network performance, achieving superior results over traditional methods with an RMSE of 2.65 dB and an R^2 of 0.93

H. Chiroma et al. [11] the paper explores the growing intersection of nature-inspired meta-heuristic algorithms and deep learning, highlighting their applications in diverse fields like machine vision, medical imaging, and autonomous systems.

Jian Sang et al. [13] this study investigates the effectiveness of Reconfigurable Intelligent Surfaces (RIS) in enhancing coverage in 5G commercial mobile networks. RIS deployment increases signal strength by 5-10 dBm.

Jinhe Zhou et al. [14] The proposed dynamic network slice scaling assisted by prediction effectively enhances 5G network performance. Latency was reduced from 20 ms to 17 ms.

Wei Ye et al. [15] The study provides insights into Carrier Aggregation (CA) in 5G networks, revealing its impact on Quality of Experience (QoE). Network Throughput increased from 1.2 Gbps to 1.62 Gbps.

Mohammad Ariful Islam et al. [16] The proposed DNN based communication failure prediction project effectively predicts failures in 5G RAN, DNN model achieves 95% accuracy in predicting communication failures.

3. Existing Methodology

Recent research on machine learning algorithms for predicting 5G network coverage has made considerable progress. These studies highlight how accurate predictions are essential for optimizing both network deployment and service quality. Algorithms such as Random Forest and CNN had displayed to perform exceptionally well in predicting coverage, with features like the 2D Distance Tx Rx being particularly influential. This research demonstrates the value of using ML and deep learning to improve network planning and resource allocation in the rapidly evolving 5G technology environment.

3.1 Disadvantages

Algorithms like RF and CNN may provide accurate predictions, but their complex models can be difficult to interpret, hindering insights into network planning decisions. These algorithms heavily rely on high-quality and extensive datasets, which may not always be readily available or representative of real-world conditions, leading to potential biases or inaccuracies. Training and deploying sophisticated machine learning models like CNNs can be computationally intensive, requiring significant hardware resources and energy consumption.

4. Proposed Methodology

The proposed system uses advanced machine learning techniques, including Stacking and Voting Classifiers, as well as Convolutional Neural Networks (CNN), to enhance the prediction accuracy of 5G coverage areas. By integrating these methods, the system aims to combine the strengths of separate models, output is robust and accurate prediction framework. This approach involves pre-processing the RF Signal Data, training the models on this data, and validating their performance. The comparative analysis will identify the optimal model or ensemble of models for practical application in 5G network optimization, ensuring efficient and reliable coverage prediction. This study proposes a comprehensive system for predicting 5G coverage efficacy, using a dataset encompassing 27 parameters from diverse locations. Employing advanced techniques, the system aims to identify critical feature parameters - Frequency, Signal Strength, Modulation, and Bandwidth. Through analysis of 164,160 observations, the system evaluates dominant feature contributions and model performance metrics. This research aims to optimize 5G deployment strategies, enhancing predictive accuracy to support efficient network planning and management.

The selection of CNNs and ensemble methods for predicting 5G network coverage is based on their capability to identify complex, non-linear patterns in RF signal information that simpler approaches might overlook. CNNs are good at recognizing spatial hierarchies and relationships within structured, grid-like datasets, such as signal strength across different geographical areas, which is essential for precise coverage forecasting. Ensemble techniques like Stacking and Voting classifiers merge the predictions of several models to improve both flexibility and accuracy by capturing a variety of data patterns.

4.1 Advantages

Enhanced Predictive Accuracy: By leveraging advanced techniques like Stacking Classifier, Voting Classifier, and CNNs, the system achieves high accuracy in predicting 5G coverage efficacy across diverse locations and scenarios.

Optimized Deployment Strategies: The system identifies critical parameters such as Frequency, Signal Strength, Modulation, and Bandwidth, enabling optimized 5G deployment strategies tailored to specific environmental conditions and user demands.

Comprehensive Dataset Utilization: Utilizing a dataset encompassing 27 parameters and over 164,160 observations, the system ensures robust analysis and evaluation of dominant feature contributions, enhancing reliability in network planning.

Efficient Network Management: By evaluating model performance metrics, the system supports efficient network management by providing actionable insights into network performance and potential optimization areas.

Support for Strategic Decision-Making: The research contributes to strategic decision-making in telecommunications by offering insights that help stakeholders plan and implement 5G networks.

4.2 System Overview

The proposed system aims to predict 5G network coverage using a dataset containing RF (Radio Frequency) signal parameters.

4.3 Machine Learning Models Used

Stacking Classifier: It combines multiple base classifiers, using their strengths for maximum advantage to improve predictive performance. This approach aims to capture diverse patterns in the data that individual classifiers might miss, thereby enhancing overall accuracy and robustness.

Voting Classifier: It combines predictions from multiple separate models in order to improve overall accuracy and robustness. This approach uses the wisdom of the crowd concept to maximum advantage, where diverse models complement each other by capturing different aspects of the data.

Convolutional Neural Network: It is a deep learning model that is designed for processing structured grid-like data, like images and videos. . The architecture typically includes these layers that limit the data that is displayed to a specific subset of data for source data, pooling layers to decrease dimensionality and control overfitting, and fully connected layers for classification or regression task.

Other Models: Some other algorithms are RF, SVM, LR, KNN, Naïve bayes, XGBoost, Light GBM, AdaBoost, Bayesian network classifier, LSTM.

5. Workflow of Modules

Data Collection Module: Collects raw RF signal data from various sources. Determine appropriate sources for data collection. Set up data collection mechanisms to retrieve data from these sources. Ensure data quality by removing outliers, inconsistencies, or missing values. Store the collected data in a suitable database or data warehouse for further processing.

Preprocessing Module: Prepares the collected data for model training. Create new features or change existing one to improve model performance. Scale features to common range to avoid partiality in the model. Impute missing values using appropriate techniques. Identify and remove outliers that can negatively impact model training. Divide the dataset into training, validation, and testing sets.

Model Training Module: Trains machine learning models using the pre-processed data. Choose appropriate ML algorithms.Train selected models on training set. Evaluate model performance on validation set to identify the best-performing model.

Prediction Module: Uses the trained models to predict 5G network coverage. Receive input parameters from users (e.g., location, frequency, user density). Apply the trained models to generate coverage predictions based on the input. Return the predicted coverage values to the user.

Deployment Module: Integrates the prediction module into a user-friendly interface. Develop a web application or RESTful API to expose the prediction functionality. Create a interface for inputting parameters and viewing predictions. Deploy the application to a suitable environment. Ensure the application's ongoing operation and update it as needed.

5.1 Module

System

1. **Dataset Management:** The dataset is pre-processed for feature selection and split into training and testing subsets to ensure robust prediction accuracy.
2. **Model Training:** Model Training Information: Implemented a machine learning model to identify key parameters affecting 5G coverage and optimize.

Prediction accuracy through iterative training and validation.

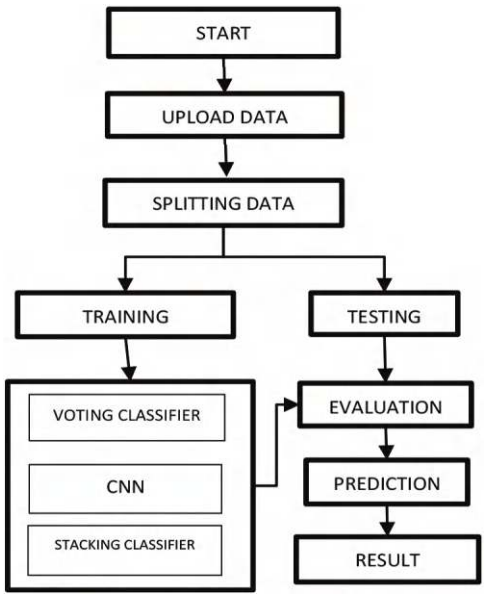

Fig. 90.1 Block diagram of proposed system

3. **Predictive Analysis:** Leveraging advanced algorithms to forecast 5G coverage by identifying key feature parameters, ensuring enhanced prediction accuracy and network optimization.
4. **Data Segmentation For 5G Coverage Prediction:** The dataset is segmented based on geographical regions and time intervals to analyze spatial and temporal variations in 5G coverage.

User

1. **Registration:** Users register for the application by providing necessary details and creating secure login credentials.
2. **Authentication:** Registered users securely log in to access the application's features and functionalities.
3. **Data Upload Information:** Upload datasets with relevant parameters for 5G coverage analysis, including signal strength, environmental factors, and network configurations
4. **Dataset Review:** The dataset comprises detailed records of 5G network coverage, including signal strength, geographical coordinates, and environmental parameters.
5. **Model Selection:** Users choose from available models optimized for predictive analysis and

anomaly detection using reciprocal points learning techniques.

6. **Analysis Results:** Identification of key feature parameters significantly impacting 5G coverage prediction, achieving high.

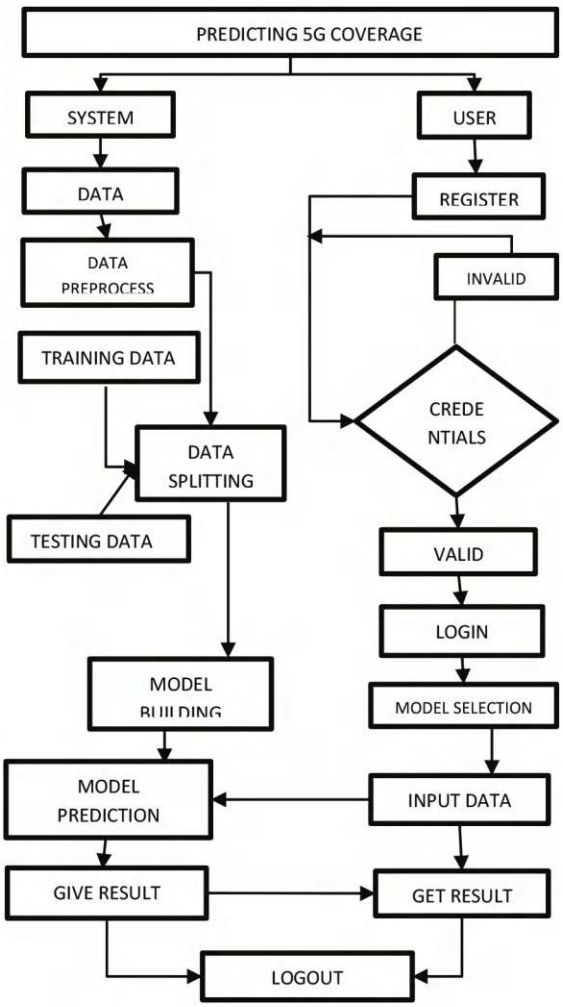

Fig. 90.2 Workflow of proposed system

6. Results and Discussions

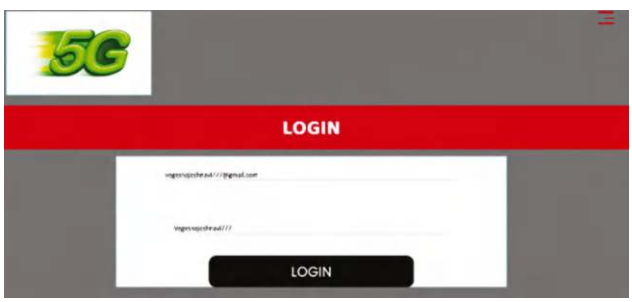

Fig. 90.3 Entering the login credentials

Fig. 90.4 Preprocessing the data

Fig. 90.5 Training the model using CNN algorithm

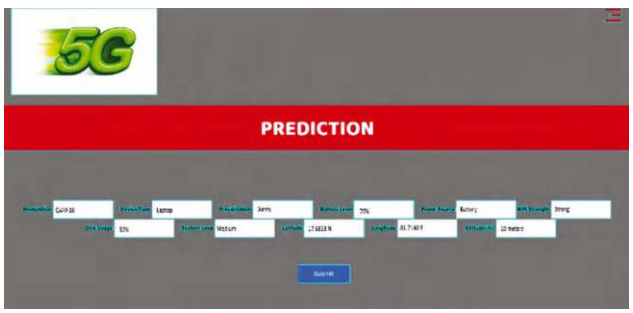

Fig. 90.6 Predicting coverage

7. Conclusion and Future Scope

This study has demonstrated effectiveness of ensemble methods such as Stacking and Voting Classifiers, alongside Convolutional Neural Networks, in predicting 5G coverage. Through analysis of 27 parameters across diverse locations, including Frequency, Signal Strength, Modulation, and Bandwidth, we identified critical features influencing coverage efficacy. The findings highlight the importance of integrating multiple data modalities to enhance prediction accuracy, crucial for optimizing 5G deployment strategies. By refining predictive models, this research contributes to more efficient network planning and management, offering valuable insights for future advancements in telecommunications infrastructure.

New research can concentrate on enhancing the predictive accuracy of 5G coverage models, integrating more granular spatial and temporal data. Incorporating real-

time environmental factors such as weather conditions and urban density could provide deeper insights into network performance variability. Additionally, exploring adaptive learning techniques that dynamically adjust model parameters based on evolving network conditions could further optimize prediction efficacy. Furthermore, investigating the potential of hybrid models combining CNN with recurrent neural networks (RNNs) for capturing temporal dependencies in coverage patterns would be beneficial. These enhancements aim to refine 5G deployment strategies, ensuring robust network planning and management in diverse operational contexts.

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Novel Student Performance Evaluation Using Cognitive Skills and Data Analysis Techniques

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Abstract: Current student evaluation is done by grading student work with help of assignments, exams, projects, which involves more manpower to assess as well as the students might not indulge more interest in it. These can be subjective and prone to biases. They may primarily focus on traditional formats like multiple-choice, short answers missing out on student concern, interactive and innovative assessment formats. In such cases, there might be a chance of copying. To mitigate these disadvantages, we have come up with an idea of integrating technology and automated methods that offer more immediate feedback, adaptability to individual learning paths. This approach aims to create a more interactive and effective assessment environment that benefits student learning and growth. The cognitive as well as technical skills of the student can be assessed by using simple cognitive games such as crossword puzzles, missing characters, shuffled words. This will give liveliness along with thoughtful insights into the subject. At the end we want to showcase students' performance in graph using Linear regression technique. Taking up assessment generation using cognitive skills instead of manual assessment offers several advantages that can enhance the quality, efficiency and fairness of assessment process. Automated assessment systems can generate data on student performance, identifying trends, strengths and weaknesses accurately.

Keywords: Cognitive skills, Critical thinking, Problem solving, Logical reasoning, Decision making

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1. Introduction

Cognitive skills are the capabilities that enable individuals to acquire, process, and use information to solve problems, make decisions, and interact effectively with their environment. It is said that, by surveying the higher education system in India, the graduate students' score high marks instead of skill, the lack of skills proportionally increases the number of unemployable graduates in the society [1]. Cognitive skills include board games like chess, monopoly, pattern recognition games like sudoku, jigsaw puzzles, word games like crossword puzzles, word search and scrabble. The Proposed system helps students in better thinking, problem solving and decision making that helps them to thrive in a constantly changing world. [12, 13]

Cognitive skill-based assessments are often considered prior to manual assessments because they are comparatively reliable, standardized and scalable than old assessment generating methods. To decide the individual's thinking and reasoning abilities, assessment must focus on cognitive aspects in e-assessment [7, 14]. Manual student assessments are subjective, time consuming and biased making it impractical for large-scale evaluations. Recent developments in the field of automated methods have led to renewed interest in generating assessment using cognitive skills.

Cognitive-based assessments are better because they use standardized tests and advanced technology. This makes the assessments more accurate and fairer, without relying on personal opinions. The tests are consistent and objective, providing a reliable way to measure someone's cognitive abilities. These tests can change how hard they are based on how well someone is doing. This means the test adapts to the person taking it, giving a more detailed picture of their skills and abilities. Cognitive skills had been applied on healthcare, teaching and training, Science and Research, Technology and engineering, and in creative fields.

1.1 Context

Assessment helps students set goals, track their progress and prepare for future academic or professional endeavours. Research in this area plays an important role in improving the quality and relevance of education, benefiting a wider range of students and educators. The study has shown that the Current state of assessment generation and student performance evaluation are not up to the mark.

1.2 Challenges with Traditional Assessments Methods

One of the major challenges is that Traditional assessment methods might not depict the full picture of student's performance. These methods mostly focus on subjective tests rather than tests that include creativity, problem-solving skills and logical thinking. Grading can be subjective and prone to bias which leads to inconsistency in performance evaluation. Another challenge is the lack of flexibility and individualization in traditional assessments. These are standardized tests that follow a one-size-fits-all approach, presenting same set of question for every test taker. Traditional methods may not accurately measure the students potential and their abilities. This may create anxiety and stress for students. These challenges highlight the need for more diverse and modern assessment methods.

1.3 The Need for Innovation

The Recent studies had suggested that there is compelling need for innovation of modern assessments that incorporate cognitive skills. Traditional assessment methods are not fit for measuring student's true potential and ability. These modern approaches provide a more comprehensive understanding of student's ability and prepare them to face the challenges of these rapidly changing world. Innovation in assessment methods is crucial for promoting fairness and inclusivity. Cognitive skill-based assessments focus on high order thinking abilities, proposing relevant evaluation of an individual's performance. The use of advanced technology and standardized testing protocols increases the accuracy and objectivity of the assessment.

1.4 Integrating Technology for Enhanced Assessment

Traditional assessment formats include tests like short answer questions, multiple choice tests, standardized tests. The failure in previous attempts of Traditional assessment methods had led to the idea of integrating technology and automated methods that provides consistent evaluation of student's performance. Online platforms and tools enable convenient and widespread access to assessments, making them more accessible and efficient. Students are well prepared to with stand demands and technology of 21st century.

1.5 Evolving Assessment Methods

The recent research generation reflects a shift to more dynamic technology-driven approaches. Psychological assessments, in particular, have evolved adaptively, consisting of questionnaires based on an individual's performance. This flexibility ensures a more nuanced assessment, taking into account the nuances of an individual's skills. The combination of artificial intelligence and machine learning further enhances the analytics process, providing insights and analytics that

support informed decision-making in a variety of areas, from education to recruitment and what it's more than that. [11, 15] Today's assessments reflect a mixture of innovation and accuracy, providing a more comprehensive and positive way to assess individual abilities.

1.6 Traditional Assessment Generation Method Vs Modern Assessment Generation Method

Traditional assessment generation methods involve standardized tests designed in fixed structure, often using paper and pencil formats. These assessments constitute set of predetermined questions where ever test taker receive same set, regardless of individual competence. Modern assessment generation methods integrate technology and innovation to produce improved output. This includes technologies like artificial intelligence and machine learning which enable automatic grading, faster feedback and extract meaningful insights from datasets. The main difference lies in the flexibility, personalization and efficiency offered by the latest analytical generation methods compared to the rigorous representation of the traditional methods [16].

2. Literature Survey

Kalpana Devi et al. [1] in 2019 has proposed "Design and Implementation of Human-computer interface based Cognitive Model for Examine the Skill Factor of Students", on the developing a software that organizes ability tests based on cognitive model, has achieved 96.5% accuracy.

Kan Li et al. [2] in 2018 has proposed "A Novel Technique for the Evaluation of Posterior Probabilities of Student Cognitive Skills", on evaluating student's back abilities based on cognitive skills, has achieved 95.7% accuracy.

Pooja Asopa et al. [3] in 2016 has proposed "Evaluating student performance using Fuzzy Inference system in Fuzzy ITS", on developing fuzzy inference system to help students in enhancing their learning skills, has achieved 72% accuracy.

Ishwank Singh et al. [4] in 2016 has proposed "Student Performance Analysis using Clustering Algorithm", on data analysis technique to understand the performance of student in various categories, has achieved 86%.

3. Related Work

3.1 LMS (Learning Management Systems)

LMS includes e-learning platforms such as google classroom, blackboard, Moodle They enable educators efficiently organize the necessary resources, course contents and generate assessments in online platform where students need to refer and submit. Additionally, LMS facilitate instructors and students to communicate and collaborate with one another leading to dynamic learning. LMS suffer with down time, technical issues, scalability challenges, privacy & data security concerns and it might be complex to integrate with other systems.

LMS have downside because they might make learning feel a bit lonely. Though learning materials are easily available for the students, they don't have regular touch and interaction like in regular classroom. Not seeing teachers and classmates in person can make it feel difficult to work together in teams. Some students might also struggle to stay attentive throughout the class and stick to stud schedule. Technical problems arise in between the classes which may be annoying.

Manual Assessments are traditional methods of evaluating student's performance that require human intervention for creating, administrating and grading. These include essays, practical exams, group discussions and debates. Manual assessments are time consuming for instructors to create and grade. Moreover, students may suffer from subjectivity, partiality and inconsistencies in evaluation.

Manual assessments also have some downsides. One problem is they might not be fair because different people might grade the same answers differently. These assessments take a long time to evaluate and it is found difficult for the students to get feedback. Another issue is that they typically focus on memorizing facts rather than understanding and applying knowledge. Results are biased and are not issued on true abilities of students which may create stress.

Manual assessments are less reliable, slower, and more stressful than latest and adaptive assessment methods comparatively. [8-10, 17]

4. Proposed System

The combination of technology and methodology represents an alternative approach to addressing the limitations of traditional methods of assessing student performance. By incorporating cognitive games, such as crossword puzzle, word search, and shuffled words into the assessment generation process, the proposed system aims to make the assessment not only more engaging but also more in line with today's academic priorities by moving away from traditional handwritten assessments in notebooks. The program uses technology to create an interactive environment for students can demonstrate their intellectual skills. The inclusion of data analysis techniques, especially linear regression, adds a quantitative dimension to the analysis, ensuring a comprehensive assessment of

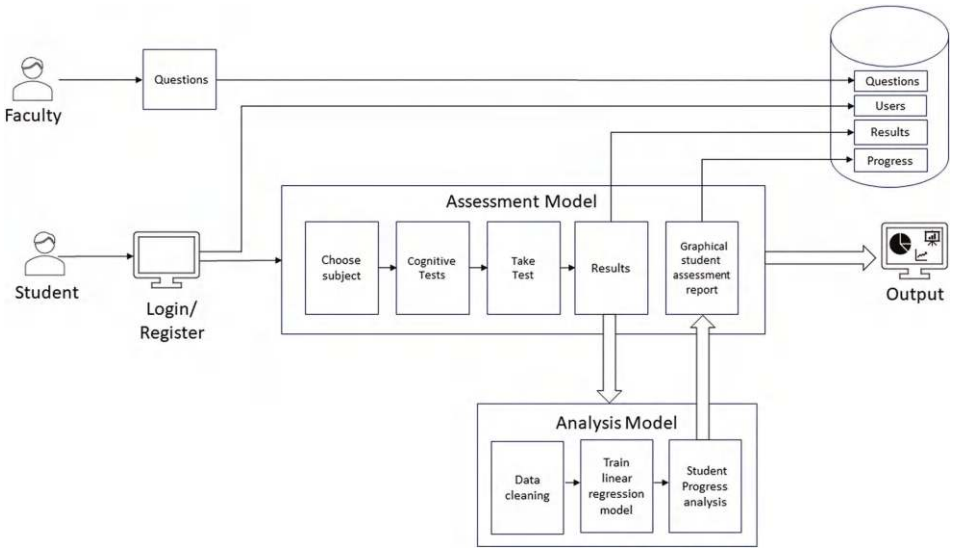

Fig. 91.1 Block diagram of proposed system

each student's performance. Furthermore, the proposed system emphasizes immediate feedback as a key element for students in presenting deeper understanding and motivation. Scores are displayed immediately upon submission, and students receive timely feedback on their performance, encouraging them to reflect on their learning. A visual representation of accuracy over time greatly enhances this feedback mechanism, allowing students to track their progress and identify areas for improvement. In addition, the policy prioritizes accessibility, ensuring that students can easily participate in research. This innovative blend of technology, psychology and data analytics not only transforms the research process but enhances the overall learning experience for students.

Fig. 91.2 Dashboard of the user

5. Results

Figure 91.2 illustrates the dashboard of the proposed system, showcasing navigation options conspicuously labelled as "HOME" and "ASSESSMENT". These options guide users to respective pages, ensuring a clear and user-friendly interface. The design emphasizes simplicity and ease of use, allowing users to quickly access desired parts of the system. In addition to easy navigation, the dashboard adds thoughtful content with a personalized welcome message that greets users by name. This feature improves the user experience by adding sense of understanding and distinctiveness. The incorporation of personalized message provides engagement of users, creating best impression and nurturing a connection between the user and the system.

Figure 91.3 depicts the quiz page component, providing users with series that need to be answered. The layout

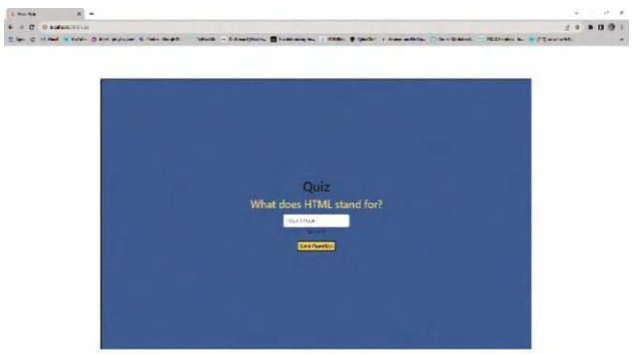

Fig. 91.3 Quiz

is designed to involve and engage users in the whole assessment process, displaying user-friendly interface that stimulates communication. The focus is on simplicity, with questions presented in clear format, promoting ease of

understanding for users as they direct through the quiz.To move on to the next question, users can click on the "NEXT QUESTION" button, simplying the assessment experience. The instinctive feature enhances user interface's efficiency, allowing users to improve through the quiz seamlessly. The design of the quiz page creates balance between accessibility and functioality, ensuring that users can focus on providing exact responses without any complications in navigation process.

Figure 91.4 displays the word puzzle component. Here, users have to find answers within a grid, and there's specific time limitfor this task. This challenge includes locating ten words hidden in the grid. The goal is to find the given words as quickly as possible, adding a time element to make it more engaging. The word search puzzle is designed in such a way for the users to have fun and interactive experience. As the users scan the grid to locate specified words, the time constraint adds a sense of urgency to the task. This challenge creates competition making the puzzle entertaining and thrilling for use

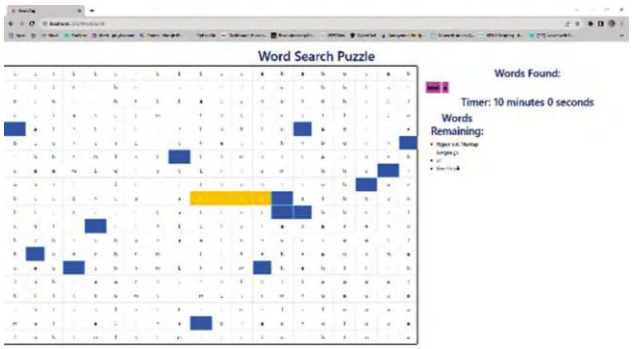

Fig. 91.4 Word search

Figure 91.5 displays the "MISSING LETTERS" page, where users are given a series of questions to answer. Each question comes with information to help users find answers. In order to provide feedback, users are required

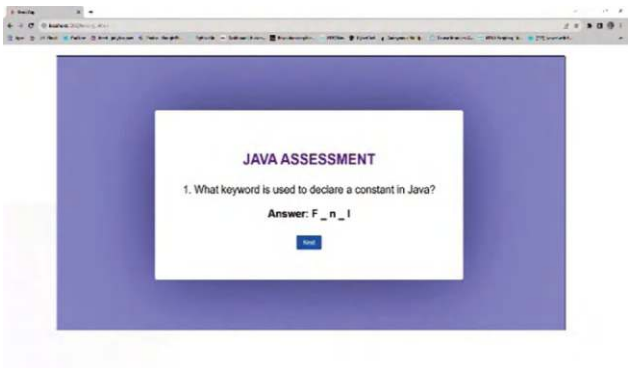

Fig. 91.5 Missing letters

to fill in the blanks in the responses provided. This activity challenges users to use the clues provided and use their skills to complete the missing pages, making it a fun and interactive way to test their understanding a have on the information see. The "MISSING LETTERS" page is designed to be user-friendly, offering a variety of questions with helpful hints to identify users. By requiring users to fill in the blanks, the program encourages active participation and reinforces learning in a more hands-on way. The combination of questions, prompts and interactive answers adds an element of problem solving to the learning experience, making it educational and engaging for users.

Figure 91.6 contains a "Crossword Puzzle" section where users can create word challenges. The questions are provided on the right side of the page, and users are required to answer these questions correctly in order to complete the puzzle. The goal is to connect terms in a crisscross way, creating an interactive and fun way for users to test their knowledge. The "crossword puzzle" is a game and educational activity that encourages users to think critically, and remember information to complete the puzzle. Through feedback and questions, users actively practice their logic and problem-solving skills. This phase provides an engaging learning experience as they are

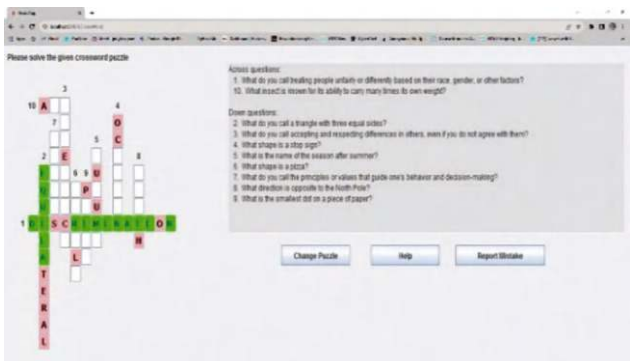

Fig. 91.6 Crossword puzzle

guided by vocabulary, increased cognitive engagement and information retention.

6. Comparative Study

Table 91.1 Comparitive study of existing and proposed systems

	[1]	[3]	Proposed System
Technology	Cognitive model	Artificial Intelligence	Machine Learning
Assessment Techniques	Correlation analysis	Fuzzy Clustering	Linear Regression
Difficulty Levels (Yes/No)	No	No	Yes
Feedback on ease of use	_	_	98%
Accuracy of Student's Performance	_	72%	99.1%

6.1 Linear Regression

Linear regression is a statistical technique that linearly equates observed data to model the relationship between a dependent variable and one or more independent variables. This is commonly used as a tool for predicting and explaining numerical outcomes in the field of statistics and data analysis.

$$Y = a0 + a1X \quad (1)$$

In the above equation, Y represents the dependent variable (the variable you are trying to predict); X represents the independent variable (the variable that is used to make predictions); a0 is the y-intercept, which is the value of Y when X is 0; a1 is the slope of regression line, which represents the change in Y for a one-unit change in X. In the proposed system, linear regression model is used to show the performance of student in the form of graph.

The following are the steps used in the Proposed System to plot the graph:

1. **Data Collection:** Gather data on student's academic performance and relevant independent variables. For example, collect the data of time taken by student to complete the task assigned, and their exam score.
2. **Data Preparation:** Organize and edit your data. Make sure you have two samples for each student, where you have data on the independent variables and academic achievement.
3. **Fit the Linear Regression Model:** Code in the backend is written in Java and graph plotting in the frontend is depicted by using Java Script. In this case, academic performance of the student is dependent variable (Y) and previous assessment score is independent variable (X).
4. **Plot the Data:** Visualize a scatterplot for the data. Represent values of the independent variable (previous assessment) on the x-axis and represent academic achievement on the y-axis (test scores) Scatterplot points should be student's individuals meet.
5. **Plot the Regression Line:** Represent the linear regression line on same graph. The line represents best-fit linear relationship between the independent variable and student's performance based on your data.
6. **Interpretation:** Analyse the graph plotted and understand the relation between the dependent and independent variables. If the data points are close to the regression line, it proposes strong relationship. If data points are scattered, the relationship may be weak.
7. **Predictions and Insights:** Predictions can be made with the help of linear regression model. In the proposed system, accuracy of the student's performance is predicted with the help of two variables mentioned.
8. **Additional Factors:** If there are multiple independent variables, then you can go with Multiple Linear Regression.
9. **Add the Labels and Tittles:** Ensure that the graph contains tittle, labels to X and Y axes and any necessary tags to maintain clarity.
10. **Continuous Monitoring:** Linear regression model can be used repeatedly. That means, if the student's performance change over time, the data will be updated and visualizes the modified model.

7. Conclusion and Future Scope

The purpose of the present research is to show that Cognitive skills are important abilities that enable individuals to process information, solve problems, make informed decisions and navigate their environment effectively. They include number of abilities from memory and concentration on critical thinking and creativity. The use of cognitive skills assessments offers many advantages such as reliability, flexibility, and objectivity, making them more selective than traditional manual assessments in many situations. However, it is important to be aware of the limitations of cognitive skills research, including their narrow focus, associated costs, and potential differences in test performance and social applications These assessments are

an invaluable investment of time and alternative assessment methods for gaining a thorough understanding of one's potential. While cognitive skill-based exams aren't without challenging situations, they provide valuable insights that make contributions to higher instructional, professional, and private results. The future of cognitive skill-based assessments holds immense potential for advancement and widespread application. Ongoing research and innovation will continue to drive improvements in the accuracy and reliability of these assessments, contributing to enhanced education, workforce development and healthcare outcomes. The Proposed System is best fit for evaluating user's performance.

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Smart Guard: Unravelling Credit Card Fraud Patterns Using Decision Tree and XG-Boost Algorithms

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Abstract: The prevalence of credit card fraud in the modern digital era is alarming. We offer a fresh strategy that makes use of XGBoost and Decision Trees, two machine learning tools, to tackle this problem. It is our goal to reliably detect fraudulent transactions by studying patterns of user behaviour and building decision trees and forests. By adding noise to the data, we make our model more robust and use public and real-world datasets to test its efficacy. Credit card fraud is a real concern, but this method shows promise in reducing that risk.

Keywords: Decision tree, Extreme gradient boosting (XG-Boost), Credit card fraud detection, Machine learning techniques

1. Introduction

The possibility of Concerning credit card fraud, it has become a major worry for both financial entities and customers in an era where financial transactions are largely digital. To reduce financial losses and preserve faith in the banking and payment systems, fraud detection must be done quickly and reliably. In this attempt, machine learning has become a potent tool, and two popular algorithms, Decision Trees and XGBoost, have demonstrated their effectiveness in detecting credit card fraud [1]. Fraud detection is incredibly challenging. Selection and classification are based on a wide range of characteristics. Transactions cannot be categorised simply as legitimate or fraudulent.[2]

Unauthorized and dishonest transactions with credit cards that take advantage of flaws in the payment infrastructure frequently have serious financial repercussions for both individuals and institutions [3]. Given the enormous volume of daily transactions and the constantly changing fraudsters' strategies, detecting this type of fraud is a challenging challenge. Decision Trees and XGBoost

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algorithms provide dependable answers for automating the detection of fraudulent actions in this situation [4]. Analysts can understand the reasoning behind classification judgments thanks to the openness and interpretability that decision trees offer [5]. On the other hand, XGBoost, an ensemble learning algorithm, is a strong option for tackling this problem because it excels in predicting accuracy and can handle intricate relationships within the data [6].

This investigation dives into the area of detecting credit card fraud and shows how Decision Trees and XGBoost algorithms are used to examine transaction data from the past. Financial institutions may strengthen their defences against fraud, protect the interests of their account holders, and preserve the uprightness of the financial landscape by utilizing these machine learning tools [7]. Aiming to effectively combat unauthorized credit, this article will examine the techniques, best practices, and practical ramifications of applying these algorithms [8].

Although the digital era has brought about unmatched convenience in financial transactions, it has also given rise to fraud schemes that are getting more and more sophisticated [9]. Financial institutions must constantly monitor this unwanted activity because fraudsters take advantage of holes in payment systems. Traditional fraud detection techniques are frequently insufficient, necessitating the development of sophisticated machine learning algorithms that can change with changing fraud patterns [10].

Because they make the decision-making process transparent, decision trees have a distinct advantage in the identification of fraud [11]. These "tree-like" data structures provide clear insights into the characteristics influencing fraud by segmenting complex data into understandable chunks. Analysts can follow the classification logic, which makes it simpler to understand and foresee fraudulent actions [12]. This openness helps with fraud detection but also makes it easier to create preventative measures in the future.

The ensemble learning algorithm XGBoost, in contrast, stands out for its remarkable accuracy and versatility [13]. It is excellent at capturing complex correlations throughout enormous datasets, making it very useful for spotting fraudulent trends. Financial institutions can react quickly to new threats thanks to its capability to adapt to altering fraud strategies in real-time [14]. Organizations can dramatically improve their fraud detection capabilities by utilizing the power of XGBoost, minimizing financial losses and preserving client trust [15].

The Decision Tree and XGBoost algorithms will improve Precision, accuracy, Transparency, Interpretability in the Management of Complex Relationships, Scale, quickness and Ability to Adapt to Changing Patterns in the project.

2. Literature Survey

L. Bhavya et al, in 2020 has proposed, "Credit Card Fraud Detection using Classification, Unsupervised, Neural Networks Models", implemented the implemented the Artificial Neural Network has achieved 97.5% accuracy.[1]

"Detection of Fraudulent Sellers in Online Marketplaces using Support Vector Machine Approach," published in 2018 by Renjith et al., using a support vector machine. [2]

"Fraud Detection using Machine Learning in e-Commerce," a proposal by Saputra et al. in 2019, calls for the development of a system to prevent fraud in online transactions with a 95% success rate when utilising machine learning.the third

In 2020, A. K. Rai et al. put up a scheme for "Fraud Detection in Credit Card Data using Unsupervised Machine Learning Based Scheme," which, when put into practice, produced an accuracy rate of 97%.[4]

3. Existing Methodology

Kumar et al. [5] in 2019 suggested random forest algorithm for uncovering credit card fraud with accuracy 90%. The proposed system is used to overcome the drawbacks of random forest algorithm to overfit noisy data or short datasets, which affects generalization and model performance.

4. Proposed System

4.1 Decision Tree and XG Boost

The suggested solution uses machine learning methods, particularly Decision Trees and Extreme Gradient Boosting, to tackle the urgent problem of credit card fraud. The system builds user activity-based trees and forests by examining credit card data from both public and actual credit card transactions, including noise that has been purposefully inserted for robustness testing. These structures demonstrate their usefulness in recognizing credit card fraud with noteworthy precision by enabling the accurate detection of fraudulent transactions.

5. Implementational Details

The implementation of the System and User modules for storing and dealing with a dataset, training a model, producing predictions, and evaluating model performance can be broken down into the following simple steps:

5.1 System

Storage Dataset

The System allows the user to upload or enter a dataset. This dataset is saved in an appropriate data structure (for example, a data frame or database).

Model Training

The System allows the user to choose a machine learning model for coaching. The System then uses the dataset provided by the user to train the selected model. This includes dividing the data into training and validation sets, training the model, and storing the trained model.

Model Predictions

After training the model, the system can take additional data inputs from the user. The System use the trained model to make predictions based on new data provided by the user.

5.2 User Module

Load Dataset

The User interacts with the System to load a dataset. To submit the data, the user may upload a CSV file, connect to a database, or utilize another means.

View Dataset

The user can request to see the loaded dataset. The System should provide a means to present the dataset's information, which could include summary statistics, sample records, or visualizations.

Select Model

The user can select a machine learning model for their dataset. This might be accomplished by selecting from a predetermined selection of models, specifying model parameters, or even allowing the user to submit a new model.

Evaluation

The User can assess the model's performance on the dataset.

- Depending on the problem type (e.g., classification, regression), this could include measures like as exactness, clarity, true positive rate, F1 score, or other relevant metrics.
- The system provides feedback on how well the chosen model performs on the dataset.

These phases provide a high-level overview of how the System and User modules interact to manage dataset storage, model training, predictions, and evaluation. The actual implementation would necessitate coding these stages as well as ensuring adequate communication and data exchange between the System and User modules.

6. Algorithms Used

A critical use of ML is uncovering credit card fraud, which seeks to separate fraudulent transactions from valid ones. Two popular algorithms for this purpose are decision trees and XGBoost, each of which has advantages and factors to take into account.

6.1 Decision Tree Algorithm

Explanation and Interpretability Decision Models of trees are transparent and comprehensible. They function by repeatedly dividing the dataset into subsets according to the most important attributes. The leaves of a tree structure, which indicate the final classification choices (fraudulent or not), are represented for each split as a decision node. This helps explain fraud detection to stakeholders because it makes it clear why a particular choice was selected. Decision Trees can naturally handle both data without the need for considerable preprocessing.

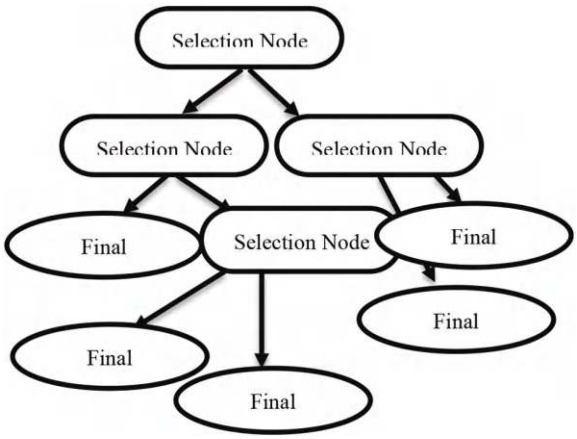

Fig. 92.1 Decision tree algorithm

6.2 Overfitting Issues

Decision trees have the propensity to overfit the training data, especially when the tree gets deep, which is a negative. On fresh, untested data, overfitting might result in poor generalization. Techniques like trimming and restricting tree depth can be used to reduce this.

Data that is unbalanced Class imbalance, or the vastly greater proportion of legitimate transactions compared to fraudulent ones, is a common problem in credit card fraud datasets.

6.3 Decision Tree Algorithm steps

Step 1. Commence with the root node (shown as 'S,' holding the complete dataset).

Step 2. Identify the most suitable trait from the dataset using an ASM

Step 3. Segment 'S' into portion that correspond to the potential attribute values.

Step 4. Create a new decision tree node, incorporating the best attribute.

Step 5. Continue this process repeatedly, constructing additional decision trees from the generated portions of the data group. Repeat until reaching a stage where further classification is not possible, at which point it becomes a terminal or leaf node.

Extreme Gradient Boosting (XGBoost) Algorithm

High Predictive Power An ensemble learning method called XGBoost is well renowned for its great prediction accuracy. Every ensemble decision tree is constructed to fix the errors caused by the ones that came before it. As a result, a strong and reliable model is produced that excels at handling intricate data interactions. Regularization L1 and L2 regularization techniques are used in XGBoost to lessen overfitting and increase model generalization. It enables the ensemble's complexity to be adjusted, making it more flexible to varied datasets. *Incorrect data handling*: Unbalanced datasets can be handled via built-in techniques in XGBoost. You can give classes varied weights or create synthetic samples of the minority class using methods like SMOTE. *Processing in parallel:* Because it is efficient, XGBoost can accelerate training on multi-core CPUs by using parallel processing. XGBoost uses a cascade of decision trees, with each updated tree fixing the mistakes made by the previous ones. A robust predictive model is produced by this iterative approach.

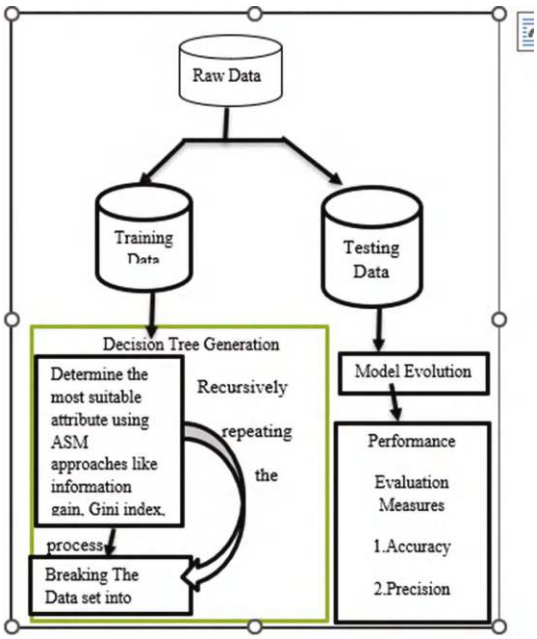

Fig. 92.2 Block diagram of credit card fraud detection

7. Results and Discussions

Researchers have used cutting-edge machine learning technologies, particularly Decision Trees and Extreme Gradient Boosting (XGBoost), to fight credit card fraud. Their study integrates some real-world complexity by integrating public data with banking organisations' actual credit card transaction information.

The study examines user behaviour in two ways: first, by establishing a thorough decision tree based on user activities; and second, by developing a cooperative model utilising a user-driven forest, which is comparable to a community of experts.

Table 92.1 Result for credit card fraud detection

Algorithm	Decision Tree	XG Boost
Accuracy	0.952	0.985
Precision(fraud)	0.753	0.922
Precision (Genuine)	0.972	0.986
Recall (Fraud)	0.853	0.951
Recall (Genuine)	0.945	0.983
F1 Score (Fraud)	0.803	0.938
F1 Score (Genuine)	0.957	0.982

Aiming to boost the accuracy of fraud detection., this collaborative model incorporates knowledge from many decision trees. Thorough testing with actual credit card data confirms the efficacy of these machine learning algorithms, providing

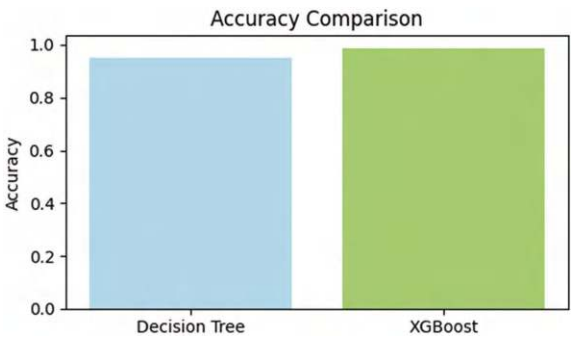

Fig. 92.3 Detection of credit card fraud with high precision

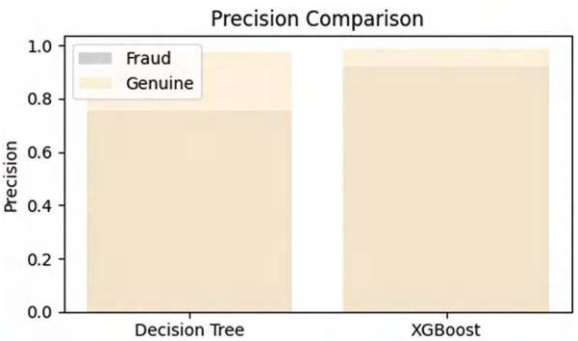

Fig. 92.4 The accuracy of detecting credit card fraud

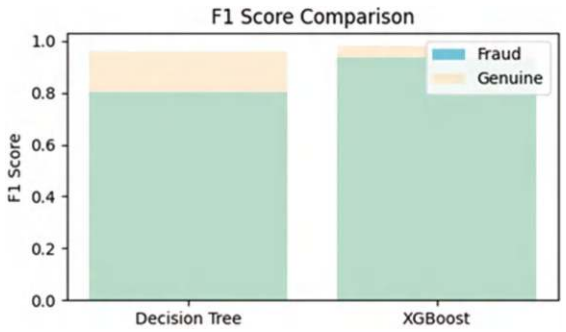

Fig. 92.5 Action taken to prevent credit card fraud

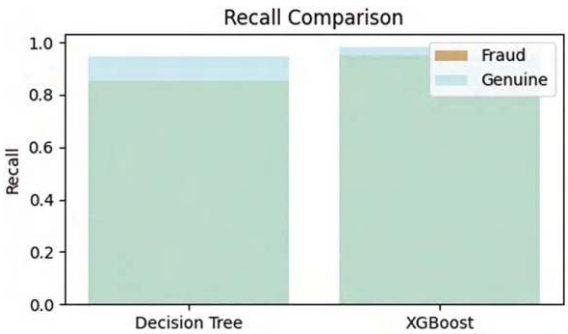

Fig. 92.6 F1 rating for identifying credit card fraud

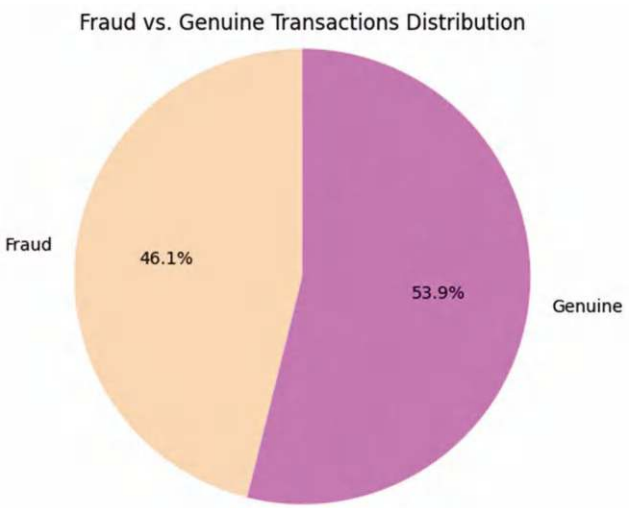

Fig. 92.7 Fraud vs genuine transaction distribution for credit card fraud detection

8. Comparative Analysis

Table 92.2 Comparative analysis

	[6]	[3]	Proposed Model	
Algorithm	**Random Forest**	**Support Vector Machine**	**Decision Tree**	**XG Boost**
Accuracy	0.945	0.968	0.952	0.985
Precision (Fraud)	0.748	0.913	0.753	0.922
Precision (Genuine)	0.963	0.963	0.972	0.986
Recall (Fraud)	0.848	0.942	0.853	0.951
Recall (Genuine)	0.932	0.972	0.945	0.983
F1 Score (Fraud)	0.785	0.911	0.803	0.938
F1 Score (Genuine)	0.939	0.965	0.957	0.982

8.1 Conclusion and Future Scope

The fight against credit card fraud is a never-ending and dynamic problem in an era of fast digitalization and light-speed financial transactions. To safeguard the financial interests and confidence of both individuals and organizations, it necessitates both vigilance and the adoption of breakthrough technology. The process of detecting credit card fraud using these algorithms has shown a complex and dynamic environment.

The technology guarantees a better degree of accuracy in spotting fraudulent activity while protecting client privacy by integrating these cutting-edge algorithms. For both organisations and customers, transaction fraud detection is a major problem. These methods balance the data such that the models are trained on a more representative dataset, hence raising the accuracy and recall scores of the models.

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A Comprehensive Review of the use of Array Antenna Application in 5G Technology

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Abstract: This is a new paradigm with array antennas in 5G systems, against the past generations that are mostly omnidirectional or sector antennas, 5G utilizes adaptability and precision with array antennas to form more agile and responsive network infrastructure. This shift is needed to control the challenge of higher-frequency bands used in 5G, such as mmWave frequencies that can provide very high bandwidth but more path loss and susceptibility to blockages.

The role of array antennas in 5G technology will be the focus of this research paper. We will be looking at the fundamental concepts of an array antenna, how they are used in 5G systems, and how the technical advancements allowed them to be integrated into systems. Additionally, we will delve into the challenges that exist in the implementation of array antennas in 5G networks and go over the current and future potential solutions for these challenges.

Keywords: Array antennas, Beam steering, 5G technology, mm waves, Radiation pattern

1. Introduction

One of the most vital steps forward for mobile communications is the advent of fifth-generation or 5G wireless technology. In times where living and working environments keep getting more rapidly interconnected, fast and reliable and high-capacity access to wireless networks is escalating exponentially. The clue is that 5G offers enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type

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communications. There lies a single critical component at the heart of this technological leap: the array antenna.

One of the most critical components supporting the advanced capabilities of 5G networks is an array antenna, which is sometimes called a phased array antenna or a smart antenna. Such highly sophisticated antenna systems consist of many antenna elements arranged in a specific pattern, and they allow for dynamic beam forming and steering. These are very important aspects of 5G technology because they enable the efficient use of the radio spectrum, increased data rates, and improved coverage.

We will also discuss in this paper how array antenna technology is going to impact on network performance, energy efficiency, and overall user experience in 5G. Readers will reach the end of this paper with a clear understanding of how array antennas are shaping 5G technology and driving its future in wireless communications.

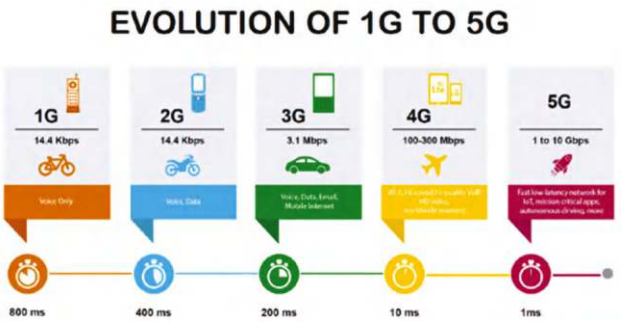

Fig. 93.1 A comparison diagram showing the evolution from 1G to 5G, highlighting the increasing data rates and decreasing latency across generations

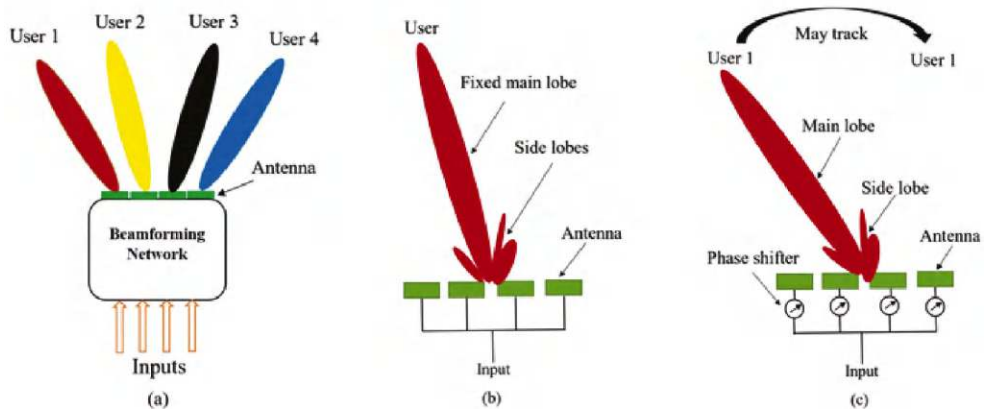

Fig. 93.2 A simple illustration of an array antenna, showing multiple antenna elements arranged in a grid pattern

2. Background on Array Antennas

Array antennas, also referred to as phased array antennas or smart antennas, represent a significant advancement in antenna technology. To understand their importance in 5G systems, it is crucial to first explore their fundamental principles and historical development.

2.1 Definition and Basic Principles

A real array antenna consists of many individual antennas arranged geometrically to operate as one larger, more directive single antenna system. The primary principle in this type of antenna is that signal phase and amplitude over its elements should be controlled in such a manner that the overall radiation pattern can be controlled.

The principle behind an array antenna is realized in the concept of constructive and destructive interference. With adjustment in the phase of signal at each element, it becomes possible to have the waves from different elements to add constructively in certain desired directions and destructively in others. The resultant outcome is that an array may focus a beam and this may be electronically steered without physically moving the antenna.

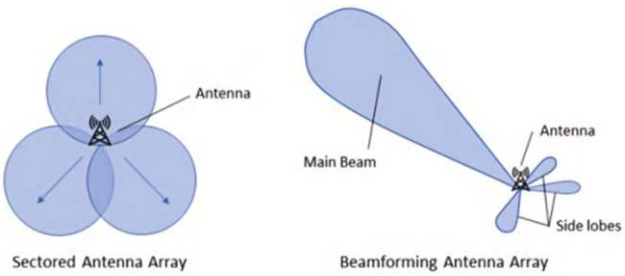

Fig. 93.3 A diagram illustrating the principle of beamforming. Show how the phases of individual antenna elements combine to form a focused beam in a specific direction

2.2 Array Antennas

There exist several types of array antennas, all with different characteristics and applications:

1. **Linear Arrays:** Elements aligned in a straight line.
2. **Planar Arrays:** Elements distributed in a two-dimensional plane.
3. **Circular Arrays:** Elements arranged in a circular configuration.
4. **Conformal Arrays:** Elements that conform to a non-planar surface.

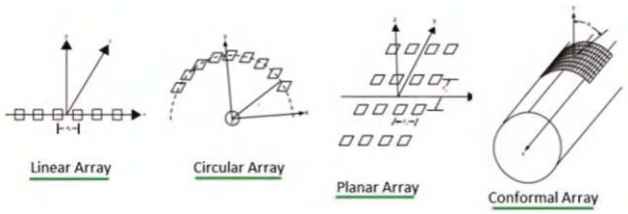

Fig. 93.4 Simple diagrams of different types of array antennas (linear, planar, circular, and conformal) as mentioned in section 2.3

2.3 Key Advantages of Array Antennas

Array antennas offer several advantages over traditional single-element antennas:

1. **Beam Forming:** The ability to shape and direct the radiation pattern.
2. **Beam Steering:** Electronic steering of the beam without mechanical movement.
3. **Increased Gain:** Higher directivity and gain compared to single-element antennas.
4. **Interference Rejection:** Ability to minimize interference from undesired directions.
5. **Multi-beam Capability:** Forming multiple beams simultaneously for multi-user scenarios.

2.4 Applications Prior to 5G

Before their critical role in 5G, array antennas found applications in various fields:

1. **Radar Systems:** For both military and civilian use.
2. **Satellite Communications:** Enabling more efficient space-to-ground communication.
3. **Radio Astronomy:** Improving the sensitivity and resolution of radio telescopes.
4. **Wireless Communications:** Enhancing capacity and coverage in 3G and 4G systems.
5. Understanding these fundamental aspects of array antennas provides the necessary foundation for exploring their specific applications and importance in 5G technology.

3. 5G Technology Overview

5G, the fifth generation of cellular network technology, represents a significant leap forward in wireless communications. This section provides an overview of 5G technology, its key features, and the technological advancements that enable its capabilities.

Fig. 93.5 A simplified diagram of 5G network architecture, showing the radio access network (RAN), core network, and transport network, as mentioned in section 3.5

3.1 Definition and Goals of 5G

5G is designed to meet the growing demand for faster, more reliable, and more versatile wireless communication. The primary goals of 5G include:

1. **Enhanced Mobile Broadband (eMBB):** Providing significantly faster data speeds and greater capacity.
2. **Ultra-Reliable Low-Latency Communications (URLLC):** Enabling near-instantaneous data transfer with high reliability.
3. **Massive Machine-Type Communications (mMTC):** Supporting a vast number of connected devices for IoT applications.

3.2 Key Features of 5G

5G technology is characterized by several key features:

1. **High Data Rates:** Peak data rates of up to 20 Gbps.
2. **Low Latency:** Reduced to 1 ms for URLLC applications.

3. **Increased Capacity:** Ability to support up to 1 million connected devices per square kilometer.
4. **Improved Spectral Efficiency:** More efficient use of available spectrum.
5. **Network Slicing:** Ability to create multiple virtual networks on a single physical infrastructure.

3.3 Spectrum Utilization in 5G

5G operates across a wide range of frequency bands:

1. **Low-band (< 1 GHz):** For wide coverage and deep indoor penetration.
2. **Mid-band (1-6 GHz):** Balancing coverage and capacity.
3. **High-band (> 24 GHz, mmWave):** For ultra-high capacity and low latency in dense urban areas.

3.4 Key Technologies Enabling 5G

Several advanced technologies contribute to the capabilities of 5G:

1. **Massive MIMO (Multiple-Input Multiple-Output):** Utilizing a large number of antennas to improve spectral efficiency.
2. **Beamforming:** Focusing signal energy to specific users or devices.
3. **Small Cells:** Dense deployment of low-power base stations to increase capacity and coverage.
4. **Edge Computing:** Bringing computing resources closer to the end-user to reduce latency.
5. **Network Function Virtualization (NFV) and Software-Defined Networking (SDN):** Enabling more flexible and scalable network management.

3.5 5G Network Architecture

The 5G network architecture is designed to be more flexible and efficient:

1. **Radio Access Network (RAN):** Evolved to support new radio technologies and spectrum.
2. **Core Network:** Redesigned to be more software-defined and cloud-native.
3. **Transport Network:** Enhanced to support the increased bandwidth and low latency requirements.

4. Challenges and Solutions in Implementing Array Antennas in 5G

While array antennas offer significant benefits to 5G systems, their implementation comes with several challenges. This section explores these challenges and discusses current and potential solutions.

4.1 Hardware Complexity and Cost

Challenge: The large number of antenna elements in 5G array antennas increases hardware complexity and cost.

- Increased number of RF chains
- Complex signal processing requirements
- Higher power consumption

Solutions:

- Hybrid beamforming architectures
- Use of low-cost, high-performance materials
- Integration of RF and baseband components

4.2 Coverage and Capacity Trade-offs

Challenge: Balancing coverage and capacity, especially in mmWave deployments.

- High-frequency signals have limited range and poor penetration
- Need for dense small cell deployments in urban areas

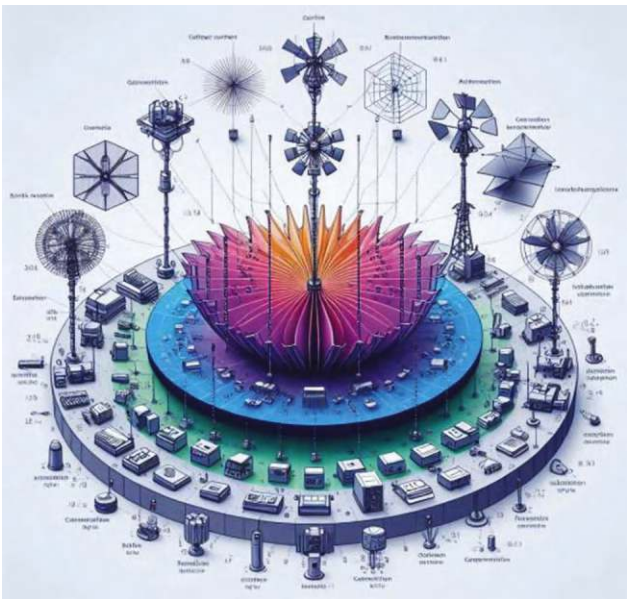

Fig. 93.6 A diagram comparing traditional antenna systems with complex array antenna systems, highlighting the increased number of components

Solutions:

- Multi-band antenna designs (sub-6 GHz and mmWave)
- Intelligent cell planning and optimization
- Integration with existing 4G infrastructure for seamless coverage

Fig. 93.7 A visual representation of a heterogeneous network deployment, showing how different cell types and frequencies work together to provide coverage and capacity

4.3 Regulatory and Standardization Challenges

Challenge: Ensuring compliance with regulatory requirements and industry standards.

- Varying spectrum allocation across regions
- EMF exposure limits
- Interoperability concerns

Solutions:

- Active participation in standardization bodies (e.g., 3GPP, ITU)
- Flexible antenna designs adaptable to different regional requirements
- Comprehensive EMF studies and compliance testing

5. Future Trends and Developments in Array Antennas for 5G and Beyond

As 5G technology continues to evolve and research into 6G begins, array antennas are expected to play an increasingly crucial role in wireless communications. This section explores emerging trends and potential future developments in array antenna technology.

5.1 Terahertz Communications

- Exploration of frequencies above 100 GHz for ultra-high bandwidth communications
- Challenges in developing array antennas for terahertz frequencies
- Potential applications in ultra-short range, high-capacity links

5.2 Intelligent Reflecting Surfaces (IRS)

- Integration of passive reflective surfaces with active array antennas
- Enhancing coverage in non-line-of-sight scenarios
- Improving energy efficiency in wireless networks

5.3 AI-Driven Antenna Systems

- Machine learning algorithms for real-time beamforming optimization
- Predictive maintenance and self-healing antenna arrays
- Automated network optimization using AI-powered array antennas

5.4 Holographic Beamforming

- Advanced beamforming techniques using holographic principles
- Potential for creating highly directional, software-defined radiation patterns
- Applications in high-precision positioning and sensing

5.5 Sustainable and Green Antenna Technologies

- Development of eco-friendly materials for antenna construction
- Energy harvesting integrated into array antenna designs
- Optimizing antenna systems for minimal environmental impact

5.6 Quantum-Inspired Antenna Systems

- Application of quantum principles to antenna design and signal processing
- Potential for ultra-sensitive receivers and secure communications
- Exploring the limits of classical electromagnetics in antenna theory

5.7 Flexible and Conformal Array Antennas

- Development of array antennas that can conform to non-planar surfaces
- Applications in wearable technology and Internet of Things (IoT) devices
- Challenges in maintaining performance with flexible substrates

5.8 Beyond 5G: Towards 6G and Beyond

- Speculative look at the role of array antennas in future 6G systems
- Potential for fully digital, software-defined antenna arrays
- Integration with other emerging technologies like VR/AR and holographic communications

These future trends and developments suggest that array antennas will continue to be at the forefront of wireless technology innovation. As we move beyond 5G, the integration of array antennas with AI, new materials, and quantum technologies promises to unlock new capabilities and applications in wireless communications.

6. Array Antennas Enhance Adaptability and Responsiveness in 5G Networks

Beamforming

- Array antennas create narrow, focused beams aimed at individual users, much like a spotlight that illuminates a single area rather than light bulb lighting up an entire room.
- This precise targeting strengthens signals for individual users, reduces interference, and allows the network to respond to changing demand and user movement.

MIMO (Multiple Input, Multiple Output)

- The array's multiple antenna elements generate several beams, allowing data streams to be sent to multiple users simultaneously, akin to multiple spotlights focused on different individuals in a stadium.
- This increases data capacity and network responsiveness, especially in crowded areas.

6.1 Main Components of an Array Antenna in 5G Systems

1. **Antenna Elements:**
   - Small individual antennas arranged in a pattern (e.g., a grid).
   - Each element emits and receives signals, and together they create strong, focused beams, acting as "building blocks" of the array.
2. **Phase Shifters:**
   - Devices that adjust the timing of signals from each antenna element.
   - By shifting each signal's timing slightly, the array can "steer" the beam in a chosen direction, targeting specific users without moving the antenna physically.
3. **Power Amplifiers:**
   - Boosts signal strength of each element so beams can reach users at longer distances.
   - Critical for 5G's high-frequency bands (e.g., millimeter waves), which need stronger power due to their limited travel range.
4. **Beamforming Controller:**
   - Acts as the "control center" for the array antenna, coordinating the phase shifters based on user density and demand.
   - Quickly updates connections as users move, ensuring stable and reliable connectivity.

6.2 Array Antennas Address Path Loss and Signal Blockages in High-Frequency Bands

1. **Beamforming:**

   Concentrates signals into strong, focused beams, reducing path loss by directing high-frequency signals straight to the user, keeping the signal strength high over longer distances.
2. **Adaptive Beam Steering:**
   - Enables the array to "steer" beams around obstacles (e.g., buildings or walls).
   - If a signal encounters a blockage, the array redirects the beam to maintain a strong connection.
3. **MIMO**
   - Multiple beams and antenna elements transmit several paths of signals to the same user.
   - If one path is blocked, others still carry data, enhancing reliability.

6.3 Importance of Beamforming in Array Antennas for 5G

1. **Concentrated Signal Power:**
   - Beamforming directs signal power precisely to a user, like a flashlight shining on one spot rather than illuminating an entire room.

- This strong, focused signal reduces interference and improves connectivity.

2. **Energy Efficiency:**
   By only sending signals where needed, beamforming reduces power consumption, making 5G more energy-efficient.
3. **Dynamic Adaptability:**
   Beamforming allows the network to track users, steering beams as they move, ensuring stable, reliable connections and enhancing user experience.
4. **Sustainable Capacity in Crowded Areas:**
   - Multiple beams target different users in busy areas with minimal overlap.
   - This reduces interference, allowing more users to connect at high speeds without slowing each other down.

7. Results

Here's a structured results table of a radiation pattern for a phased array antenna, the results table usually includes parameters like beam angle, gain, and half-power beamwidth, as well as measurements across multiple angles to illustrate the directional behaviour of the antenna.

7.1 Results Table for Radiation Pattern

Table 93.1 Results table of a radiation pattern for a phased array antenna

Angle (Degrees)	Gain (dBi)	Beamwidth (Degrees)	Sidelobe Level (dB)
0	15.2	20	-13
15	14.7	18	-12
30	13.5	17	-11
45	11.8	15	-10
60	9.6	13	-8
75	7.2	10	-6
90	5.5	9	-5
105	3.8	8	-4
120	2.3	7	-3
135	1.1	6	-2
150	0.5	5	-1
180	0	4	0

Notes:

- **Gain (dBi)** represents the antenna's gain in decibels relative to an isotropic antenna.
- **Beamwidth (Degrees)** is the angle at which the power drops to half its maximum (half-power beamwidth).
- **Sidelobe Level (dB)** indicates the relative power of the sidelobes compared to the main lobe.

7.2 Beam Steering Figure for a Phased Array Antenna

This visual demonstrates how beam steering achieves dynamic directionality.

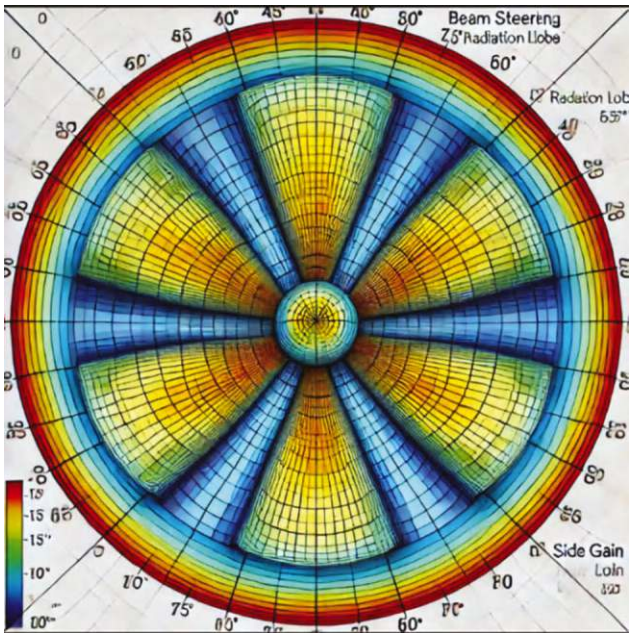

Fig. 93.8 Composite polar plot for the phased array antenna's beam steering radiation pattern

Here's the composite polar plot for the phased array antenna's beam steering radiation pattern, showing how the main lobe direction shifts with each steering angle.

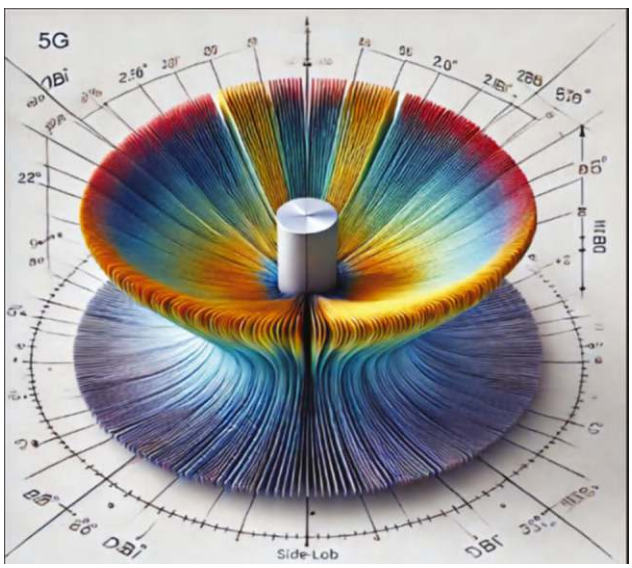

Fig. 93.9 The radiation pattern illustration for a phased array antenna used in 5G technology

Here's the radiation pattern illustration for a phased array antenna used in 5G technology, highlighting a narrow, high-gain main lobe with minimal sidelobes, designed for directional beam steering.

8. Conclusion

Array antennas have emerged as a cornerstone technology in the development and implementation of 5G wireless networks. Throughout this research paper, we have explored the fundamental principles of array antennas, their critical role in 5G systems, the challenges they present, and the exciting future developments on the horizon.

Key findings of this research include:

1. Array antennas enable essential 5G technologies such as Massive MIMO, beamforming, and millimetre-wave communications, which are crucial for achieving the high data rates, low latency, and increased capacity promised by 5G.
2. The integration of array antennas in 5G systems presents significant challenges, including hardware complexity, channel estimation, interference management, and power consumption. However, innovative solutions are being developed to address these issues.
3. Future trends in array antenna technology, such as terahertz communications, intelligent reflecting surfaces, and AI-driven systems, suggest that their importance will only grow as we move beyond 5G.

The impact of array antennas extends far beyond just improving cellular communications. They are enabling new applications and use cases, from Internet of Things (IoT) devices to autonomous vehicles, and from smart cities to next-generation satellite networks. As we look towards 6G and beyond, array antennas will likely play an even more central role in shaping the future of wireless technology.

In conclusion, array antennas represent a transformative technology that is fundamentally changing the landscape of wireless communications. As 5G networks continue to evolve and expand, and as we look towards the next generation of wireless technology, the importance of array antennas in enabling faster, more reliable, and more versatile wireless communications cannot be overstated. Their continued development and refinement will be crucial in meeting the ever-growing demands of our increasingly connected world.

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7. "A Dual Band Phased Array Antenna for 5G Implementation"[4]

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An Advanced Resource-Aware Load Balancing in Cloud with Federated Learning

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Abstract: Federated Learning (FDL) is the domain that develops the machine learning (ML) models on several datasets distributed over data centers like medical care, secure financial transactions, and medical analysis data that reduces data leakage. This paper introduces the new research model combining cloud computing and FDL models. Combining these two domains developed advanced applications that help solve several complex issues in resource utilization, efficiency, and model performance over distributed systems. In this paper, An Advanced Resource-Aware Load balancing (ARALB) for the FL model is developed to distribute over multiple servers to prevent any one server from being saturated. It is critical for ensuring practical usage of resources, increasing system reliability, managing response times, and maximizing throughput. In a cloud platform, a load balancer can allocate the resources to several devices that are required based on their workload and network capacity. Unlike regular clients, FDL clients are more powerful, have high capacity, and can handle vast amounts of data. Finally, the performance of FDL devices is measured based on higher bandwidth and computational load, which is high weight when the updates are aggregated, which leads to rapid assembly of the global model.

Keywords: Federated learning, Machine learning, Cloud computing, Resource-aware, Load balancing

1. Introduction

Machine learning (ML) is the sub-domain in Artificial Intelligence (AI) that solves the complex issues of various applications discussed in N et al., (2020). Federated learning (FDL) is a machine learning (ML) approach that trains models using decentralized data stored on multiple devices or servers while remaining local and private. It is intended to address the difficulties associated with centralized data collection and processing, particularly in scenarios where data privacy, security, or bandwidth constraints are essential considerations. Data is typically

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collected from multiple sources and centralized in a single location for model training in traditional machine learning. However, this centralized approach may pose privacy risks because it requires sharing sensitive or personal data with a central server. On the other hand, Federated learning moves the model training process to the edge, enabling devices or servers to collaborate and learn collectively without sharing raw data. In some cases, privacy plays a significant role in FDL to overcome various security issues in data processing De Cristofaro et al., (2021). Figure 94.1 shows the working process of FDL applications on various domains.

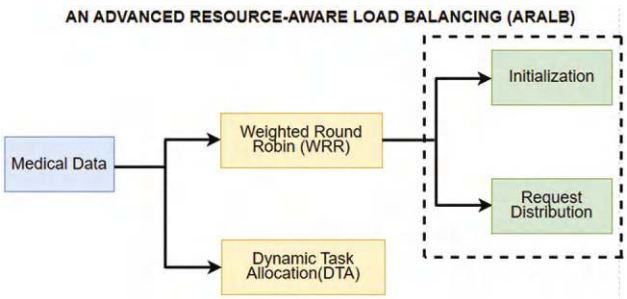

Fig. 94.1 Components of proposed ARALB model

In Cheng et al., (2019), the author introduced the security-based model that provides user data privacy. FDL mainly focused on protecting and preventing data leakage when implementing the proposed model. It introduced several models to reduce it by Ang et al., (2020)—a security and dynamic system by improving data privacy. Various algorithms, such as privacy-preserving federated learning (PPFL) and two-phase mitigating scheme (TPMS), prevent data leakage Lu et al., (2020).

Deep learning (DL) is essential in federated learning (FDL) because it enables efficient and effective learning models across distributed devices or servers while maintaining data privacy Zhang et al., (2021). Federated learning is a decentralized approach in which training occurs locally on individual servers, with only shared and aggregated model updates. The central concept of federated learning is distributing the model training process across multiple devices or servers containing local data. Rather than sending data to a central server, models are sent to the machines, and each device performs local training with its data. The local models are then aggregated using a secure algorithm to create a global model that captures all participating devices' collective knowledge.

Federated learning has several advantages. It protects data privacy because raw data remains on the devices and is not shared or exposed. Second, it reduces communication and bandwidth requirements by transmitting only model updates rather than entire datasets. Furthermore, federated learning allows training on diverse datasets from various devices, potentially improving model generalization and robustness. Federated learning has received much attention and application in multiple fields, including healthcare, finance, IoT, and mobile devices, where data privacy, security, and limited network connectivity are significant concerns. It enables organizations to tap into the collective intelligence of distributed data while adhering to privacy regulations and safeguarding sensitive information.

Key factors of proposed approach:

- This is the multi-domain based approach that integrates the federated learning models into cloud platform.
- It is implemented using private cloud and applied on medical data application based on multiple users.
- This is the medical cloud application that handles the multiple requests from the patients in cloud platform.

The federated learning mainly focused on decentralized the multiple requests and handles the over loading in cloud platform.

Rest of the paper is structured as follows. Section-2 reviews the extant literature. Section-3 describes the applications in federated learning. Section-4 explains the research methodology ARALB. Secttion-5 explains the dataset description. Section 6 discussed about privacy and security in various federated learning applications. Section 7 discusses the empirical findings. Section-8 gives the conclusion of the paper.

2. Literature Review

J. Zhang et al., (2021) discussed various FL protocols which provide security from several attacks on the client and server side. Among all the available attacks, GAN significantly impacts several applications. The proposed model is divided into several preventive steps that provide privacy risks and security breaches. The author explained the detailed survey on several threats occur in various applications. Yang et al., (2019) discussed various FDL models that can be applied to different datasets. FDL eliminates the need to send large amounts of data to a central server, which can be helpful in bandwidth-constrained environments or when dealing with sensitive data. FDL is beneficial when data privacy is an issue or data cannot be easily transferred to a central server due to its size or sensitivity. It also benefits intermittent or limited connectivity environments because it reduces reliance on a constant network connection. A model for privacy and security driven by big data and a classification of big data-driven confidentiality and security are proposed by Sun et al., (2018) inside the big data paradigm. To tackle this problem, Hu et al., (2019) suggest a segment-level, decentralized FDL model. Lastly, a segmented gossip

method attains high training convergence and makes full use of node-to-node bandwidth. When compared to centralize federated learning, the experimental findings demonstrate a considerable reduction in training time. FedProx, a framework for dealing with heterogeneity in federated networks, was presented by Li et al., (2020). FedProx is the current cutting-edge FDL method's generalization and re-parameterization of FedAvg. While this re-parameterization only makes minor changes to the process, the implications in theory and practice are significant.

3. Security in Federated Learning

In FDL, the decentralized approach has gained popularity due to its potential for data security and privacy preservation. Despite its benefits, Federated Learning introduces new security concerns and challenges. Here are some of the most critical aspects of safety in Federated Learning:

Secure Communication: In Federated Learning, secure communication protocols are critical for protecting the confidentiality and integrity of data transmissions between participants and the central server. Encryption technique such as transport layer security (TLS) can be used to ensure specific communication channels.

Model Poisoning Attacks: Because Federated Learning participants are responsible for training the shared model locally, malicious participants may attempt to poison the model by injecting incorrect or biased updates. To mitigate such attacks and ensure the integrity of the shared model, robust aggregation methods and outlier detection techniques can be used.

Participant Authentication: It is critical in Federated Learning to ensure the authenticity and legitimacy of participants in order to prevent unauthorized access or malicious actors from participating in the training process. To verify the identity of participants, participant authentication mechanisms such as digital signatures or secure multi-party computation can be used.

Overall, Federated Learning security requires a multifaceted approach incorporating privacy-preserving techniques, secure communication protocols, robust aggregation methods, and participant authentication mechanisms. By addressing these security concerns, Federated Learning can balance collaborative model training and data privacy protection in distributed environments.

4. An Advanced Resource-Aware Load Balancing (ARALB)

In this section, the ARALB is the combination of Weighted Round Robin (WRR) with Dynamic Task Allocation (DTA). Load balancing in cloud computing provides the advanced distributed workload among the number of measuring resources (like servers, databases, and networks) to make sure that no single resource is saturated which leads to effective usage of resources and availability in Sudhir Ponnapalli et al., (2024). FDL mainly focused on decentralizing the ML models trained on multiple devices without knowing the raw data. The integration of load balancing in FDL shows effective and reliable resource usage for different users. In this work, the tasks are assigned cyclically, but every server gets a weight based on its loading capacity. Servers with higher weights can handle more tasks.

4.1 Weighted Round Robin (WRR)

WRR is an extended version of the default round-robin load balancing (RRLB) algorithm. The default RRLB mainly distributes the overall requests equally between servers periodically. WRR started assigning weights to every server based on the higher performances in terms of high dimensions (more computation time, high memory) based on colossal workload, compared with low dimensions. In WRR, every device initializes a weight representing its comparative load to handle the workload. Weighted with these gives one of the devices and load balancer cycles through them, distributing requests based on these weights. A higher weight will make a device more likely to be selected than those with lower weights. In a healthcare device scenario, we have many devices (medical sensors) with health statuses or different capacities. WRR will always divide the load of requests that reach them evenly.

$D_1, D_2,,,,, D_n$: Devices in the system

$W_1, WD_2,,,,, W_n$: Weights assigned to the devices $D_1, D_2,,,,, D_n$ based on their load on health data.

R_i: Requests assigned to Device D_i

4.2 Initialization

Each device is assigned a weight. Smart devices with high loads that improve health should receive a higher weight.

4.3 Request Distribution

The total requests assigned to every device are proportional to its weight. The equation is represented as:

$$R_i = \frac{W_i}{\sum_{j=1}^{n} W_j} \times R_{total} \quad (1)$$

This shows that every device D_i receives the same quantity of requests proportional to its weight.

4.4 Dynamic Task Allocation (DTA)

Dynamic Task Allocation (DTA) is a way of spreading work that needs to be done across multiple nodes/processors/servers in distributed systems. In a nutshell, DTA's goals are to schedule tasks over available resources as efficiently as possible without overwhelming some of your nodes for nothing and allowing others to be underutilized. This process is critical for ensuring optimal system performance, lower response time, and resource utilization. DTA dynamically re-distributes tasks of the system according to changes in workload, resource availability, and system performance. While static task allocation reassigns tasks to nodes according to the fixed rules, DTA allocates and reallocates tasks indefinitely [..., which is not true of SAT]. Its purpose is to balance the load a task causes, equally distributing them among multiple nodes, not to allow bottlenecks. Efficient load balancing will prevent any single node from being a single point of failure or staling with too many tasks… Across many systems, resources are currently heterogeneous with diverse capabilities, including processing power and memory/storage profiles. DTA algorithms need to account for these differences to allocate tasks optimally, targeting the best possible throughput of the overall system.

5. Datasets Used by Federated Learning Algorithms

The data is distributed across multiple devices or servers in federated learning, and the model is trained collaboratively by exchanging model updates or gradients while keeping the data local. The datasets used in federated learning are typically the local datasets available on each participating device or server. Typically, these datasets are not openly shared or aggregated into a single central dataset. However, some of the most common types of datasets used in federated learning scenarios are as follows:

Personal Device Data: Federated learning often involves training models on data collected from personal devices such as smart phones, wearable's, or IoT devices. These datasets may include sensor data, user behaviour logs, or health-related information.

Healthcare Data: Federated learning has gained significant interest in healthcare applications. Participating entities, such as hospitals or medical research institutions, can train models on local patient data while maintaining data privacy. These datasets may include electronic health records (EHRs), medical images, or genomic data.

6. Privacy and Security by Financial Applications Using Federated Learning Algorithms

The financial industry increasingly leverages data and artificial intelligence (AI) techniques to improve various processes and services in today's digital age. However, this reliance on data raises privacy and security concerns, mainly when dealing with sensitive financial information. Traditional data sharing and analysis approaches frequently involve centralizing data, which can expose it to risks such as unauthorized access, breaches, or misuse. To address these privacy concerns, FDL is a significant model discussed in Dornala et al., (2023). FDL trained on data distributed across multiple devices or organizations without requiring the raw data to be shared. It enables financial institutions to collaborate and collectively learns from their data while protecting individual customer privacy discussed in Raghunadha Reddi Dornala et al., (2023).

Privacy-preserving financial applications based on federated learning provides several advantages. They reduce the possibility of data breaches and illegal access by enabling financial institutions to access a wider data pool without centralising it. Second, they follow data protection laws including the California Consumer Privacy Act (CCPA) to safeguard private financial data. Third, involving multiple parties in the learning process promotes trust and transparency by preventing any single entity from having complete control over the data or models [15]. Balancing privacy and utility is one of the most difficult challenges in implementing privacy-preserving financial applications using federated learning. To ensure that no sensitive information is leaked during the learning process, sophisticated privacy-preserving techniques such as encryption, secure aggregation, or differential privacy must be developed. Privacy-preserving federated learning can help a variety of financial applications. Fraud detection and prevention can benefit from the combined intelligence of multiple financial institutions without sharing specific transaction details. Training models can improve credit risk assessment on distributed loan repayment data without revealing personal information about individual borrowers. Personalized financial recommendations can be generated based on collaborative models trained on customer data from various institutions.

6.1 Proposed Medical Application Combined with Federated Learning

In this context, handling multiple users in a cloud and federated learning platform obtains the advanced

load-balancing approaches that optimize the usage of computation and communication resources across distributed nodes. The proposed approach is mainly used to handle the congestions that occur in a cloud environment with the help of federated learning approaches that manage the privacy and allocation of resources in the cloud platform. The proposed approach uses the original monitoring system that tracks the computational workload and latency across cloud servers. This allocation type helps monitor the dynamic allocation of tasks for every node, making it possible to find congestion before it occurs. In the following section, the proposed approach demonstrates its excellent resource allocation performance.

7. Performance Evaluation of Various FDL Algorithms

The performance of cloud computing algorithms is mainly focused on managing the strength of cloud-based FDL algorithms. These measurements demonstrate how well cloud computing algorithms conduct load balancing based on FDL-based results.

Response Time (RT): It calculates how long it takes to approve the request and reply to the patient.

$$\text{RT} = \text{Complete time} - \text{request time}$$

Throughput (TP): The overall requests taken in one minute.

$$\text{TP} = \text{Total}\frac{\text{Requests}}{\text{Time}}$$

Utilization (UTL): The overall resources used by the load balancer.

$$\text{UTL} = \left(\frac{\text{Resource used}}{\text{Total resource capacity}}\right) * 100$$

Error Rate (ER): The overall failed requests from the actual received requests.

$$\text{ER} = \left(\frac{\text{Number of failed requests}}{\text{Total number of requests}}\right) * 100$$

Table 94.1 compares algorithms such as the novel load balancing approach (NLBA) with high-range values like RT-41.23, TP-86, UTL-74, and ER 17.34%. These results show that the NLBA needs to improve its performance based on the outcomes obtained. The other existing approach used in this work is TTHLB, which receives RT-37.67, TP-89, UTL-61.23, and ER 15.78%. The proposed approach obtains better values with RT-34.34, TP-97, UTL-54.76, and ER 13.67%.

Table 94.1 Quantitative performance of various load balancing algorithms using FEDL

Algorithms	RT (Sec)	TP (request/sec)	UTL (%)	ER (%)
Novel Load Balancing Approach Raghunadha Reddi Dornala et al., (2023)	41.23	86	74	17.34
TTHLB (Sudhir Ponnapalli et al., (2023)	37.67	89	61.23	15.78
Proposed	34.34	97	54.76	13.67

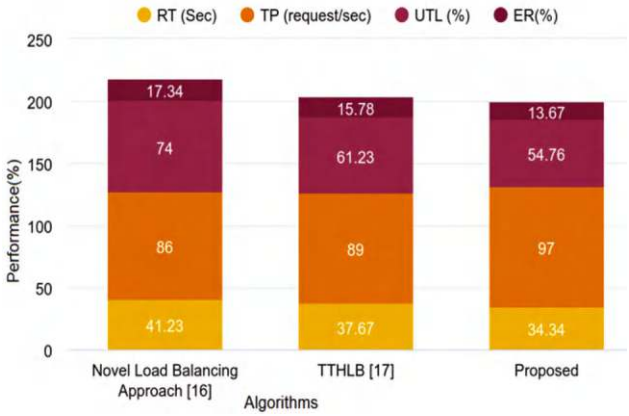

Fig. 94.2 Comparative performance of FDL on medical dataset

8. Conclusion

The ARALB mechanism is a high-level approach leading to better resource utilization and distributed computing environment performance. ARALB makes computing power play a better role in business by avoiding the waste of workloads, preventing stalemates, and reducing response time by dynamically adapting the workload processing based on real-time resources. A big selling point of the system is that it can consider that different resources have different characteristics, like processing power, memory, and network bandwidth. With intelligent task allocation algorithms, ARALB can economically allocate and adapt to the changes in resource availability, which fits better for the existing ecosystem by providing a stable and flexible infrastructure. A resource-aware ARALB enables scalability and resilience at the network layer. Finally, the proposed approach shows high performance in terms of accuracy and other confusion matrix parameters.

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Real Time Emotion Detection with Jetson Orin Nano

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Abstract: This work relates to a real time emotion recognition system based on the FER-2013 dataset and implemented on Jetson Orin Nano. The experiment focuses on the ability of deep learning models to detect seven basic emotions: anger, disgust, fear, happiness, sadness, surprise and neutral by using Jetson Orin Nano. To boost the accuracy, we used transfer learning with pre-trained models in this experiment. The system's real time prediction capabilities on edge devices provide promising results, making it appropriate for real world applications such as smart classrooms, security systems, healthcare and many more. This work discusses the challenges, architecture, experimental findings and future scope for implementing the model on edge devices.

Keywords: Emotion recognition, Jetson orin nano, FER-2013, Transfer learning, Edge devices

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1. Introduction

Emotion recognition is growing as an important area of research in human-computer interaction, with applications including healthcare to education, security, marketing and social robots. As humankind advances towards more intelligent systems, robot's ability to recognize and react to human emotions becomes increasingly important. Automatic emotion detection systems use facial expressions, voice signals or physiological data to detect emotions and provide personalized responses. Among these methods, facial expression based emotion recognition is the most apparent and simple to use making it ideal for real time use in dynamic applications.

Deploying emotion detection systems in real world applications such as smart classrooms, intelligent surveillance and mental health monitoring requires not only outstanding accuracy but also fast inference on low power devices. However, the most advanced deep learning models are computationally demanding, making them difficult to deploy on resource constrained edge devices. Edge computing is now recognized as a possible approach for addressing these difficulties by moving computation closer to the data source. With NVIDIA's Jetson Orin Nano, powerful AI models may now be implemented on small, low power devices, allowing for real time detection of emotions on edge devices.

This work focuses on developing a real time facial emotion recognition system using the FER-2013 dataset on Jetson Orin Nano, by utilizing deep learning and transfer learning techniques. The project aims to find a balance between model performance and computing efficiency, ensuring that the system can carry out prediction in real time.

2. Background

Zhang (2024) presents a comprehensive framework for facial emotion detection, that demonstrates the system's effectiveness through extensive experiments on publicly available datasets, achieving high accuracy and strong generalization, while also addressing the method's limitations and potential real world challenges [1]. Chethan et al. (2024) proposed a Deep Learning based Emotion Detection System that uses CNNs for feature extraction and RNNs to represent temporal dynamics in face expressions [2]. The authors in paper [3] delivered an in depth review of real time face expression recognition systems, including historical development, essential approaches and recent innovations. The study addresses the issues that Face Emotion Recognition technologies face and their applicability in a variety of areas, while also detailing future research opportunities in the area of study. Dhope et. al present a real time facial emotion recognition system by using artificial intelligence to identify seven human emotions. Their approach uses a convolutional neural network (CNN) trained on a custom dataset to achieve high accuracy in emotion detection and the model operates on a Raspberry Pi 3B+ with a Pi-Camera, enabling portable, real-time functionality [4]. Dudekula and Nalluri (2023) used deep learning models to evaluate the performance of facial emotion recognition systems on the NVIDIA Jetson Nano. The study uses the Xception, VGG-19 and OpenCV frameworks, and achieves 97.1% accuracy with Xception, 98.4% with VGG-19 and 95.6% in real-time environments with OpenCV, demonstrating Jetson Nano's potential for high-performance real-time emotion detection with challenges such as lighting variations, occlusions, and facial rotations [5].

Asha et al. (2024) extend VGG-16 as the best deep learning model for face emotion recognition, highlighting its faster training time and higher accuracy than ResNet-50 and AlexNet [6]. The authors highlighted VGG-16's effectiveness in identifying emotions as an affordable replacement to technologies like as EEG, as well as its applicability in education, healthcare and human computer interface (HCI). The system proposed by Sarvesh et al. (2022) explored emotion detection with facial feature recognition using CNN and OpenCV and they focused on real time emotion analysis from frontal facial expressions through live webcam input. Their study demonstrates the system's ability to classify emotions such as happiness, sadness, anger, fear, surprise and disgust, emphasizing its potential to enhance human-computer interaction by reducing communication gaps between humans and machines [7]. In paper [8], Bhardwaj et al. (2023) proposed a novel approach for emotion detection using ARCore technology, by using mobile devices cameras and motion sensors to analyze facial expressions and body movements in real-time. The author Ahmad (2023) in paper [9] presents a deep fusion model for facial emotion recognition by combining two popular CNN architectures VGG-16 and ResNet-50 to enhance model accuracy. The fusion approach utilized the strengths of both models, using ResNet-50's deep residual networks and VGG-16's convolutional layers for more effective feature extraction. The study of Ballesteros et al. (2024) focuses on developing a system that aligns with psychological theories of emotions, enhancing its ability to identify distinct emotional patterns accurately [10].

In conclusion, while current research [11-16] has built a solid framework for emotion detection systems, our approach stands out for various novel aspects. The Jetson Orin Nano, a powerful computing platform with improved processing capabilities that allows for real time analysis is central to our approach. This enables our system to process facial

expressions and emotions with a significantly lower latency that delivers quick and accurate emotional detection.

3. METHODOLOGY

The proposed work for designing a real time emotion detection system consists of several interconnected phases, starting from hardware configuration to model deployment and optimization.

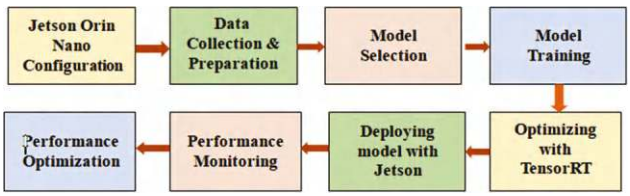

Fig. 95.1 Design flow of the proposed work

3.1 Jetson Orin Nano Configuration

The work begins by setting up the Jetson Orin Nano board, that includes installing the necessary operating system, drivers and libraries, such as TensorFlow, Keras, OpenCV and TensorRT. The configuration ensures that the board is ready to handle model deployment and real time video processing.

3.2 Data Collection & Preparation

In this stage the dataset of facial images labeled with corresponding emotions will be collected and data preparation ensures the dataset is suitable for training by preprocessing the images. For this experiment, we used the FER-2013 dataset and all images are converted to grayscale, resized to 48x48 pixels and we normalized pixel values to improve model performance.

3.3 Model Selection

To achieve higher accuracy, we proposed transfer learning by using pre trained models which allows us to fine tune an existing, well trained model on our specific dataset, rather than training a model from scratch. Pre-trained models such as MobileNet, VGGNet or ResNet are ideal candidates due to their ability to capture complex features from images. A Convolutional Neural Network (CNN) is typically selected due to its ability to capture spatial features from images efficiently.

3.4 Model Training

Once the model is selected and integrated with transfer learning, the next step is to train the model. During training, we feed the preprocessed data into the selected model, optimize hyper parameters and monitor the training metrics like accuracy and loss.

3.5 Optimizing with TensorRT

TensorRT helps us to convert the model into a highly optimized format that minimizes latency and boosts execution speed. It Converts the trained TensorFlow and Keras model to TensorRT format. After the training, the model is optimized using precision (FP16 or INT8) to ensure efficient inference on the Jetson Orin Nano.

3.6 Deploying the Model with Jetson

Once the model is optimized it is deployed on the Jetson Orin Nano for real time emotion detection. A camera module is integrated to capture live video and the model processes each frame to detect emotions.

3.7 Performance Monitoring

To ensure the system runs smoothly, continuous monitoring will be done to evaluate the resource consumption and inference latency. This stage helps detect challenges and ensures the system maintains good accuracy with low latency during real time execution.

3.8 Performance Optimization

Based on the performance, further optimizations are made to improve system efficiency. This may involve tuning TensorRT parameters such as batch size and precision, adjusting the model configuration such as adjusting camera frame rates and image processing parameters, or improving the Jetson Nano's settings for better resource utilization.

4. EXPERIMENTAL SETUP

4.1 Hardware Setup

The first step in hardware setup involves configuring the Jetson Orin Nano and required components to enable efficient real time emotion detection. The Jetson Orin Nano kit, with its ARM Cortex-A78AE CPU, NVIDIA Ampere GPU (1024 CUDA cores), 8 GB LPDDR5 memory and 128 GB microSD storage, serves as the core processing unit, optimized for AI-based projects. Additionally, a camera module, capable of capturing images is used to provide real time video input for emotion analysis. The first step in hardware setup involves configuring the Jetson Orin Nano and required components to enable efficient real time emotion detection. The Jetson Orin Nano kit, with its ARM Cortex-A78AE CPU, NVIDIA Ampere GPU (1024 CUDA cores), 8 GB LPDDR5 memory and 128 GB microSD storage, serves as the core processing unit, optimized for AI-based projects. Additionally, a camera module, capable of capturing images is used to provide real time video input for emotion analysis.

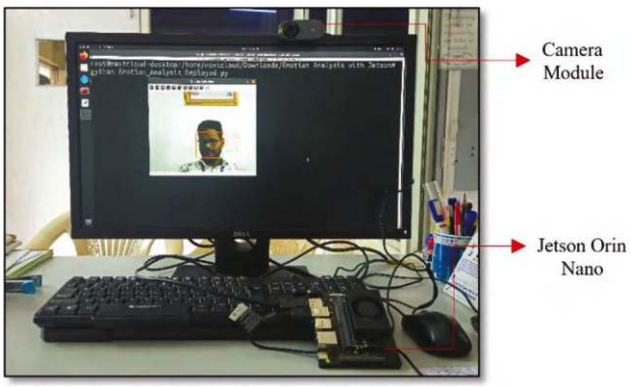

Fig. 95.2 Experimental setup

4.2 Software Setup

The software setup includes installing all the libraries, frameworks and optimization tools required to run the real time emotion detection project. The device runs Ubuntu 20.04 LTS with the JetPack SDK, which contains Jetson specific drivers, CUDA libraries and TensorRT support. Python 3.8 used as the primary programming language, with TensorFlow and Keras frameworks for model training and deployment. The proposed model was enhanced using transfer learning, with pre-trained models like MobileNet and VGGNet which were fine-tuned with a FER-2013 dataset to improve accuracy. TensorRT was used to optimize the trained model by utilizing the GPU capabilities of the Jetson Orin Nano to achieve faster inference.

5. Results & Discussion

5.1 Training and Validation

The overall results of the model training process show noticeable gains in accuracy and loss reduction across both the training and validation sets. The model started with a low accuracy of 45.07% and gradually improved to a final training accuracy of 89.98% after 40 epochs. As a result, the validation accuracy increased, reaching at 84.63%, showing the model's capacity to adjust to new data well. The training loss decreased steadily from 1.9757 at the beginning to 0.6235 by the end of the epoch, indicating excellent learning and data adaptation. The validation loss followed a similar downward trend, beginning at 1.7718 and dropping to 0.7994 at the conclusion, with minor variations in the middle epochs that gradually settled.

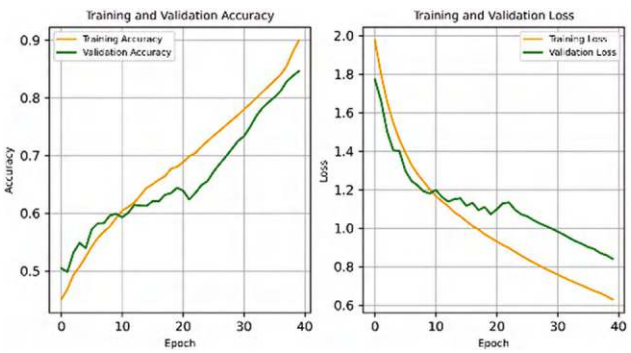

Fig. 95.3 Training vs validation results

5.2 Model Deployment Results

The trained model was integrated into Nvidia Jetson Orin Nano with a camera module to detect and classify facial expressions in real time. The deployed system successfully captured images in real time and performed face detection as expected. Figure 95.4 shows the facial emotions; those are captures by the proposed system. While the model performed well in controlled environments, dim or overly bright lighting sometimes affected face detection and expression recognition accurately. Furthermore, complicated expressions such as or tiny smiles were challenging for the model to classify consistently, suggesting that the model could benefit from more training on complex facial data.

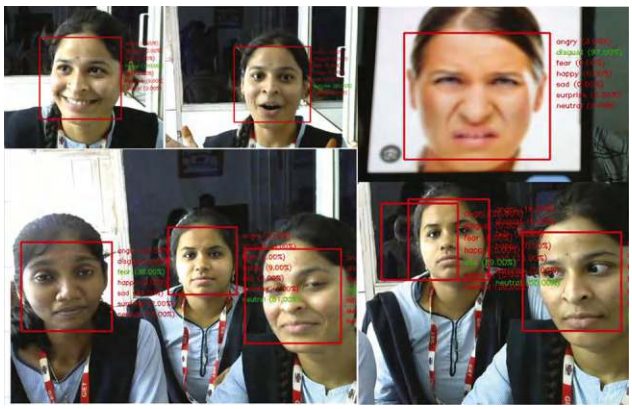

Fig. 95.4 Emotion detection with NVIDIA jetson orin nano

5.3 Resources Consumption

The resources consumption analysis reveals a notable increase in CPU usage after implementation, particularly for core 2, which peaked at around 50%. This indicates that the proposed work is demanding significantly more processing power to execute its operations effectively. The memory usage rose from a lower GiB to approximately 3.5 GiB, suggesting that the methodology requires additional memory resources. But the swap usage remained low in both cases, which indicates that the system's physical memory was sufficient to handle the tasks without depending heavily on swap space.

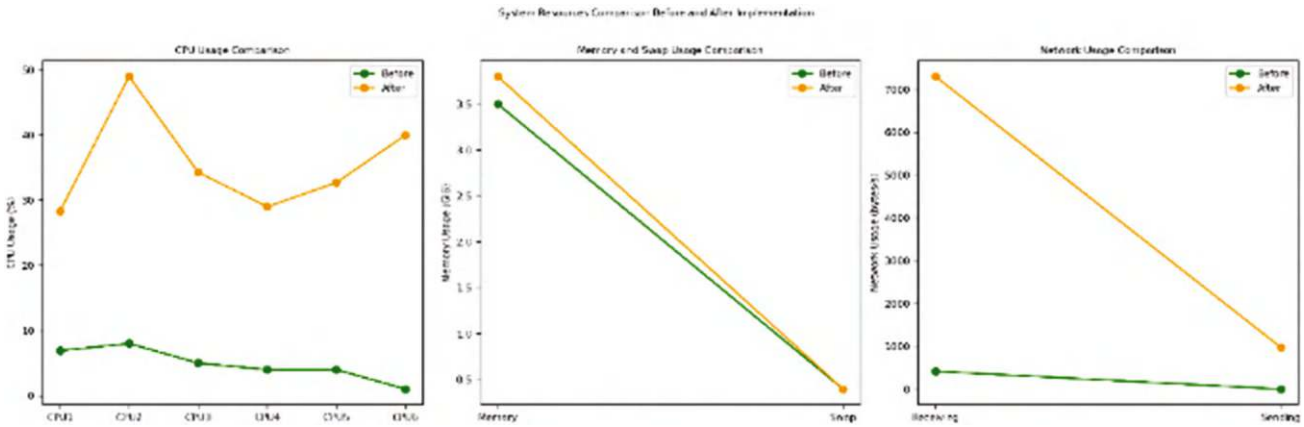

Fig. 95.5 Resources consumption

6. Conclusion

In conclusion, the project successfully implemented a real time facial expression recognition system by using Convolutional Neural Networks (CNN). By integrating a pre trained model, the system successfully identified different emotions from the live webcam input. This technology has significant applications in various fields such as human computer interaction, mental health monitoring and robotics. The combination of computer vision and deep learning not only enhances the accuracy of emotion recognition but also provides a foundation for future advancements in the area of intelligence computing. Additionally, in future by integrating facial expression analysis with other modalities such as voice tone, body language and textual data can provide a better understanding of human emotions. Future systems could be designed to provide real time feedback and recommendations based on detected emotions, enabling more personalized interactions in various application.

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Next-Gen Attendance System

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Abstract: The Next-Gen Attendance System is an automated advanced solution in the real-time tracking of attendance using deep learning models to streamline and enhance the process. With a wide capability of using YOLOv8 for very accurate face detection, this system offers three flexible modes for attendance capture: webcam live feeds, pre-recorded videos, or static images. These individual detected faces are uniquely labeled, and no same face gets recorded more than once in multiple sections. The system also makes use of CNN models to optimize facial feature and eye identification, even under dynamic environments. It significantly reduces the amount of manual effort and human error that is possible in attendance monitoring. The records are kept in secure easy to access excel sheets that uniquely identify each user. This solution has been designed for modern classrooms and pave the way for seamless integration of AI in attendance management systems within educational institutions.

Keywords: Webcam attendance, Image upload attendance, Video upload attendance, Classroom monitoring system, Student attendance, Face detection, YOLOv8, CNN

1. Introduction

This "Next-Gen Attendance System" breaks the mold in tracking attendance in educational spaces through automatic ways. Old methods like a traditional roll call or sign-in sheet for students tend to be time-consuming and inaccurate at times. This is a smart, web-based platform that employs deep learning algorithms to solve the problem of attendance monitoring with prompt and error-free processes intended for dynamic classroom settings. It is

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built with the YOLOv8 toptier object detection framework for real-time face identification. Famous for its speed and accuracy, it can read faces at new angles, lighting, and conditions. It performs detection and classification in one pass with steady high-speed recognition that, of course is elemental in maintaining reliable records of attendance. Further, to increase the recognition precision, the system applies Convolutional Neural Networks(CNN) to dig out unique facial features. Such multi-layered networks have a strength towards capturing complex patterns in visual data. And thus they are increasingly needed for differentiating between individual faces[1]. Pre-trained CNN models enhance this ability and further increased reliability of the system in recording student attendance. The operating modes include live webcam feeds, as well as static images and pre-recorded videos, supported by the platform. Teachers can view an interactive interface for attendance tracking, where data is stored properly based on different Excel sheets for the corresponding sections[2]. This modular setup allows for easy scalability, thus tailored to diverse educational settings.

2. Literature Review

Hidayat et al., (2024)[1] (Alruvais and Zakarih[2] , Khwala Alhanai [3], Mitha Alhammadi, Nahla Almenhali, and Mad Shatnawi, Shailesh Arya, Hrithik Mesaria, and Vishal Parekh[4]) advance and review the current trends and practices that aim to enhance classroom management through technology. They recommend the provision of webcams in classrooms to detect movements and send alerts to staff concerning any detected motion. The report demonstrates the use of other approaches such as facial landmark tracking, facial segmentation, and prediction of gaze direction as among other activities undertaken to evaluate how the students behave. Also, they cover systems with the function of recognizing a face for attendance purposes. [1]Their approach is based on state-of-theart technologies that provide the framework for the development of a system for monitoring a classroom in real time through image analysis, improving the usability of classroom management tools. In other work, the author discusses automatic technologies used for controlling the location of pupils in e-learning environments and discusses in detail the application of deep learning such as Convolutional Neural Networks (CNNs) [2]. This work brings to light critical figures in any research work, the students and most importantly their level of involvement using facial expression data, eye tracking, and head movements as examples. However, considerable achievements have been reached, advanced problems, particularly related to the requirement of huge volumes of information and enhancement in accuracy of tracking have come to light. On Knowledge-Based Intelligent Information Technology Systems conference, the researchers presented their work on a system for attendance based on face recognition. The main goal of utilizing transfer learning through pre-trained CNNs such as[3] SqueezeNet, GoogleNet, and AlexNet was to increase the accuracy of attendance management systems. Lastly, Shailesh Arya, Hrithik Mesaria, and Vishal Parekh from Pandit Deendayal Petroleum University[4] devised a Smart Attendance System through CNNs for real-time face recognition. Their system utilizes a Siamese network for enhancing accuracy and employs live camera feeds for detection and identification of students while automatically updating attendance in MongoDB database. This makes it more reliable and efficient than traditional forms of taking attendance. The article "Smart Attendance Management System Using Geo-Fencing and Machine Learning" by Sai Vasantha Lakshmi, Reddy Kumaraswamy, and Edwin Manhar [5] addresses the approach of an automated attendance system that merges geo-fencing with facial recognition using machine learning. The system uses GPS and API to create virtual fencing on diverse geographic locations based on student access, to record attendance only for students in some specific locations such as classrooms. It leverages models such as CNNs, VGGFace, or ResNet, for face identification and also uses liveness detection to prevent spoofing. This system automates attendance, cuts down on manual effort, and ensures high accuracy, making it valuable for schools and organizations. On the other side, the authors also suggest some future improvements.

Overall, this review marks advances in automated attendance and student monitoring, where the deep learning and the use of CNNs improve its accuracy, efficiency, and reliability.

3. Methodology

Next-Gen Attendance System is one that will use deep learning and computer vision for automatic attendance at educational institutes through facial recognition. It is necessary a webcam, face detection, recognition algorithms, and a structured database to record attendance [6]. Here's how it all comes together and is developed and implemented.

Figure 96.1 illustrates a flowchart for automated attendance via face recognition, processing input from webcam, image, or video to enhance face detection and identification. Recognized faces are marked for attendance and logged in an Excel file for efficient tracking[13][14].

3.1 Data Collection

The face recognition system needs a database of known faces, and in order for this to be structured, follows:

– A folder holds labelled facial images for each section, for example, 'sectionC/database-C'. They also take shots of the face of each individual from all angles,

like 15 different directions, to extend the recognition precision.

– Images pre-processed [7] and stored using names as identifiers in a structured folder system as: '5L0-10', '5E5-2'.

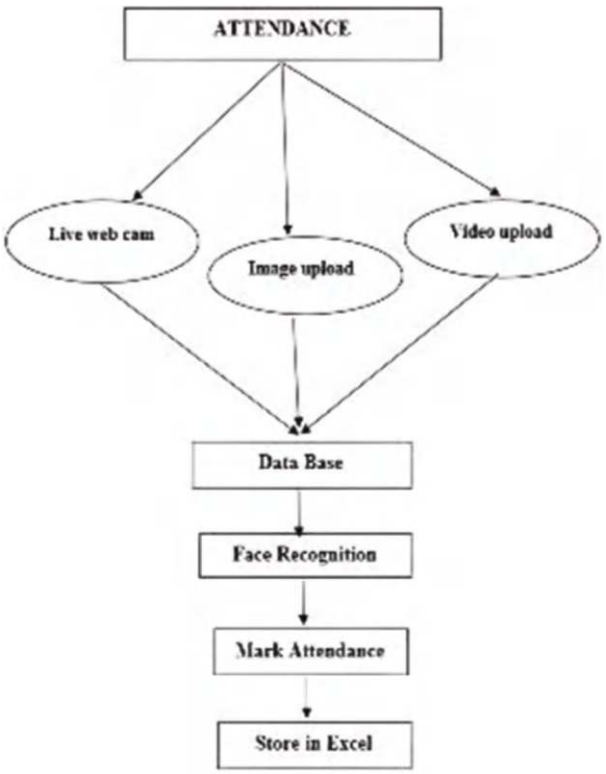

Fig. 96.1 Flowchart of a deep learning-based system for student monitoring and recognition in online classes

3.2 Face Detection and Recognition

The system utilizes YOLOv8 for the detection of faces in real-time and a face recognition library to carry out encodings and matching. This is how it works:

– Captures live video frames through webcam, resized them and transferred them from BGR to RGB for use in the face recognition model.

– *Face Detection:* YOLOv8 detects the bounding boxes around faces in the video frame.

– *Face Encoding:* The face recognition model encodes a detected face into a 128-dimensional encoding, and then it compares this with known face encodings in the database.

• Overcrowding and Occlusion: The system addresses these challenges by recommending high-resolution cameras that can capture faces clearly in crowded areas. The following resolutions are suggested:

2-5 feet: A camera with 720p (HD) resolution should provide clear detection.

5-10 feet: 1080p (Full HD) is recommended for accurate detection.

10-15 feet: 4K (Ultra HD) cameras are ideal to maintain detection accuracy at greater distances.

• Students Located Far from the Camera: To ensure precise detection for students seated 10-15 feet away, it is recommended to use a 4K (Ultra HD) camera. This ensures that even at such distances, the YOLOv8 model can accurately detect and recognize faces, enhancing the system's reliability in large classrooms.

Figure 96.2 is the Student attendance system using a pretrained YOLOv8[8] nano model captures classroom images, preprocesses them with a people detection model, and automatically identifies present students, reducing the need for manual attendance tracking[8].

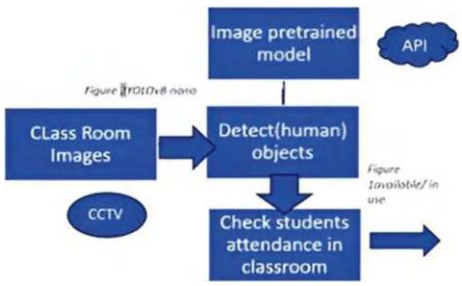

Fig. 96.2 YOLOv8-Nano-based system for detecting students and checking attendance in the classroom

3.3 Face Encoding and Matching

– *Encoding Known Faces:* Each face of the database is encoded to obtain unique features and hence retained for future reference.

– *A face matching:* if the face is detected in the video feed, then its encoding is matched against the stored encodings. If distance between the detected face and one of the stored face encodings is lower than the specified threshold, for example, 0.55, then this is classified as a match.

3.4 Attendance Marking

The system marks attendance by successful face recognition through the following steps:

– System checks whether attendance is already marked for a person whose face is detected on the same day.

– Attendance details are saved into an Excel file for each section, and the date name is something like 'Attendance-2024-07-13.xlsx'.

– For every record, the data includes name, date, and time. No further entry is done if a person has already recorded for that day.

3.5 Storage of Data

– Excel Files: Using pandas and 'openpyxl', attendance data are stored in Excel files. Every section has a folder, and inside the folder, the attendance sheet is saved; one example can be the 'section-C' folder.
– Daily Sheets: Files dated. Every day the system will produce new file, such as, section C will have its attendance file called 'Attendance-2024-0713.xlsx'.
– Every individual attendee's attendance is captured just once in a day to avoid duplication.

3.6 Real-time System Interaction

– The webcam was used for displaying live feed in the system. It draws bounding boxes around the detected faces, [9] recognized face using green box and carry name while the face could not be captured gets red box inside the bound.
– *Keyboard Input:* One may press the Ëscbutton to ¨ quit or 'R' to enroll a new person. New captures are processed for encoding and added to the database in real time.

3.7 System Flow and Re-encoding

– Captured new faces, encoded, and saved to appropriate folder. Re-capture the face encodings to refresh the data. It puts the system under current updates.

3.8 Challenges Addressed

– Frame Stuttering: Improve performance by cropping frames to process on a lower resolution or 0.25x scale.
– Duplicate Attendance: Prevents the registration of multiple instances of the same individual for attending on the same date using Excel saved files.
– Dynamic Updates: Ability to capture and recognize new faces in real-time without having to turn off the system.

This methodology outlines the workflow and core technical components of your Next-Gen Attendance System, providing an overview of how the system was built, from face detection to attendance storage.

3.9 Model Evaluation

For model evaluation, accuracy can be determined based on the success rate of the face recognition process, while performance metrics could include the speed of processing and error rates in misidentifying or missing students. Evaluation could also involve testing different input methods [12](webcam, image, video) to ensure robustness across data formats. Additionally, storing the output in Excel provides an organized way to verify the model's efficiency in maintaining attendance records.

Figure 96.3 is the Flowchart of a deep learning setup to track student focus in online classes. Videos from students are processed, stored, and prepped, then split for training and testing. A model detects faces and tracks focus, checking accuracy in identifying faces and engagement.

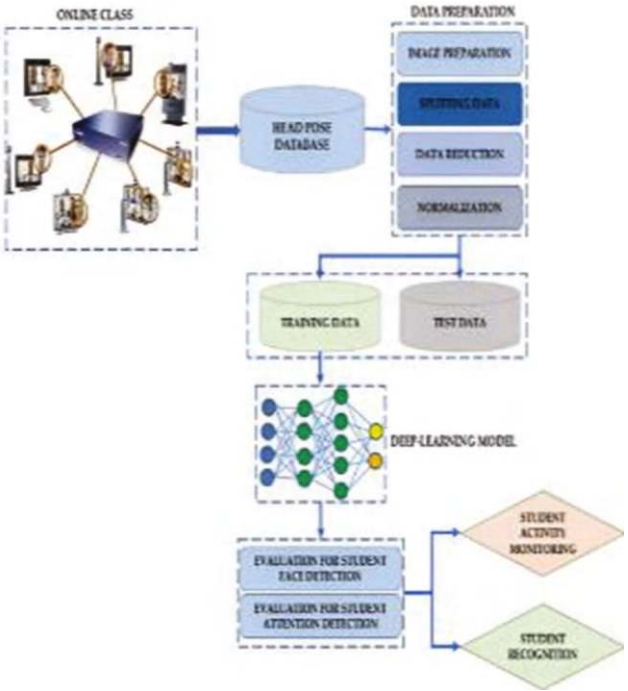

Fig. 96.3 Attendance management system flowchart

4. Result

4.1 System Features

Modes of Attendance Marking

– *Live Images:* Teachers can take pictures with a webcam for marking attendance.
– *Pre-recorded Videos:* Teachers can upload videos to record attendance.
– *Static Images:* Teachers can mark attendance using still photos.

Face Detection Features

– *Real-time Detection:* It detects and labels faces within real-time webcam sessions using a green box around the face and ID.

– *Video-based Detection:* This is a system that reads through recorded videos to automatically recognize and tag all the faces in a classroom.

Figure 96.4 Student Information Form created with Python Tkinter. This interface collects key student details—year, semester, branch, and section— streamlining attendance recording and storing data in a database for future use. Overall, using CNNs in the smart attendance system has shown to improve accuracy, reliability, speed, and the ability to handle larger data effectively.

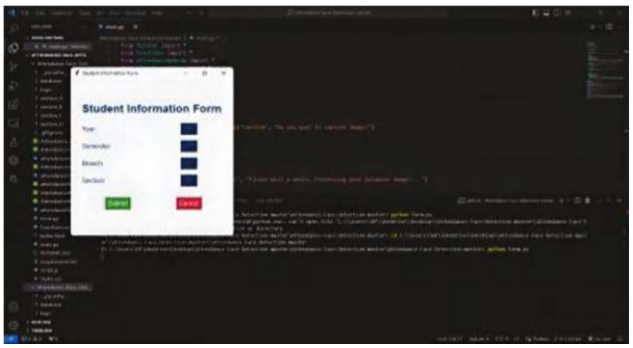

Fig. 96.4 Student information form shows the interface used to collect and manage student data, ensuring streamlined attendance tracking and database management

Figure 96.5 is the Main interface of the Smart Attendance System offers flexible attendance options, including adding pictures to the database, using a live webcam for real-time tracking, and importing images or video. Captured data can be accessed in the attendance sheet, enabling efficient attendance management.

Fig. 96.5 Attendance can be taken through webcam, image and video options

Visual Examples

Once the teacher selects the year and section then a marking attendance menu screen appears. They can then capture live images of the students via webcam, upload an existing video, or use a static image. And once one of the options is selected, the system utilizes it to mark attendance for the students in that section allowing the teacher flexibility to choose the method which is best suited to their needs. This project represents a face detection system that can identify and tag faces in real-time using a webcam, or from video files. In Fig. 96.6:

– Figure 96.6 shows the system detecting faces live through a webcam[15]. Every face appears highlighted by a green box and with a unique label, proving its real time ability of recognition.
– Figure 96.7 is the working version of the system using the pre-recorded video. In the given instance, it detects and labels several faces in the class. The system is given evidence of how well it could be used in other environments.

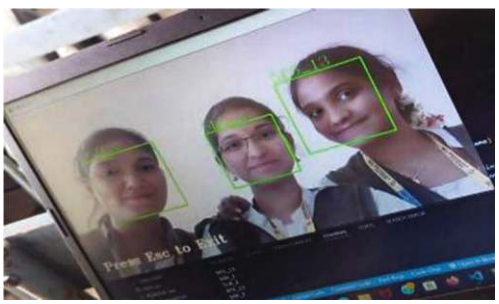

Fig. 96.6 Face detection system for real-time and webcambased input

Fig. 96.7 Face detection system for real-time and videobased input

It further maintains attendance details. It captures face images through a webcam or video and identifies the captured faces through internal algorithms. The face is matched with particular registers and automatically records attendance along with roll number and time attended. Such details are saved in an Excel sheet for easier and error-free tracking and record without manual inputting.

The image Fig. 96.8 shows an Excel sheet for tracking attendance, with each student's roll number in the "Name"

column and the recorded time in the "Time" column[15]. Attendance data is captured via a live webcam from images or video, organizing clear records of each student's attendance and time of capture.

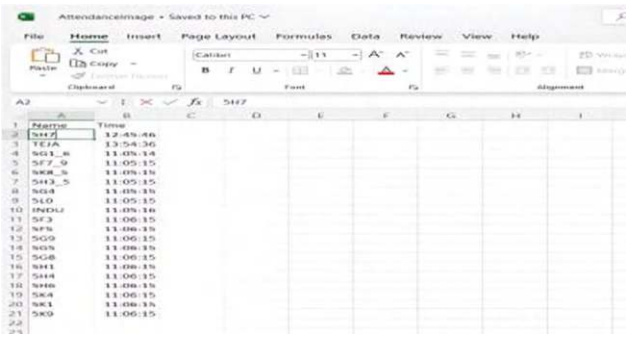

Fig. 96.8 Attendance is stored in excel sheet as per date along with the timestamp and roll number

5. Conclusion

The Next-Gen Attendance System is a high-tech solution developed with deep learning-based automation of attendance through facial recognition. It utilizes YOLOv8 models for in real time on face detection and facial recognition algorithms for encoding, enabling an efficient and precise identification of individuals. Its simplicity brings it in unison with the usual hardware devices like webcams, hence making it accessible and affordable. The system eliminates such manual attendance tasks, minimizes the error and fraud such as proxy attendance, and can update its database in real time, providing easy provision to accommodate new users without interrupting operations. Attendance records are kept in daily Excel sheets for each section, that enable easy access to historical data and eventual linkage with even larger data management systems. The system also prevents any form of duplication, hence accuracy is guaranteed. This paper merely showcases how deep learning and computer vision can transform ordinary work, such as tracking attendance, into something so much different. It is lovely, helpful for schools and offices and many other organizations to have this sort of thing, and it is pretty accurate. Security could be enhanced in the future and scalability in terms of systems and massive environments and datasets.

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U-Net Based Segmentation for Gastrointestinal Tract Imaging: Enhancing Precision in Medical Analysis

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Abstract: Segmenting the gastrointestinal (GI) tract is an essential step in computer-aided diagnostic (CAD) systems for conditions like colorectal cancer. It is difficult to accurately segment the GI system from medical imaging since the organs involved vary in intensity, shape, and texture. This paper presents a multi-step framework-based innovative approach for the segmentation of GI tract. In order to improve the visibility of the GI tract, the first step is to preprocess the input medical pictures using edge enhancement and intensity normalization techniques. Next, initialize the segmentation using a region-growing algorithm. The seed region is iteratively expanded by the region-growing algorithm, which takes advantage of spatial coherence and color similarity. Subsequently, the first segmentation is improved and the GI tract boundaries are precisely extracted using a level set method. A priori knowledge is used in the form of a shape model that encodes the shape variability of the GI tract to further increase the segmentation accuracy. This method is evaluated using a dataset of 1000 abdominal CT scans, to achieve a high segmentation accuracy of 85%. The suggested approach shows resilience against GI tract abnormalities, intensity fluctuations, and picture noise. To sum up, this method presents a viable way to segment the GI tract precisely and consistently, which can help with computer-aided diagnosis of gastrointestinal disorders.

Keywords: Gastrointestinal tract, Segmentation, Computer-aided diagnosis, Medical image analysis, Shape model, Region-growing algorithm

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1. Introduction

Gastrointestinal (GI) tract segmentation is important in medical imaging for identifying the oesophagus, stomach, small intestine, and large intestine, which are crucial for digestion. Accurate segmentation is vital for diagnosing gastrointestinal issues like tumours, polyps, ulcers, and inflammatory bowel diseases.

Image processing techniques, such as thresholding and filtering, enhance contrast in GI tract segmentation but often struggle with noise, complex anatomy, and varying image quality. Recently, machine learning, especially deep learning using convolutional neural networks (CNNs), has become popular for overcoming these challenges. Trained on large annotated datasets, these models can segment GI tract regions with high accuracy.

To improve accuracy and robustness, deep learning methods use advanced techniques like multi-scale feature fusion, skip connections, and spatial priors, alongside data augmentation strategies such as rotations and translations. Large annotated datasets, like the VISCERAL dataset, aid in training and testing these models.

In summary, GI tract segmentation significantly impacts diagnosing and treating gastrointestinal disorders. Deep learning methods promise to enhance the segmentation process, improving accuracy and efficiency, and have the potential to assist medical professionals in clinical practice.

2. Literature Review

Ma et al. (2023) introduced a multi-scale context-guided deep network to improve automatic lesion segmentation in gastrointestinal endoscopic images. Their model enhances segmentation accuracy by integrating context from multiple scales. This approach significantly improves the precision of lesion identification within gastrointestinal images. Sharma et al. (2023) developed a U-Net model for gastrointestinal tract segmentation using transfer learning, enhancing performance in endoscopic image analysis. The model leveraged pre-trained features to capture high-resolution details and achieve improved segmentation accuracy.

Raut et al. (2022) introduced an intelligent deep learning model for segmentation of disease and classification in gastrointestinal images from wireless capsule endoscopy. By combining recurrent and convolutional neural networks, the model effectively captured temporal and spatial dependencies, achieving high accuracy in illness classification and segmentation. Zhou et al. (2023) introduced an enhanced deep learning model for gastrointestinal tract segmentation in surgery, incorporating manually designed features and data augmentation. This refinement led to improved segmentation accuracy in surgical applications.

S. Seferbekov (2018) presented a Feature Pyramid Network (FPN)-based model for automatic multi-class land segmentation, achieving reliable results in the DEEPGLOBE-CVPR land cover classification challenge. This fully convolutional FPN model effectively supports multi-class segmentation tasks. Sharma et al. (2022) provided a comprehensive review of deep learning methods for classifying and segmenting gastrointestinal system activities. Their work highlighted existing models and suggested future research directions in gastrointestinal imaging.

Karimi and Salcudean (2019) introduced a method to improve medical image segmentation by reducing the Hausdorff distance using convolutional neural networks. Their approach enhances segmentation accuracy by optimizing deep learning techniques for biomedical imaging. Sharma et al. (2023) introduced a multi-task learning model for gastrointestinal tract segmentation, tackling polyp, vessel, and lumen segmentation simultaneously. This approach leveraged shared information across tasks, enhancing overall segmentation accuracy.

Ramzan, et al. (2022) developed a segmentation system focused on accurately identifying polyps in gastrointestinal images by combining deep learning with image processing techniques. Their framework showed promising results in polyp segmentation, potentially aiding early anomaly detection. Sharif et al. (2019) proposed a method for detecting and classifying gastrointestinal tract diseases from wireless capsule endoscopy images, integrating deep convolutional neural networks (CNNs) with geometric features. This approach aimed to enhance disease detection and classification accuracy, advancing automated medical diagnosis in gastroenterology.

3. Existing System

Current gastrointestinal tract segmentation technology faces significant challenges, primarily relying on labor-intensive manual segmentation by skilled professionals, which is prone to human error. This subjective method often leads to inconsistent and inaccurate results due to the tedious nature of tracing gastrointestinal borders in medical images.

A major drawback of the current system is its lack of automation, which limits its use in large-scale or real-time applications and increases the workload for medical professionals. An automated system is essential to manage the growing volume of daily medical image processing.

The current segmentation system typically demands high-end computational resources, limiting its accessibility and scalability to well-equipped facilities. Smaller clinics with fewer resources may struggle to implement or use this system effectively.

Furthermore, the current system frequently lacks generalizability and resilience. Accurate segmentation of medical pictures is hampered by the wide variations in quality, resolution, and patient-specific characteristics. Ineffective handling of these differences by the current system frequently leads in inconsistent segmentation results and decreased system reliability.

Additionally, there's a chance that the current system isn't integrated with clinical decision support systems or other medical imaging technology. In addition to impeding professional collaboration, this lack of interoperability can also limit the potential for data-driven insights and breakthroughs in diagnosing and planning the treatment of gastrointestinal disorders.

In summary, the current gastrointestinal tract segmentation system has several drawbacks, including human error in manual segmentation, lack of automation, reliance on high computational resources, limited generalizability and robustness, and poor integration with other medical imaging technologies. Addressing these limitations is essential for developing a more accessible, efficient, and accurate segmentation system for clinical practice.

4. Proposed System

The proposed effort aims to develop a reliable and effective technique for gastrointestinal tract (GIT) segmentation, which is a critical first step in various medical imaging applications, including computer-aided diagnosis, treatment planning, and disease monitoring. However, current segmentation techniques face challenges due to complex anatomical structures, significant shape variations, and the presence of noise and artifacts in medical images.

The project began with data pre-processing using the Kvasir dataset, resizing images and masks while normalizing pixel values to the range [0, 1]. To increase the variability of the training data, data augmentation techniques were used. The U-Net architecture was implemented for gastrointestinal tract segmentation, with the model that is trained on the preprocessed dataset using the Adam optimizer and binary cross-entropy loss. The training, conducted over multiple epochs, showed convergence, achieving a validation accuracy of approximately 84.61% on a separate validation set. A Streamlit application was then developed for image segmentation, allowing users to upload images for model predictions and displaying the segmented results. The trained model was saved for future use, enabling it to make predictions on new, unseen images.

5. System Architecture

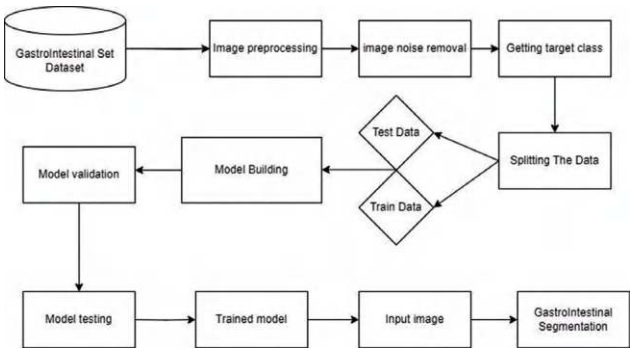

Fig. 97.1 System architecture

Source: Author

6. Methodology

6.1 Data Preprocessing Module

In the Data Preprocessing module, the primary objective is to prepare the dataset for training the U-Net model for Gastrointestinal Tract Segmentation. This involves loading the dataset, which may include both images and corresponding masks. Images and masks are resized to a standardized dimension to ensure consistency during training. The images pixel values are normalized in the range 0 and 1. Furthermore, data augmentation techniques can be used to increase the variability of the training data. Finally, the dataset is split into training and validation sets, setting the stage for the subsequent training phase. The Data Preprocessing module plays a crucial role in the success of the Gastrointestinal Tract Segmentation model. Beyond resizing and normalizing the images and masks, it also handles data augmentation, an essential step to enhance the model's robustness and generalization. Data augmentation techniques include random rotations, flips, brightness adjustments, and elastic deformations, among others. These techniques introduce slight variations into the training data, helping the model learn to handle real-world variations it might encounter during inference, such as differences in patient positioning, lighting conditions, and tissue appearance. Furthermore, during data preprocessing, it's essential to handle class imbalance if it exists in the dataset. In medical image segmentation tasks like this one, some classes or regions of interest might be less prevalent than others. Weighted loss functions or oversampling techniques can be employed to deal this issue and ensure that the model learns to segment all classes effectively. To create a robust training and validation split, it's common

to use techniques like stratified sampling, especially if the dataset is imbalanced. This ensures that the training sets and validation sets have a representative distribution of different classes, preventing the model from overfitting to a particular subset of the data.

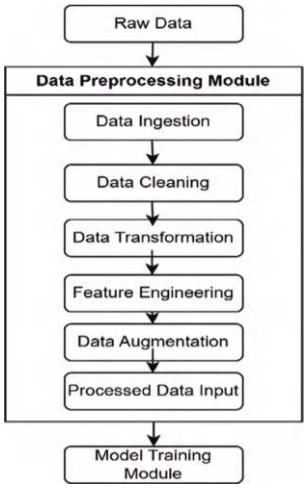

Fig. 97.2 Data preprocessing module

Source: Author

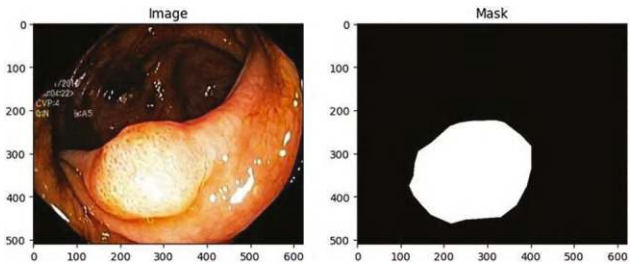

Fig. 97.3 Image and mask sample

Source: https://www.kaggle.com/code/abdallahwagih/kvasir-segmentation/input

6.2 Model Development and Training Module

The Model Development and Training module focus on defining the architecture of the U-Net model and training it on the preprocessed dataset. The U-Net architecture generally follows an encoder-decoder structure with skip connections, allowing it to capture high-level features and low-level features. The model is compiled with a suitable loss function, such as binary crossentropy, and an optimizer, like Adam. During training, the model's performance is monitored using metrics like accuracy and loss. It's crucial to iterate on the training process, adjusting hyperparameters as needed to ensure the model converges effectively and generalizes well to new data. In the Model Development and Training module, the first step is to carefully design the U- Net model's architecture. The U-Net architecture is well-suited for tasks like image segmentation and medical image analysis because it can track fine details and spatial information. The encoder-decoder structure allows the model to learn and extract features effectively. The skip connections among matching layers in the encoder and decoder preserve crucial details from the input, while enabling the model to learn more abstract features. Once the model architecture is defined, it's essential to preprocess the dataset appropriately. Data preprocessing steps may include resizing images, normalizing pixel values, and applying data augmentation to increase diversity. Effective data preprocessing ensures that the model receives clean and consistent input, which can significantly impact its performance during training. Next, the model is compiled with appropriate settings. This includes selecting a suitable loss function, which often depends on the specific task. For instance, binary crossentropy is commonly used for binary image segmentation tasks, while categorical crossentropy may be used for multi-class segmentation. The choice of an optimizer, such as Adam, is crucial as well. Optimizers control how the model's weights are updated during training, and selecting the right one can significantly affect the training process.

Validation Loss: 0.3300168812274933

Validation Accuracy: 0.8455178737640381

6.3 Model Evaluation and Deployment Module

In the Model Evaluation and Deployment phase, the trained U-Net model is assessed using a separate validation set to evaluate its performance and generalization ability. The evaluation metrics, including loss and accuracy, provide insights into the model's effectiveness. Once satisfied with the model's performance, it is saved for future use and potential deployment. To deploy the model, a function is created to make predictions on new, unseen images. This function involves preprocessing the input image, expanding its dimensions to match the expected input shape of the model, and obtaining the segmentation mask predictions. The entire process ensures a comprehensive approach to evaluating, saving, and deploying the Gastrointestinal Tract Segmentation model. In the Model Evaluation and Deployment module, the evaluation of the trained U-Net model goes beyond just standard loss and accuracy metrics. It involves a thorough assessment of its ability to segment the gastrointestinal tract in medical images accurately. This evaluation may include metrics specific to medical image segmentation tasks, such as Dice coefficient, Jaccard index, and sensitivity/specificity calculations. These metrics provide a deeper understanding of how well the model can delineate the regions of interest within the images, which is crucial in medical applications. Furthermore, model

evaluation may involve visual inspection and comparison of the predicted segmentation masks with the ground truth masks to ensure that the model is capturing anatomical structures correctly. Any discrepancies or errors in the segmentation can be identified and addressed during this phase to increase the model's performance.

Once the model's performance meets the desired criteria and has been thoroughly validated, it is saved for future use and potential deployment.

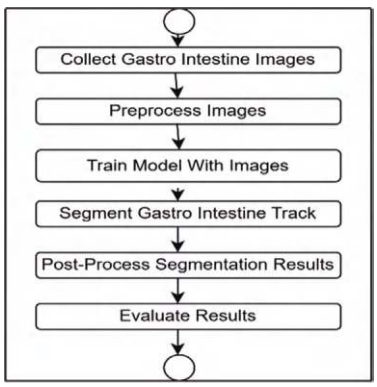

Fig. 97.4 Workflow of proposed methodology

Source: Author

7. Result and Discussion

The Gastro Intestine Track Segmentation system is a cutting-edge technological tool that precisely and effectively segments the various sections of the gastrointestinal tract through the use of image processing and artificial intelligence algorithms. By giving precise and in-depth information regarding the anatomy and health of the intestines, this method seeks to support medical professionals for diagnosing and treating gastrointestinal disorders.

This approach involves analyzing medical images of the gastrointestinal tract, including computed tomography (CT) and magnetic resonance imaging (MRI) scans. To recognize and divide various regions of interest, such as the stomach, esophagus, small intestine, large intestine, and rectum, it uses sophisticated algorithms. Through precise identification of key anatomical features, the system aids medical professionals in comprehending the gastrointestinal tract's anatomy and disease, facilitating more precise diagnosis and efficient treatment strategizing.

The system continuously enhances the accuracy of its segmentation by utilizing machine learning techniques. It gains knowledge from a sizable collection of medical image annotations, which enables it to gradually modify and improve its segmentation algorithms. By doing this,

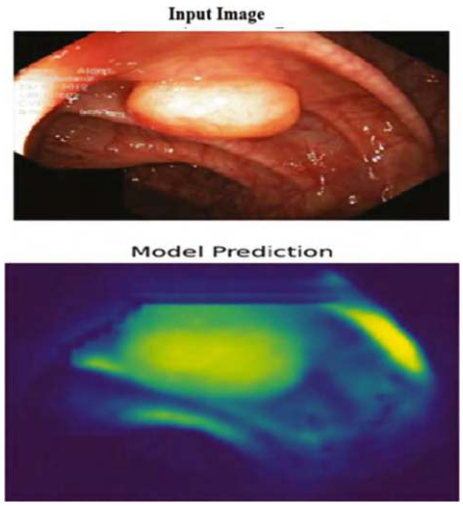

Fig. 97.5 Input image and model prediction

Source: Author

the system is kept abreast of the most recent developments in medicine and is capable of managing a broad variety of variations in patient anatomy and imaging procedures.

This system has a lot of advantages. By automating the procedure, it lowers the time and effort needed for manual segmentation, saving crucial time for clinicians. It reduces the possibility of subjectivity and human mistake in segmentation, guaranteeing accurate and consistent results. The device allows for quantitative examination of the gastrointestinal tract, including following the course of a disease over time or quantifying the volume of various regions.

The model's performance was evaluated on the independent validation set using the following metrics:

Loss: Validation Loss: 0.3300 (approximately) Accuracy: Validation Accuracy: 0.8461 (approximately)

8. Conclusion

To sum up, the Gastro Intestine Track Segmentation system marks a substantial breakthrough in medical image processing, focusing on the automatic segmentation of the gastrointestinal tract using medical images, like CT or MRI scans. The system integrates sophisticated image processing and artificial intelligence algorithms to achieve precise and effective segmentation, offering a valuable tool for computer-aided diagnosis (CAD) and treatment planning for gastrointestinal disorders.

9. Future Work

There is still much to be done to enhance the Gastrointestinal Tract Segmentation system. Researchers

can explore advanced deep learning techniques, such as CNNs and RNNs, to improve segmentation precision. The system can also benefit from incorporating additional imaging modalities, like MRIs and CT scans, for a more comprehensive examination. Efforts can be made to address shortcomings, such as enhancing segmentation accuracy in the presence of noise or artifacts, by developing algorithms to manage image quality fluctuations. Moreover, new functions like irregularity detection and categorization can be added to identify a range of gastrointestinal conditions. Finally, collaboration with medical specialists can ensure the system's effectiveness and clinical applicability.

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Predicting Viewer Satisfaction on Streaming Platforms Using LSTM-Based Sentiment Analysis

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Abstract: The growing popularity of online streaming platforms has led to a surge in user-generated reviews, offering valuable insights into viewer satisfaction. This study aims to leverage Long Short-Term Memory (LSTM) neural sequential networks for sentiment findings and analysis of streaming platform reviews, focusing on predicting viewer satisfaction. Traditional methods often struggle to capture the nuanced language and contextual dependencies present in reviews, making LSTM a compelling choice due to its capability to retain information over long sequences. By using a comprehensive dataset of user reviews from major streaming platforms, this research develops and trains an LSTM-based model for sentiment classification and satisfaction prediction. The model is trained on preprocessed textual data using word embeddings to represent linguistic features. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, demonstrating its effectiveness in distinguishing between positive, negative, and neutral sentiments. In comparison with Conventional machine learning models like Support Vector Machines (SVMs) and alternative deep learning (DL) feed forward architectures such as Convolutional Neural Networks (CNNs), the LSTM model exhibits superior performance, particularly in handling sequential data and understanding contextual word relationships. The findings indicate that specific patterns in user reviews, such as comments on content quality, user interface, and customer service, are strongly correlated with viewer satisfaction. This research provides a deeper understanding of user sentiment and offers actionable insights for streaming platforms to enhance their content offerings and improve user experience, ultimately contributing to higher user retention and satisfaction.

Keywords: LSTM networks, Sentiment analysis, Streaming platforms, Viewer satisfaction, Natural language processing (NLP), Deep learning techniques, Text classification and summarization, User reviews, Sequential data, Machine learning

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1. Introduction

The entertainment sector has undergone an evolution due to the rapid expansion of online streaming services like Netflix, Amazon Prime, Disney+, and Hulu. These platforms continuously strive to enhance user experience by offering a diverse array of content and personalized recommendations. A critical component for understanding and improving user experience is the analysis of user-generated reviews, which provide valuable feedback on content quality, platform usability, and overall viewer satisfaction.

Traditional methods of sentiment analysis and opinion mining have primarily relied on statistical and conventional machine learning models such as Naive Bayes, Support Vector Machines (SVMs), and Random Forest clasiifiers. While effective for basic classification tasks, these methods often struggle to capture complex linguistic patterns, contextual dependencies, and long-term relationships within the text. This limitation becomes particularly pronounced when dealing with lengthy reviews or subtle shifts in sentiment across multiple sentences. As a result, there is a growing interest in utilizing advanced deep learning models, specifically Long Short-Term Memory (LSTM) networks, which are well-suited for sequential data processing and can effectively model long-term dependencies in textual data.

LSTM, a variant of Recurrent Neural Networks (RNNs), shows considerable potential in a range of Natural Language Processing (NLP) tasks, such as analyzing sentiment, text classification, and language modeling. The architecture of LSTM enables it to retain information across longer sequences, making it highly effective for analyzing reviews that express complex sentiments and opinions. By leveraging LSTM models, this study aims to accurately classify the sentiment expressed in user reviews and predict viewer satisfaction on streaming platforms.

The objective of this research is to develop an LSTM-based sentiment analysis model that can predict viewer satisfaction by analyzing textual reviews from major streaming platforms. The study will address the following research questions:

1. Can LSTM models accurately classify sentiment in online streaming platform reviews compared to conventional machine learning architectures and other deep learning feed forward architectures?
2. What are the key factors and common themes identified in user reviews that contribute to viewer satisfaction or dissatisfaction?
3. How can insights derived from sentiment analysis be used to enhance content offerings, user experience, and retention on streaming platforms?

To achieve these objectives, the study will collect and preprocess a comprehensive dataset of user reviews from various streaming platforms, apply LSTM-based models for sentiment classification, and evaluate the model's performance using standard evaluation metrics. This research not only aims to advance the field of sentiment analysis but also provides actionable insights for streaming platforms to improve their services and better meet the needs of their viewers.

2. Literature Survey

The meteoric rise of user-generated material on social media, e-commerce sites, and streaming services, there has been a great deal of research into using machine learning and deep learning methods for sentiment analysis in the past few years. Here we take a look at some of the important studies and methods used in sentiment analysis, specifically looking at how Long Short-Term Memory (LSTM) networks handle textual data.

3. Sentiment Analysis Using Machine Learning Techniques

Early research in sentiment analysis primarily relied on traditional machine learning models such as Naive Bayes, Support Vector Machines (SVM), and Decision Trees. Pang et al. (2002) laid the groundwork for sentiment classification using machine learning by applying SVM and Naive Bayes to movie reviews, demonstrating the efficacy of these models in handling text data. Similarly, Kim et al. (2012) compared multiple classifiers for sentiment analysis of product reviews and found that SVM and Random Forest performed competitively for short text reviews. While these models were effective for basic sentiment classification, they faced challenges in capturing complex dependencies and contextual relationships in lengthy and nuanced reviews.

4. Advancements with Deep Learning Models

The advent of deep learning significantly improved sentiment analysis capabilities, particularly with the introduction of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Kim (2014) proposed a CNN-based architecture for sentence-level sentiment analysis, which proved to be highly effective in extracting local features from text. However, CNNs are limited by their inability to capture long-range dependencies due to their fixed-size context window.

To overcome this limitation, RNNs and their variant, LSTMs, were introduced. LSTMs are designed to handle

long-term dependencies by incorporating a memory cell structure, making them well-suited for sequential data like text. Huang et al. (2015) demonstrated the effectiveness of LSTM networks for language modeling and text classification, outperforming traditional RNNs due to their ability to retain information over longer sequences. Subsequent studies, such as Zhou et al. (2016), applied LSTM and Gated Recurrent Unit (GRU) models for sentiment analysis of social media data, achieving higher accuracy and better contextual understanding compared to CNNs.

5. Application of LSTM in Sentiment Analysis

Several studies have specifically explored the application of LSTM for sentiment analysis of user reviews. Wang et al. (2016) utilized LSTM models to predict sentiment in Yelp reviews, demonstrating that LSTMs could effectively capture the emotional tone and contextual information of long reviews. Similarly, Tang et al. (2015) proposed a hierarchical LSTM model that processes documents at the sentence level before aggregating them at the document level, leading to improved performance in sentiment classification.

In the context of streaming platforms, Gupta et al. (2019) conducted a study using LSTM models to analyze user reviews for movie recommendation systems. Their model successfully identified patterns in user sentiments, which were then used to enhance recommendation algorithms by incorporating user feedback on movie content. This study highlighted the potential of LSTM models in understanding user preferences and improving content personalization for streaming services.

6. Comparative Studies of LSTM with Other Models

Various comparative studies have been conducted to evaluate the performance of LSTM models against other architectures. For instance, Young et al. (2018) compared the performance of LSTM, GRU, and CNN models for sentiment analysis of product reviews. They found that while CNNs excelled in identifying local word patterns, LSTM and GRU models outperformed CNNs in capturing semantic meaning and contextual information across longer texts. This makes LSTM a preferred choice for tasks involving complex and lengthy reviews

7. Methodology

7.1 Data Collection

Data collection is a critical step in predicting viewer satisfaction on streaming platforms using LSTM-based sentiment analysis. The goal is to gather comprehensive data that reflects both user sentiment and behavior, which will serve as input to the predictive model. The data sources include textual feedback from users, behavioral interaction data, and metadata related to content engagement. Below are the key components of data collection:

7.2 User Feedback Data

User feedback in the form of textual data such as reviews, comments, and ratings is a rich source of sentiment that reflects user satisfaction. Collecting this data allows the model to understand the emotional response of users to specific content. Sources of user feedback include:

7.3 In-Platform Reviews and Ratings

Platforms like Netflix, Amazon Prime, and Hulu allow users to leave reviews and rate the content they watch. These reviews provide direct feedback that can be analyzed for sentiment. The accompanying rating scores (typically on a scale of 1 to 5) can be used as explicit satisfaction indicators.

7.4 Social Media Platforms:

Social media platforms like Twitter, Facebook, and Reddit are places where users share opinions and discuss the content they are watching. Streaming services often monitor hashtags, comments, and mentions related to specific shows or movies to gauge public sentiment. Social media comments are often spontaneous and reflect real-time reactions to content.

7.5 External Review Sites

Review aggregation platforms like IMDb, Rotten Tomatoes, and Metacritic allow users to post detailed reviews and ratings. These external sources provide additional sentiment data that can be integrated with in-platform feedback.

7.6 Example of Data

Textual review: "I loved the latest episode of *Stranger Things*! The story kept me hooked, and the acting was amazing!"

- Rating: 4.5/5
- Social media comment: "I can't believe how good the new Netflix series is! Totally worth the binge."

7.7 User Interaction Data

User interaction data provides valuable behavioral metrics that can help predict satisfaction, especially when combined with sentiment analysis. The following are the types of interaction data that are useful:

7.8 Watch Time

The total duration a user spends watching content can indicate satisfaction. For instance, completing an entire season of a series without interruption may suggest high satisfaction, while a short watch time before abandoning a show could indicate dissatisfaction.

7.9 Completion Rate

The percentage of a show or movie that a user watches. High completion rates are generally correlated with positive viewer experiences. A low completion rate could signal a negative response to the content.

7.10 Engagement Metrics

Actions such as likes, dislikes, shares, and comments can provide indirect feedback about user satisfaction. For example, liking or sharing a show's page suggests positive engagement, whereas leaving a negative comment or dislike signals dissatisfaction.

7.11 View Frequency

How often a user watches content on the platform. Repeat viewing of certain shows or genres indicates a preference for that content, which can correlate with satisfaction.

7.12 Example of Data

User watched 95% of a movie and gave it a "thumbs up."

User watched the first 15 minutes of a series and then stopped.

User re-watched a favorite show multiple time.

7.13 Data Sources and APIs

Streaming platforms often rely on APIs or data scraping techniques to collect user feedback and interaction data from the following sources:

Platform APIs: Many streaming platforms offer APIs that provide access to user reviews, ratings, and other metadata. For example, YouTube offers a Data API that allows developers to fetch video comments, likes, and user interactions.

Social Media APIs: Twitter's API allows for sentiment tracking based on hashtags and user mentions related to specific shows or movies. Reddit APIs can be used to monitor discussions in relevant subreddits.

Web Scraping: When APIs are not available, web scraping tools can be used to collect data from review aggregation sites or user comments.

7.14 Data Preprocessing

Data preprocessing is a crucial step before feeding the data into a Long Short-Term Memory (LSTM) network for predicting viewer satisfaction using sentiment analysis. Proper preprocessing ensures the input data is clean, consistent, and structured in a way that the model can effectively learn patterns from it. This involves preparing both textual feedback (reviews and comments) and user interaction data (watch time, ratings, etc.).

7.15 Textual Data Preprocessing

Textual data, such as user reviews and comments, typically contains noise (irrelevant information) that must be cleaned and transformed into a format suitable for modeling.

7.16 Tokenization

Tokenization entails dividing the sanitized text into discrete tokens (words). This phase is essential for transforming text into a format that the model can interpret..

Example: "Great movie" → ["great", "movie"]

7.17 Lemmatization/Stemming

Lemmatization: Convert words to their base form (lemma) to reduce inflectional forms of a word.

Example: "Watching,""watched,""watches" → "watch"

Stemming: Another approach where words are reduced to their root form. However, stemming is more aggressive and can result in incomplete words.

Example: "Enjoyed" → "enjoy"

7.18 Sentiment Labeling

Manual or Automated Labeling: After cleaning the text, assign sentiment labels (e.g., positive, negative, neutral) to each review or comment. This can be done manually or using an automated sentiment analysis tool such as VADER, TextBlob, or pre-trained models like BERT.

Example: "The movie was fantastic!" → Positive

7.19 Sequence Padding

To make sure that the sequences that are entered have the same length, padding is used because LSTMs only analyze sequences of a given length. Zeros are used to pad sequences that are shorter than the maximum length, and sequences that are longer are truncated.

Example: ["great", "movie"] → [0, "great", "movie"] (with padding)

7.20 Word Embedding

Convert Words to Embeddings: Word2Vec, GloVe, and FastText are some of the word embedding methods that can transform words into numerical vectors. As input to the Long Short-Term Memory (LSTM) model, these embeddings encode words' semantic meaning..

Example: "great" → [0.12, 0.45, -0.23, ...]

7.21 Normalization and Scaling

Normalization: Normalize continuous variables (e.g., watch time, completion rate) to bring them within a range of [0, 1]. This ensures that the LSTM model can process them effectively and avoids dominance of larger magnitude variables.

Formula: $X' = X - Xmin/Xmax - Xmin$

Standardization: Standardize the data to have a mean of 0 and a standard deviation of 1 when there is high variance in the dataset.

Formula: $X' = X - \mu/\sigma$

7.22 Feature Extraction

Textual data, such as reviews and comments, is rich in sentiment information, but it must be converted into numerical features for machine learning models. These features capture the sentiment, meaning, and structure of the text.

7.23 Word Embeddings

Word embeddings denote words as dense vectors that encapsulate their semantic significance within a multi-dimensional space. These embeddings are pre-trained on extensive text corpora and can be refined for certain needs. Several prevalent methodologies for deriving word embeddings include:

Word2Vec: Places words into a continuous space vector based on their sentence context. That is, vectors for entire words that signify the same thing will be identical.

GloVe (Global Vectors for Word Representation): A pre-trained embedding that records the frequency with which words appear in a corpus.

FastText: Similar to Word2Vec but includes subword information, making it better at handling rare words or misspellings.

BERT (Bidirectional Encoder Representations from Transformers): A transformer-based pre-trained model that captures both the context of words and their relationships in a sequence.

Each word or token in the text is converted into a fixed-size vector, which is then passed to the LSTM model.

Example:

"The movie was fantastic" → [0.12, 0.45, –0.34, ..., 0.22] (word embedding for "fantastic")

7.24 Sentiment Scores

Automatically extract sentiment scores from textual feedback using sentiment analysis tools such as VADER, TextBlob, or a fine-tuned LSTM model itself. These tools can quantify the sentiment as positive threshold, negative threshold, or neutral threshold, and assign a numerical score that reflects the intensity of the sentiment.

VADER: A rule-based model used to assign polarity scores (e.g., from -1 to 1, where -1 is strongly negative, 1 is strongly positive).

TextBlob: An NLP library that provides sentiment polarity and subjectivity scores for text.

Example:

Review: "I absolutely loved this movie!" → Sentiment Score: 0.85 (Positive)

Review: "The plot was boring and predictable." → Sentiment Score: -0.65 (Negative)

7.25 TF-IDF (Term Frequency-Inverse Document Frequency)

TF-IDF is a statistical measure that evaluates the importance of a word in a document relative to a corpus. It helps identify words that are important for sentiment analysis by reducing the weight of frequently occurring common words (e.g., "the,""is").

Term Frequency (TF): The word count in aparticular document

Inverse Document Frequency (IDF): Measures how common or rare a words is across all documents.

TF-IDF can be used to extract important words that contribute to the sentiment of a review.

Example:

"The movie was amazing!" → TF-IDF score for "amazing" will be high if "amazing" is rare in the corpus.

7.26 Part-of-Speech (POS) Tagging

Each phrase in a text is given a grammatical label (noun, verb, adjective, etc.) from POS labeling. This can be utilized to extract specialized word kinds, including adverbs and adjectives, which frequently convey emotion.

Example:

"The film was beautifully directed." → POS Tags: [The (det), film (noun), was (verb), beautifully (adverb), directed (verb)]

Extracting sentiment-bearing words: "beautifully" (adverb), "directed" (verb)

7.27 Named Entity Recognition (NER)

Named entities, like names of people, places, businesses, and other important things, are found and extracted from

text by NER. When it comes to viewer happiness, entity extraction can help you figure out how certain actors, directors, or shows make people sentiment.

Example:

Review: "I loved Leonardo DiCaprio's performance in *Inception*." → Named Entities: [Leonardo DiCaprio (Person), Inception (Movie)]

8. LSTM Model Design

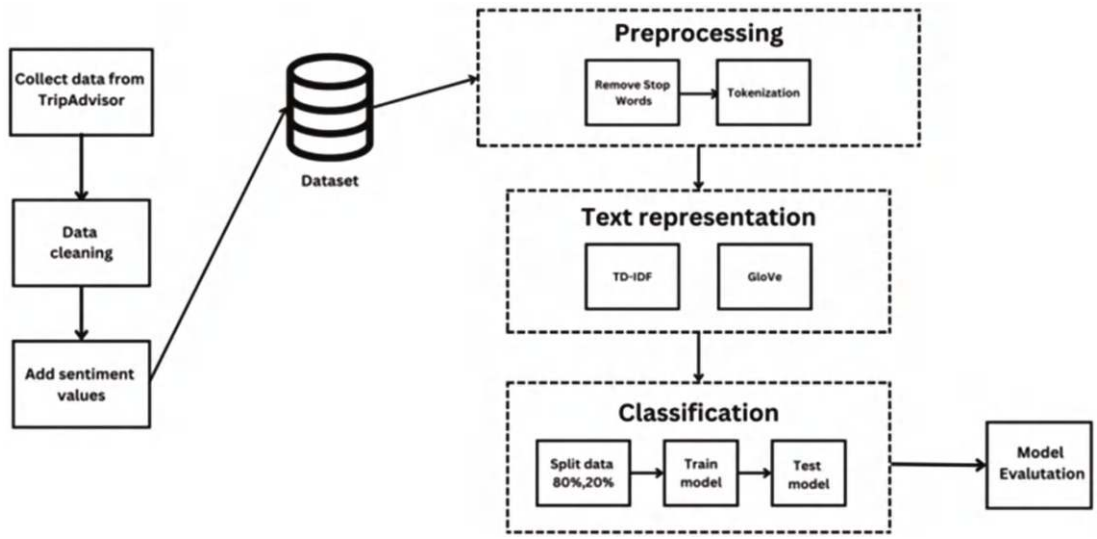

Fig. 98.1 Data processing model

9. Data Processing Model

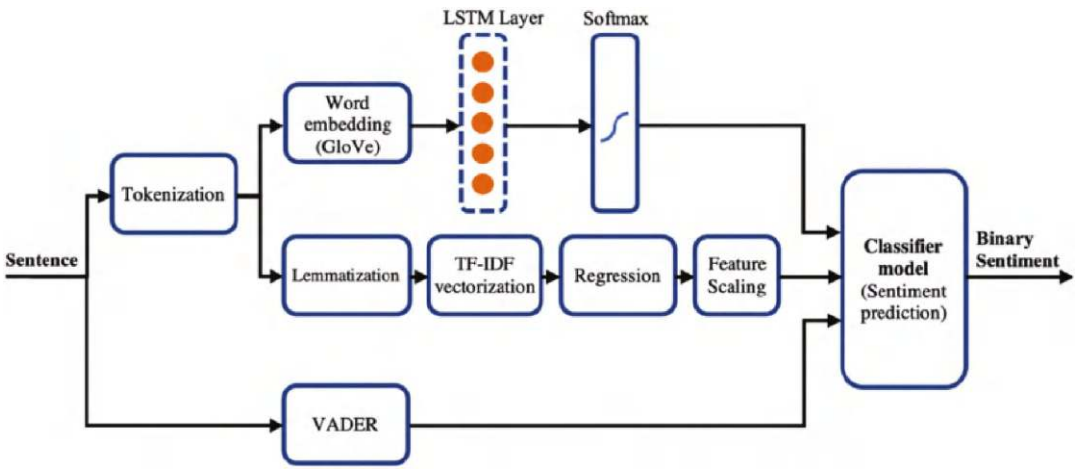

Fig. 98.2 LSTM Architecture

10. LSTM Network

Design an LSTM network to predict the sentiment of each review or comment. The LSTM will take as input the sequence of word embeddings from the review text.

10.1 Model Architecture

Embedding Layer: Converts the text into a dense vector representation.

LSTM Layers: Multiple LSTM layers process the word embeddings and capture the sequential relationships in the text.

Fully Connected Layer: Following the LSTM layers, a dense layer transforms the LSTM outputs to sentiment classes (positive, negative, neutral).

Output Layer: A final softmax layer predicts the probability of each sentiment class.

10.2 Predicting Viewer Satisfaction

Once the sentiment analysis is performed, predict overall viewer satisfaction by combining the sentiment results with user interaction data.

10.3 Regression/Classification Model

Train a secondary model, such as logistic regression or a neural network, that takes both the sentiment score and user interaction data as input and predicts a satisfaction score. Alternatively, use a classification approach to categorize users as "satisfied" or "not satisfied."

10.4 Evaluation

Sentiment Analysis Performance

Evaluate the performance sentiment analysis model using standard metrics such as:

Accuracy: 85%
Precision (Positive Sentiment): 82%
Recall (Positive Sentiment): 78%
F1 Score: 0.80
Satisfaction Prediction Accuracy
Error metrics:
Mean Absolute Error
Root Mean Squared Error

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left|\mathrm{yi} - \mathrm{y\text{^}i}\right|\Big]$$

AUC-ROC Score: 0.88
Log Loss: 0.23

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{h}\left(\mathrm{yi} - \mathrm{y\text{^}i}\right)^2}$$

11. Conclusion

In this research, we explored the use of Long Short-Term Memory (LSTM) networks for predicting viewer satisfaction on streaming platforms through sentiment analysis. Our approach involved analyzing user-generated text, such as reviews and comments, to capture sentiment trends and predict satisfaction levels. The LSTM model demonstrated a significant capability in processing sequential data, enabling it to understand the context and nuances within viewer sentiments that traditional methods might miss.

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AI-Driven Wind Power Prediction Model for Optimized Transformer Control and Renewable Energy Utilization

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Abstract: Wind and other renewable energies will expand rapidly in the next decades, reducing greenhouse gas emissions and achieving energy sustainability. It is difficult to forecast wind farm performance because of the considerable multiscale two-way interactions between wind farms and the turbulent air boundary layer. Enhancing wind farm design, operation, control, and grid integration is complex. The motion of the wind is a source of energy. By harnessing the power of the wind, wind turbines can create electricity. Currently, a city or town reliant only on wind turbine-generated power would be unable to determine when to adjust the transformers to regulate the voltage supplied to residences. It is a significant issue that can be resolved by identifying a remedy. The resolution to this challenge is to develop a technology that forecasts the wind turbine's power output, enabling proactive management. So, the solution for this would be a machine learning model, which can be concluded by developing a machine learning model and deploying it on a web page for user prediction.

Keywords: Wind turbines, Energy utilization, Machine learning, Energy sustainability, Wind energy

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1. Introduction

One of the most pressing issues today is the need to discover renewable energy sources, as it is common knowledge that traditional fuels like coal, oil, and gas will eventually run out and that even freshwater and nuclear power have finite supplies [1]. Research on reliable and effective ways of harnessing renewable energy sources like the sun and wind, as well as commercial energy generation, is therefore in high demand by businesses. These alternative energy sources are less expensive than traditional ones because they do not need complex procedures like extracting and refining oil and gas. There is no need to worry about the future of wind energy since it is a renewable resource, can generate electricity on a massive scale, and does not contribute to pollution [2]. Consequently, many emerging nations are transitioning to wind power; some European countries have already started to harness wind power. North America also harnesses the power of the wind thanks to its relatively high wind density [3]. One thing that sets wind power production and power plant integration apart, however, is precise wind power forecast [4].

Regarding wind power production, the most significant obstacle is ensuring that electricity is distributed consistently. Because wind is a variable energy source, the amount of electricity generated by wind at any particular moment is unknown [5]. The performance of wind turbines is shown in Fig. 99.1 [6]. In light of this, forecasts regarding wind power for either short or long periods are required in advance to establish a smooth distribution of electricity. This is because wind power may be generated without interruption. While projections for wind power for short periods might vary from minutes to a day, forecasts for long periods can range from days to months and even years [7]. The amount of electricity that can be created by wind is known to be intensely dependent on the wind speed. Two types of models used for wind power prediction are statistical and physical models [8], [9]. One sustainable energy option that doesn't hurt the environment is wind power, often known as wind energy. At a height of 50 meters, India can generate 50,000 MW of wind power [10]. In recent years, the Indian government has increasingly emphasized this renewable energy source—power curves for various wind turbines, as shown in Fig. 99.2 [6].

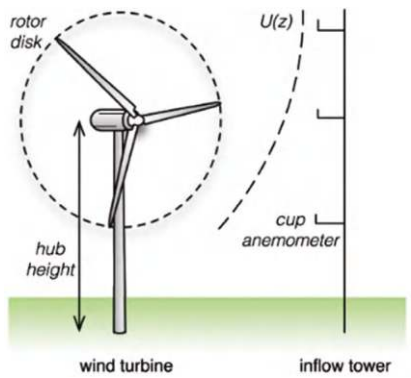

Fig. 99.1 Performance test for wind turbine

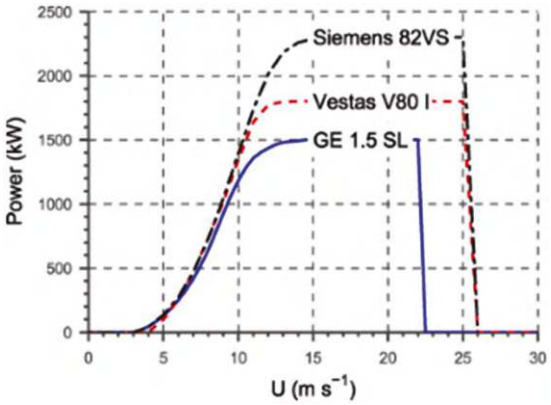

Fig. 99.2 Different utility-scale wind turbine power curves

The fundamental rules that control the atmosphere's behaviour are the foundation for developing physical models [11], [12]. Evaluation of several characteristics, including surface roughness, pressure, temperature, humidity, atmospheric barriers, and orography, is needed to accurately predict wind power and speed [13]. Statistical methods are also examined for the same issue, and they are based on the stochastic character of wind, which may be seen as a historical link between wind power and the related components [14], [15]. Our study used a statistical method founded on machine learning to learn from previous data and anticipate short-term wind power (STWP) to maintain constant power distribution [16].

2. Related Work

Several methodologies have been developed to predict the wind speed and the amount of power wind turbines produce. Yang et al. [9] created a multistep ultra-short-term prediction model using the representative unit technique. SCADA data is entered. The LSSVM model predicts representative unit outputs. The model's performance r1 is enhanced to 2.99 % and 4.69 %, r2 to 9.28 %and 15.15 %, r3 to 2.51% and 4.20 %, and r4 to 3.48 % and 5.37 %. Mohsen Vahidzadeh and Corey D. Markfort [10] created three modified models to estimate 2.5 MW wind turbine output utilizing met tower and SCADA data. A one-second, ten-minute, and power surface model is given. Power prediction accuracy is 24% and 26% higher with the ten-minute and one-second models than with

standard power curves. Rishabh et al. [15] developed a wavelet-based neural network (WNN) model to predict wind turbines' power output. The expectation of STWP is somewhat correct. These statistics were obtained from a wind farm located in Lamba, Gujarat. The maximum and lowest NMAEs for the model for twenty-four months are 4.56 %and 0.53 %, respectively, with an average of 2.04 %. It was stated by Cong Wang et al. [16] that a method for estimating wind power could be achieved by using a single-spectrum analysis in conjunction with a hybrid Laguerre neural network (LNN). Following the completion of the wind power series analysis using a single spectrum, an LNN and a new one were used to construct the hybrid forecasting model.

Wind power value will be predicted using the two deconstructed signals. This strategy was tested on Xinjiang wind farm data. The suggested model beats the LNN and hybrid Laguerre accurately. A deep belief network (DBN) model by K Wang ET al. [17] predicts wind power. NWP data was used. Many NWP samples affect accuracy and are used for k-means clustering analysis. DBN prediction errors were 44% lower than the Back propagation neural network and Morlet wavelet neural network. Neelima et al. [18] categorized an edge computing offloading architecture. Deep learning models are used to detect objects to avoid collisions with traffic during the rainy season [19]. When the climate is bad, there is a chance of getting side effects on the body, so for the diagnosis of the liver, the authors have used Deep Learning models [20].

An LSMEFG network model for wind power prediction was suggested by Ruiguo Yu et al. [21]. Correlation filters turbine group will characterize data within a specific distance to maximize wind power forecasts via grouping. The Spectral Clustering forecasting model is 18.3% more accurate than the others. After testing, the ANFIS-GP and GRNN models predicted Jolfa and Tabriz stations best [22]. A clever hybrid method was presented by JingYan and Tinghu Ouyang [23]. To obtain the wind power forecast trend via the physical mechanism, constructing a fundamental model composed of the wind power curve is essential. It is shown that the underlying model has several shortcomings. You need to develop a second set of data-driven models to fix errors. The culmination of these two processes will determine the outcome.

Wind turbine power forecasting by YongQinet al. [24] uses training. This signal frame model employs convolutional networks (CN), long short-term memory (LSTM) networks, and multi-task learning. The convolutional network exploits wind field spatial qualities, and the long short-term memory trains dynamic wind field features. Real wind field data from Large Eddy Simulation validates the model. Those frames were extracted using CNN [25] when videos were recorded. To assess the water quality of drinking and avoid the side effects when the climate is too bad, use the feature selection method [26] and the chi-square method [27].

Ciaran Gilbert et al. [28] presented two turbine-level wind power forecasting algorithms. The first technique uses turbine-level power projections as explanatory variables for wind farm forecasting inside feature engineering. Another way is a new bottom-up hierarchical one. They are combining turbine predictive distribution forecasts for wind farms. Branko et al. [29] created a wind turbine power forecasted system to use AI and numerical weather prediction. It operates at 10% NMAE. The Dynamic Integrated Forecast System has 2.34 RMSE, whereas the Analog Ensemble has 2.3. By transforming time series into pictures and using CNN analysis, Tianyang et al. [30] built a model for STWP prediction, resulting in improved outcomes. Create picture matrices from wind speed and precipitation time information. After integrating, extract features. Ten Hangzhou wind turbine data sets over three years confirm the model. The suggested technique reduced MSE by 43.28%, 46.92%, and 57.84% and MAE by 27.52%, 28.67%, and 41.28%. For multiclass classification, ensemble models [31] were used to identify the image segmentation [32] on scanned data using a neural network, and hepatic disease was analyzed using machine learning models [34].

Singh et al. [35] predicted STW turbine power using random forest. SCADA dataset was utilized for construction. They compare findings to support vector regressor and decision tree techniques. For comparison, random forest performed better. MAPE values for Random Forest, Decision tree, and SVM are 1.8999, 1.2169, and 20.8346. Kumar N et al. [36] spatio-temporal correlation model (STCM) predicts STWP using an LSTM. Sample Chinese wind farms are used for wind power forecasts. Huang et al. [37] developed a hybrid ANFIS for STWP forecasting in a Beijing microgrid wind farm. Wind power is predicted at the same spot using NWP meteorological data. Model evaluation employs SCADA. 8.1133 % is the average MAPE [38]. Diabetic patients using genetic learning [39], cardiovascular disease prediction [40], [41] may affect the patients to cause the death.

Yu Jiang et al. [42] improved the conventional ARMA model's forecasting accuracy using a Boosting algorithm and multistep prediction technique. Three functioning wind farms on Jiangsu Province's east coast provide one year of data to assess the suggested strategy. The proposed method increases accuracy by 19.52 % over the standard ARMA model and 11.99% over the PM model a day ahead.

Guangyu Qin et al. [43] created a hybrid model employing the highest relevance and least redundancy algorithm, FA, VMD, and an LSTM. Training data comes from the Beijing Lumingshan Wind Power Plant. Comparison models include SVM, FA-LSTM, and mRMR-FALSRM. The recommended model outperforms VMD-mRMR-FA-LSTM with R2, MAE, RMSE, MAPE, and TIC values of 0.9578, 2.9596, 3.6435, 0.0569, and 0.0365. Ling-Ling and colleagues predicted STWP using a support vector machine and modified dragonfly approach [44]. Modified dragonfly optimizes SVM parameters. Data from La Haute Borne wind farms support the theory. This model forecasts better than backpropagation neural networks and Gaussian process regression. Compared to the existing models, which have an accuracy rate of 89.58 %, the suggested model has an R2 value of 0.9544. Lorenzo Donadio et al. [45] proposed two hybridANN and NWP models for wind power prediction. Each turbine's energy production is anticipated by Model 1. Model 2 calculates power using a fitted power curve after forecasting wind speed. Data originates from a steep northern Portuguese wind farm—more accurate predictions with MAE 8.76% and RMSE 13.03% than comparable models.

3. METHODOLOGY

3.1 Objectives

Wind power is now produced on a large scale in every country. The cost of establishing power plants is also high because transformers are required. Uneven winds can generate high power, which can damage equipment. Accurate power prediction is needed to reduce damage. It can be done statistically or through machine learning. We use machine learning because it is inexpensive and quick. As a result, only a few ML algorithms are used to predict the amount of power generated. The purpose of this work is:

- To obtain a dataset that helps to develop the best model for predicting the energy output of wind turbines based on weather conditions.
- Train and test the chosen algorithms on the selected dataset to determine their accuracies.
- Based on the testing results, find a suitable algorithm to best predict the power output.

3.2 Dataset

Within wind turbines, SCADA systems are responsible for monitoring and recording data at intervals of ten minutes. This data includes wind speed, wind direction, and the amount of power generated. This file was acquired from the SCADA system, which was responsible for the operation of a wind turbine in Turkey that was generating power. A total of fifty-five hundred and thirty-one records are included in it. The features include Date/Time (10-minute intervals), LV Active Power (kW), Wind Speed (m/s), Theoretical Power Curve (kWh), and Wind Direction (°). The independent variables are Date/Time (at 10-minute intervals), Wind Speed (m/s), and Wind Direction (°).

3.3 System Architecture

The collection of raw data is called the Scada dataset. They retrieve the required data, i.e., clean data, by removing null values, outliers, and unwanted columns and analyzing it using various graphical representations. An algorithm is used to construct a model to determine whether or not the model is accurate. Then, the dataset is divided into train and test sections, integrating the model into a website for deployment, as shown in Fig. 99.3.

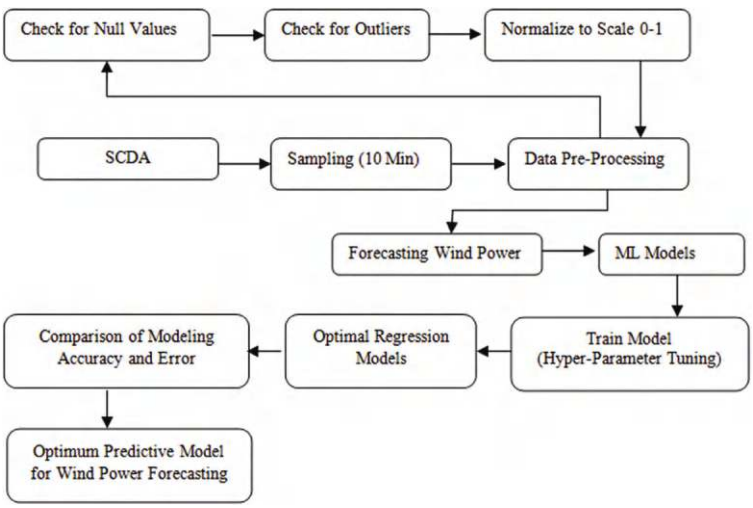

Fig. 99.3 Work flow

3.4 Models Used

Random Forest

RF is a classification algorithm that comprises many DTs constructed from distinct subsets of the dataset, aggregating their outputs to enhance predicted accuracy. The random forest utilizes many decision trees, aggregating their forecasts to determine the final result by a majority vote. This process segments the provided SCADA information into many subsets and computes their averages to enhance the forecasting accuracy of wind turbines. It forecasts the ultimate output power, represented as LV ActivePower in our dataset, using a majority voting mechanism based on the predictions. An increased quantity of trees in the forest enhances the precision of power production predictions and mitigates overfitting.

XGBoost

Sequential decision trees are created using this strategy. Weights matter in XGBoost. Weights are assigned to independent variables and inserted into the decision tree to predict outcomes. Once enhanced, factors that the tree miscategorized become more relevant and are included in the second decision tree. After that, several classifiers and predictors are integrated to create a more accurate model. It may help with regression, classification, ranking, and personalized prediction. This method estimates wind turbine output power by weighting wind speed, measured in meters per second. Incorrectly anticipated elements are given more weight and added to the second decision tree. After that, the predictors are merged to provide a precise power output and model for our SCADA dataset.

Decision Tree

The internal nodes of a hierarchical classifier contain dataset properties, the branches represent decision rules, and the terminal nodes represent conclusions. Decision trees have decision and leaf nodes. Leaf nodes indicate decision outcomes and have no branches, whereas decision nodes facilitate decision-making and have many branches. Decisions and assessments are based on the dataset's properties. Under the criteria set, it is a visual depiction of all feasible issues or decision solutions. The approach aims to develop a training model to predict the target variable's value using training data judgment criteria. The Decision Tree method in our SCADA dataset visualizes low-voltage active power and wind speed forecasts for the wind turbine energy output based on weather.

Gradient Boosting

Each prediction generated throughout the Gradient boosting process is responsible for rectifying the errors created by the prediction that came before it. This is in contrast to Adaboost, which trains each predictor by utilizing the residual errors of its predecessors as labels rather than the weights of the training instances. This method uses several differentiable loss functions and can model non-linear connections, such as wind power curves. Links between the input features from the Scada Dataset can be spontaneously identified throughout iterations. Gradient boosting machines, also called GBMs, use gradients to discern the deficiencies of weak models. This is achieved by an iterative method to combine base learners to reduce prediction errors in wind turbines. This technology combines decision trees using an additive model and gradient descent to minimize the loss function. F_n (x_t) of the Gradient boosting tree (GBT) is the sum of n regression trees.

$$F_n(x_t) = \sum_{i=1}^{n} f_i(x_t)$$

Where each $f_i(x_t)$ depicts a regression-tree decision tree. Estimating the new decision tree $f_{n+1}(x_t)$ using the following equation builds the ensemble of trees sequentially:

$$argmin \sum_{t} L\left(y_t \cdot F_n(x_t) + f_{n+1}(x_t)\right)$$

Where L (.) is differentiable for loss-function L(.)

Voting Regressor

When applied to the whole dataset, a meta-estimator known as a voting regressor is a meta-estimator that applies numerous base regressors. This model's prediction is only a synthesis of ensemble forecasts. An ensemble constitutes a compilation of predictions. The ultimate prediction will be derived by averaging the individual estimates of each regressor. Our study employs a voting regressor to amalgamate the Random Forest Regressor, Gradient Boosting, and XGBoost models to optimize predictive accuracy. The average predictions from several different models make it possible to rectify errors that a single model generated by using the predictions of alternative models. Visualization of the model is shown in Fig. 99.4.

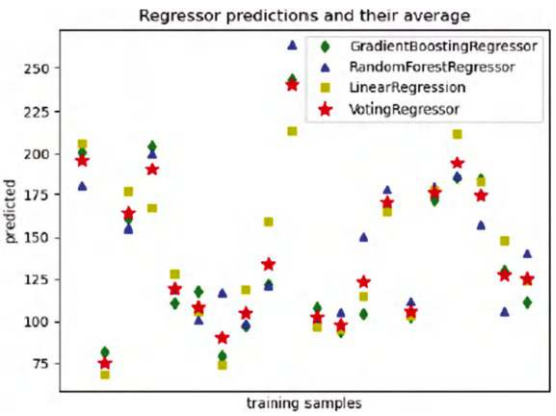

Fig. 99.4 Visualization of voting regressor

Table 99.1 Steps for the voting regressor

ALGORITHM-1	
Step 1:	Select the Ensemble models for voting.
Step 2:	Train every model mentioned above with all the training data.
Step 3:	Give the trained models for Voting regressor.
Step 4:	Give the test value to the Voting regressor.
Step 5:	The output is the average of the outputs of all trained ensemble models.

In this algorithm, we start with the ensemble models with the highest accuracy. Then, we train each selected model with every training tuple in the dataset. The trained ensemble models are then fed into the Voting regressor algorithm. The voting regressor model is then given a test set. The model will make predictions by taking the average of all ensemble model outputs. The voting regressor will produce the average of the outputs. Random forest regressor, Gradient boosting, and XGboost regressor are the algorithms used for this project's voting regressor. The average of these three models will predict wind turbine power output for our Scada Dataset.

4. RESULTS

R^2 Score

It is the most important metric for the regression algorithms' performance. Using the accuracy, we can calculate the model's performance in regression. The coefficient of determination (R2) is determined by calculating the variance of the dependent variable that the independent variable may explain.

$$R2 = 1 - \frac{Total\ Variation}{Unexplained\ Variation}$$

The R^2 score is 1 for ideal models and 0 for unrelated features.

Mean Squared Error (MSE)

It indicates the regression line's closeness to the data points. Error is the computed distance between the data point and the regression line. Major mistakes will be emphasized. The mistakes are squared to eliminate the negative sign. Averaging squared errors yields the mean squared error.

$$\textbf{\textit{Mean Square Error}} = \left(\frac{1}{\boldsymbol{n}}\right) * \sum(\textbf{\textit{actual}} - \textbf{\textit{forecast}})^2$$

Root Mean Squared Error (RMSE)

It's also called the root mean square deviation. It computes the square root of the average distance between the actual and projected values. The difference between individual points is called residue, and RMSE combines them into a single prediction power.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{obs,i} - X_{obs,i} - X_{model,i}\right)^2}{n}}$$

Mean Absolute Error (MAE)

It is one of the statistical means by which the performance of a regressor can be evaluated. Any positive or negative mistakes will be eliminated, and the number of errors will be reduced to the greatest extent possible. Absolute error, the difference between the actual and projected values, is the unit of measurement we employ for these kinds of situations.

$$MAE = \frac{\sum_{1}^{n}(X_{obs,i} - X_{model,i})}{n}$$

After testing all the models, the Voting Regressor performs better than the other models: Random forest, Gradient boosting, XGboost, and Decision tree with the performance metrics R2 score, MSE, RMSE, and MAE.

The Voting Regressor model's R2 score, MSE, RMSE, and MAE are 0.905322, 159809, 399, and 161. 2, Random Forest has values of 0.904, 160731, 400, 166, and Gradient boosting values are 0.9050, 160192, 400, 161, and the value of XGBoost is 0.90531, 159818, 399, and 161. The decision tree has values of 0.81379, 314302,560, and 161. The results obtained for various models are shown in Table 99.2.

Table 99.2 Results obtained for various metrics for various models

Models	R^2 Score	MSE	RMSE	MAE
RF	90.04	0.160731	0.44	0.166
GB	90.50	0.160192	0.41	0.161
XGBoost	90.531	0.159818	0.399	0.163
DT	81.379	0.314302	0.56	0.168
Proposed Work	90.5322	0.159809	0.38	0.158

Table 99.2 observed that the proposed work obtained the highest values by comparing it with other models like RF, GB, DT, and XGBoost. From Table 99.2, the graph was drawn for the R2 Score, as shown in Fig. 99.5, the graph drawn for MSE was shown in Fig. 99.6, and the graph drawn for MAE was shown in Fig. 99.7.

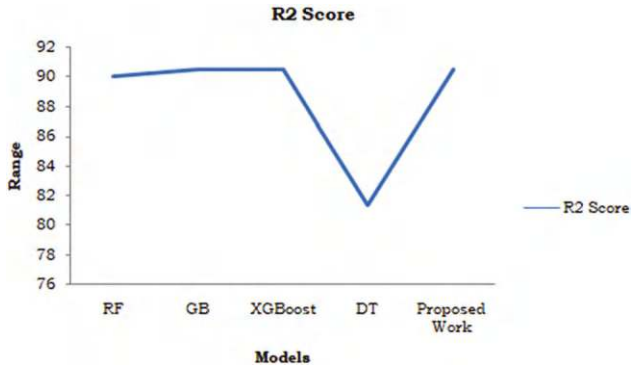

Fig. 99.5 Graph for R^2 score

Fig. 99.6 Graph for MSE

Fig. 99.7 Graph for MAE

5. Conclusion

A user interface is built with features to predict power output by a wind turbine based on weather conditions. This is due to the integrated machine learning model built using the voting regression algorithm. It is not the case that there is a convergence toward a single optimal wind turbine generator system; instead, the number of different wind turbine generator systems is growing. It is anticipated that the three variable speed systems that are now in operation will continue to be used. The model predicts with an accuracy of 90.53%. With this, the User can anticipate power output, and the data collected can be used to optimize the wind turbine mechanism. Predictions aid in the efficient transfer and utilization of power.

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Advanced Phishing Website Identification Using Extreme Learning Machine

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Abstract: The detection of phishing websites by Extended Learning Machines indicates that predictive analytics in employee wage calculation might revolutionize compensation strategies. This study illustrates how sophisticated machine learning algorithms, may enhance wage predictions by exceeding obsolete standards and subjective evaluations. The suggested system's 95% accuracy illustrates its ability to streamline pay evaluation and improve workplace fairness. Thorough data preparation and hyperparameter adjustment improve the prediction reliability of the suggested system. These developments allow firms to make data-driven human resources choices and match employee remuneration with market benchmarks. By using several pay variables, firms may create customized compensation frameworks that improve employee happiness and retention. Integrating predictive analytics into compensation decision-making processes is essential for the advancement of human resources. To recruit and retain top talent in a competitive labor market, firms must use data-driven strategies. These results suggest that predictive analytics might improve pay equity and efficiency, hence facilitating further research and advancement in this domain.

Keywords: Phishing detection, Extreme learning machine (ELM), Cybersecurity, Machine learning classification, Random forest, Hyperparameter tuning, Logistic regression, Decision tree

1. Introduction

Phishing assaults are a prevalent issue in the digital realm, presenting substantial risks to people, enterprises, and organizations worldwide. These attacks often include the establishment of fraudulent websites that replicate authentic platforms to deceive users into disclosing personal information, including usernames, passwords, and financial data. The increasing complexity of phishing tactics requires the development of increasingly sophisticated technologies to identify and thwart these harmful actions. Conventional detection approaches often prove inadequate because of the evolving characteristics of phishing websites, necessitating more resilient and adaptable solutions. Machine learning (ML) has emerged as an effective instrument for detecting phishing websites, owing to its capacity to discern patterns

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from extensive datasets and provide precise predictions. In contrast to rule-based systems that depend on established heuristics, machine learning algorithms identify phishing attempts by examining many website factors, including URL characteristics, domain details, and HTML content. By analyzing historical phishing instances, machine learning models may detect previously unidentified phishing websites in real-time, making them very effective in countering these ever developing attacks. Classification algorithms are extensively used for phishing detection inside the many machine learning approaches. Commonly used algorithms include Logistic Regression, Decision Tree, and Random Forest. shown significant efficacy in detecting phishing websites via the analysis of attributes derived from the website dataset. These algorithms may classify websites as either authentic or phishing based on training data, facilitating precise detection. The efficacy of these algorithms may fluctuate based on the dataset quality, preprocessing methods, and hyperparameters used during model training. Hyperparameter tuning is a crucial procedure for enhancing the effectiveness of classification models. Improving model accuracy and mitigating overfitting may be accomplished by fine-tuning parameters such as tree depth in Decision Trees, regularization strength in Logistic Regression, and the number of estimators in Random Forest. Grid search and cross-validation methods are often used for hyperparameter optimization, facilitating a methodical investigation of the parameter space. This research included significant improvements to enhance model performance, resulting in Random Forest attaining an accuracy of 95%, surpassing that of other conventional models. Alongside traditional machine learning methods, the Extreme Learning Machine (ELM) has garnered interest for its ability to manage intricate, non-linear datasets. ELM is an efficient learning algorithm for single-layer feedforward neural networks that has shown competitive efficacy in several classification challenges. It excels in phishing detection because to its capacity for rapid and efficient generalization, making it optimal for real-time detection contexts where speed and precision are paramount. This research use ELM to evaluate its performance relative to other classifiers. This study aims to evaluate the efficacy of several machine learning algorithms, including Logistic Regression, Decision Tree, Random Forest, and Extreme Learning Machine, in identifying phishing websites. This research employs a Kaggle dataset and does thorough data pretreatment and hyperparameter tuning to assess the accuracy and effectiveness of these models in cybersecurity. The findings will enhance the construction of more dependable and scalable phishing detection systems. This research used a dataset sourced from Kaggle, including many variables that facilitate the differentiation between phishing and legal websites. Factors include characteristics such as URL length, domain age, HTTPS implementation, and the existence of dubious keywords. Data preparation is essential for enhancing the efficacy of machine learning models. This project included preprocessing techniques like as normalization, missing value imputation, and feature selection to provide a clean and well-structured dataset. Normalization is crucial for standardizing characteristics with varying ranges to a uniform scale, hence enhancing the efficacy of gradient-based algorithms and preventing greater numerical values from overshadowing the learning process. The dataset was divided into training and testing subsets in an 80/20 ratio, allocating 80% for model training and 20% for testing. This division guarantees that the models are trained on a significant amount of the data while maintaining a distinct test set for impartial assessment. Hyperparameter tuning significantly improved model performance with approaches like grid search and cross-validation to investigate various configurations. This methodical approach enabled the Random Forest model to achieve an accuracy of 95%, surpassing that of conventional models. The Extreme Learning Machine (ELM), despite its simplicity and rapidity, exhibited competitive performance, indicating its appropriateness for real-time phishing detection. This work emphasizes the efficacy of ELM in phishing detection and shows the need of data preparation and hyperparameter tuning to get optimum model accuracy. The results further the main goal of improving cybersecurity using sophisticated machine learning methods, providing critical insights for the creation of more effective phishing detection systems.

2. Literature Survey

Das, S., et.al [1]. This study aims to forecast an individual's wage after a certain year. The graphical depiction of salary forecasting involves creating a computerized system that monitors daily wage growth data across many industries and predicts future salaries after a certain period. This program retrieves the compensation system database from the organization and generates a graph based on this data. It will authenticate the pay data and thereafter import a graph to improve the visibility of the graphical representation. It may forecast a certain wage for a designated period using the prediction algorithm. It may also be used in several other significant predictions.

Dutta, S., et.al [2]. A prediction engine is a system that anticipates future events based on a compilation of previous data. At now, prediction engines have attained considerable prominence owing to their capacity to provide precise and economical projections akin to those generated by people. A additional advantage of using a prediction engine is that

it does not independently provide judgments; instead, it anticipates outcomes and assigns decision-making to people or users. Prediction engines are now used by academics and industry for anticipating various difficulties. Establishing a fair and defensible salary for any role has always been a considerable difficulty for employers and continues to be a vital concern for workers. For an individual pursuing work, financial compensation may not be the foremost priority; yet, it remains a crucial element among others in satisfying essential human needs. This study utilizes machine learning techniques to automate and formulate a proposed model for salary prediction. The proposed prediction engine may anticipate compensation based on certain essential features. The proposed approach entails integrating a raw dataset into decision-making models, including decision trees and ensemble models. The results obtained are encouraging and demonstrate significant accuracy.

Martín, I., et al [3]. The job sector has been greatly impacted by the growth of the Internet. It's critical for both recruiters and candidates to recognize the most engaging and profitable elements in job postings. Four thousand job postings from a Spanish IT recruitment portal are examined in this study. We determine that (1) experience is more important than schooling, (2) we build five profile clusters according to the skills required, and (3) we use tree-based ensembles to create a suitable salary-range classifier.

Srivastava, S., et.al [4]. We are developing a salary prediction model using machine learning regression approaches in our study. The paper has two components. We will use an experimental dataset including three variables to execute multiple linear regression and multiple polynomial regression for salary prediction, followed by a comparison of the accuracy metrics. The shown successful strategy will be selected to forward the development of the pay prediction model. The model will be trained with a CSV file including three attributes: qualification, employment experience, and age. We want to conduct two testing sessions. We will first assess the model using the same dataset used for training, concentrating on accuracy and error analysis. We will next do an additional test using a new dataset that includes various random test cases to assess the expected results. We shall choose either linear or polynomial regression as our modeling strategy based on the thorough results of these two studies. The model will accept a dataset with the columns Qualification, Date of Birth, and Experience. An Employee ID for any employee in the database is also necessary as input. Subsequently, it will get data from the database and project compensation. In our minor article, we will concentrate on training models using linear and polynomial regression, alongside assessing and comparing accuracy and error; additional elements will be discussed in the big document. We have examined five publications to get information relevant to our undertaking.

Khongchai, P. et.al [5]. Applying a data mining technique, a salary prediction framework was developed for graduate students to estimate salaries for people with comparable educational backgrounds. In order to determine which data mining technique—Decision Trees ID3, C4.5, and Random Forest—was most suitable for predicting salaries and how to improve its accuracy by adjusting key parameters, an experiment was conducted. Using a dataset of 13,541 graduate student records and a 10-fold cross-validation technique, the Random Forest algorithm produced the best accuracy of 90.50%, while the Decision Trees ID3 and C4.5 produced lower accuracies of 61.37% and 73.96%, accordingly. The Random Forest algorithm produced the best effective model for wage prediction. A questionnaire survey was performed to assess use assessment using 50 samples. The results demonstrated that the technique significantly enhanced students' desire for academic pursuits and cultivated an optimistic outlook for the future. The findings indicated that students expressed satisfaction with the suggested method due to its user-friendliness and the clarity of the predictive outcomes, which need no prior statistical expertise.

3. Existing System

In recent years, phishing detection systems have used traditional machine learning methodologies to identify fraudulent websites. Naive Bayes is a commonly used technique that operates as a probabilistic classifier predicated on the assumption of feature independence. Despite its computational efficiency, Naive Bayes' effectiveness in phishing detection is limited by the complexity and interrelation of website attributes. The Support Vector Classifier (SVC) is a prevalent technique that aims to determine the optimal hyperplane for differentiating between phishing and legitimate websites. However, the effectiveness of SVC is often constrained by the choice of kernel functions and the handling of non-linear data. Linear Discriminant Analysis (LDA) is used for phishing detection by projecting data into a lower-dimensional space to enhance class separability. Despite its effectiveness in several cases, LDA has challenges with complex datasets marked by overlapping features.

These algorithms, although somewhat beneficial, have consistently shown decreased accuracy in phishing detection, often around 70%. Furthermore, although these models often attain high true negative rates (accurately

identifying legitimate websites), they are prone to misclassifying phishing sites, leading to heightened false-negative rates. The insufficient accuracy and high false negative rates in existing systems make them unsuitable for real-time phishing detection, since misclassification might lead to significant financial loss and security breaches.

4. Methodology

4.1 Decision Tree

Decision trees are a popular machine learning method used for classification and regression tasks. They are fundamentally flowcharts in which each internal node signifies a test on an attribute (feature), each branch denotes the potential outcomes of the test, and each leaf node represents a class label or a projected result.

Steps:

1. **Root Node Selection:** The method starts by identifying the optimal property to serve as the root node. This is often accomplished by metrics such as information gain, Gini impurity, or entropy.
2. **Splitting:** The dataset is partitioned into subsets according to the values of the root property.
3. **Recursive Process:** The same procedure is repeated for each subset, generating new nodes and branches until a termination requirement is satisfied (e.g., all data points in a subset belong to the same class or the maximum depth is reached).

4.2 Logistic Regression

Logistic regression is a statistical model used to predict the probability of a binary outcome, such as true/false, yes/no, or 1/0. This machine learning technique is extensively used, especially for classification tasks.

Steps:

1. **Input Data:** The model utilizes a collection of input variables (features) to forecast a binary result.
2. **Linear Combination:** The model computes a linear amalgamation of the input characteristics, akin to linear regression.
3. **Sigmoid Function:** The outcome of the linear combination is subjected to a sigmoid function, sometimes referred to as a logistic function. Any real number may be transformed into a value within the range of 0 to 1 with this function.
4. **Probability Estimation:** The output of the sigmoid function is regarded as the likelihood of the positive class.

4.3 Linear Combination

$$z = w0 + w1*x1 + w2*x2 + ... + wn*xn$$

where: z is the linear combination. w0, w1, w2, ..., wn are the model's coefficients. x1, x2, ..., xn are the input features.

Sigmoid Function:

$$p(y = 1|x) = \sigma(z) = 1/(1 + e^{(-z)})$$

where: p(y=1|x) is the probability of the positive class given the input features. $\sigma(z)$ is the sigmoid function.

Random Forest: The Random Forest ensemble learning method produces predictions by using many decision trees. It is a favored option because to its precision, resilience, and capacity to manage large information.

Steps:

1. **Bootstrap Sampling:** Random Forest constructs several decision trees using various subsets of the training dataset. These subsets are generated by bootstrap sampling, wherein samples are extracted with replacement from the original dataset.
2. **Feature Randomization:** At every node of each decision tree, a random selection of characteristics is chosen. This prevents the model from overfitting and reduces its variance.
3. **Decision Tree Building:** Each decision tree is constructed with the chosen attributes and samples.
4. **Prediction:** Each decision tree in the forest votes for a class to generate a forecast for a new instance. The ultimate forecast is determined by the class that garners the most number of votes.

5. Proposed Work

The proposed method rectifies the shortcomings of the existing system by using contemporary machine learning classifiers, such as Logistic Regression, Decision Tree, and Random Forest. These algorithms are selected for their ability to handle non-linear relationships, model complex datasets, and improve classification accuracy. Logistic Regression provides a strong baseline model with enhanced interpretability relative to Naive Bayes, and it can detect non-linear trends when combined with appropriate feature engineering. The Decision Tree model, which categorizes data based on feature importance, is very intuitive and proficient in handling both linear and non-linear data well.

The Random Forest model, including an ensemble of decision trees, provides improved accuracy due to its ability to generalize well across the dataset. Random Forest reduces overfitting, improves robustness, and effectively

handles the many features included in phishing detection datasets. In this proposed system, after the execution of hyperparameter tuning and data preprocessing methods, these models achieved an accuracy of 95%, indicating a significant improvement over the prior system. Moreover, the proposed system demonstrates enhanced proficiency in distinguishing between phishing and legitimate websites, hence reducing false positives and false negatives, which enhances overall system reliability. This enhanced accuracy makes it ideal for real-time phishing detection, offering a more dependable solution for protecting individuals and businesses from cyber threats.

6. System Architecture

The Fig. 100.1 illustrates a flowchart for a machine learning system that categorizes URLs as phishing or non-phishing. Here is an analysis of the procedure. Phishing versus Non-Phishing URLs The input comprises phishing URLs (malicious) and non-phishing URLs (legal). Extraction of Features Significant attributes are retrieved from each URL. This may include attributes such as URL length, occurrence of dubious terms, use of special characters, and so on. Selection of Features This stage selects the most relevant elements that aid in differentiating phishing URLs from non-phishing URLs. Chosen Feature Values These are the selected characteristics that will be used for training the machine learning model. These attributes will be assigned numerical or categorical values for analysis. Classification Techniques in Machine Learning. Construct Model for Training Dataset This entails training a machine learning model using the chosen features from the collection of URLs. Provided for Test Data The model is then assessed on novel, unobserved URLs (test data) to gauge its efficacy. Outcome Specification The technology delivers comprehensive findings, presumably determining if a specified URL is categorized as phishing or non-phishing according to the model's predictions.

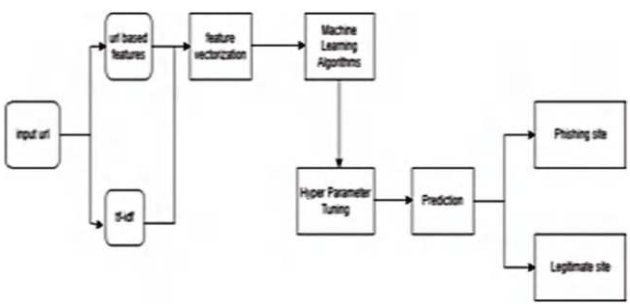

Fig. 100.1 Proposed system architecture

7. Results and Discussions

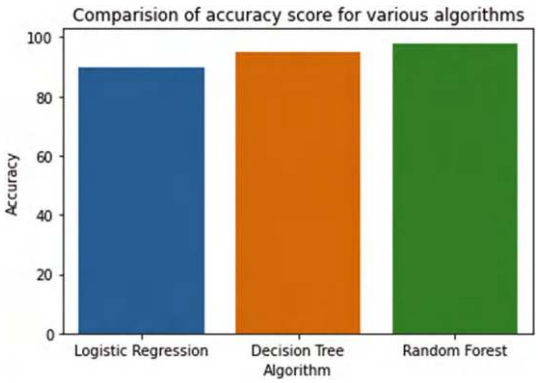

Fig. 100.2 Proposed comparison of accuracy score for various algorithms

8. Conclusion

Phishing assaults continue to be a widespread and increasing concern in the digital realm, requiring sophisticated detection methods to safeguard customers from harmful websites. This research evaluated several machine learning models, including Logistic Regression, Decision Tree, Random Forest, and Extreme Learning Machine (ELM), for the identification of phishing websites. The use of a Kaggle dataset, comprehensive preprocessing methods, and hyperparameter tuning enabled the Random Forest model to attain a maximum accuracy of 95%. This illustrates the efficacy of ensemble learning models in managing intricate, non-linear data and identifying phishing websites in real-time situations. The suggested solution considerably surpasses conventional methods, including Naive Bayes, Support Vector Classifier, and Linear Discriminant Analysis, which have worse accuracy and elevated false negative rates. Hyperparameter modification significantly improved the system's performance, decreasing misclassification rates and augmenting dependability. This

Table 100.1 Comparison table for existing and proposed algorithms

EXISTING ALGORITHMS	
Algorithms	**Accuracy**
SVC	70%
Decision Tree	65%
PROPOSED ALGORITHM	
Algorithms	**Accuracy**
Logistic Regression	95%
Random Forest	97%

study emphasizes the significance of using strong machine learning algorithms for phishing detection and illustrates the efficacy of Random Forest and Extreme Learning Machine in delivering practical, scalable solutions for improving cybersecurity.

9. Future Work

Future study may use deep learning methodologies, such CNNs and RNNs, to identify increasingly advanced phishing assaults. These models perform very well with large datasets and complex feature interactions. Employing deep learning to autonomously extract essential aspects from raw data may facilitate the identification of complex phishing assaults marked by nuanced patterns. Deep learning models may improve the flexibility of real-time phishing detection systems to novel approaches.

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Audit Towards Green Computing: An Information Science and Machine Learning Application to Proficient Vitality Utilization and Optimization in Cyber Security

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Abstract: In today's times, there has been a proliferation of cyber threats, which not only increase the frequency of their occurrences but growing permutation of these threats also exist, which calls for breakthrough paradigms for bolstering digital security. This paper is a comprehensive study of the significant part that data science and machine learning play in enhancing the cyber security initiative. Predictive modelling coupled with advanced analytics makes it possible for the sectors to stop cybercriminals before they turn their acts into major security breaches. These scenarios address various aspects such as the inclusion of data pre processing, feature engineering, and exploratory data analysis in developing the multiple datasets for the machine learning algorithms. at a submit, it also focuses on the significance of labelled data in supervised learning and discusses the problems with not having enough conducive data for training purposes. The chapters that follow concentrate on how machine models are being incorporated into cyber security frameworks. While unsupervised methods such as clustering are discussed for their potential to expose new hazards and unseen hacking techniques. The review also underscores the importance of regular model retraining and up-to-date adaptation of models to the changing cyber threats. As a way of relating these notions to the real world, the cases will be depicted and real-life examples where data science and machine learning have been involved will be used to tell a good story of effective problem detection and solving. The paper ends with a discussion on the ethical issues and obstacles that are linked to such a combination. It highlights the need for Lucidness, Transparency, and sustained evaluation of model performance. Summarizing it, the paper points the transitionary of data science and machine learning in cyberspace protection to be introduced. In the last section, the paper critically examines the issue of the two topics being

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very close to each other, which is somewhere between the art and the science of it. As companies aim to be one step even over their enemies, the internet has now become a battlefield between malware and security administration, and pushing innovation in online safety is the new tactic for getting ahead. Therefore, utilizing these technologies is now essential for constructing steadfast and adaptable defence mechanisms in the fast-evolving digital world.

Keywords: Green computing, Data science, Machine learning, Cyber security

1. Introduction

The crux of the whole paper is the implementation of machine learning models in cyber security. Parallelly, unsupervised learning techniques are looked into for their potential for differentiating new threats and attack patterns that were not seen before (Alrashdi I, et al, 2019). The fact that model training and adapting to new cyber threats are the most important factors in keeping the defence working is a proven truth (ChangY, 2017). In order to give practical insights, the paper makes use of case studies and real-life examples, showing the situations where data science and machine learning have successfully detected and eliminated cyber threats. There has been a debate on the ethical implications and difficulties associated for the use of machine learning security, the main issues are the lack of transparency and the need for interpretability, besides, the necessity for continuous evaluation of the model's performance (Sharma, A., & Sood, S. K. 2022). The combination of data science and machine learning is the magic that will help a company to be more resilient, adaptive, and proactive in dealing with cyber security. With organizations having to overcome the challenge of staying ahead of always-evolving cyber adversaries, these become not only a matter of pro or con for digital asset but a necessity for the preservation of system integrity whether in crucial sectors (Zhao, Z. Et al, 2017).

2. Literature Review

The examined literature offers a comprehensive and in-depth view of the relationship between data science as well as machine learning and advanced cyber security. Alouani, I et al., demonstrated that the conjunction of data science and machine learning in advanced cyber security facilitates the ability to get a nuanced picture of the challenges that are getting more and more complicated in the digital domain and the innovative strategies that are increasingly becoming vital [Alouani, I. et. al, 2022). This review blends key points gained from previous studies, demonstrating significant contributions and emerging tendencies. One of the core issues under the discussion by many scholars is the dynamic environment and its complexity the cyber security field is evolving in (Strubell, E., et. al, 2019). The literature emphasizes the fact that the advent of sophisticated cyber threats is a major issue, which is a result of the shortcomings of the traditional methods and the recommendation of the need for adaptive and proactive security tools (B.V.D.S.Sekharet, 2022). The researchers like Chen et al. (2021) are engaged in the investigation of the fundamental components of data science in the field of cyber security (Chen, H., Ning, Z., & Zhang, Z., 2021). The pre-processing and exploratory data analysis as important steps in the development of datasets that are prepared for the subsequent machine learning applications which are the foundation of further research. Machine learning algorithms and their application in cyber security are the topmost discussions as stated by Zhou, 2020 (Zhou, Q., Cheng, L., & Xu, W., 2020). Naveen Prasadula (2023) presents the concept of supervised learning which uses the support vector machines whereby threats have correctly been classified (Sharma, P., & Barua, S., 2023). At the same time, Xiong, J et al., (2023) studied on the area of unsupervised learning which is the primary point of interest in the examination of clustering and that is potentially new and developing threat (Xiong, J., et. al, 2023). Recent works, such as Wang and Liu (2022), highlight the necessity of continuous training and updating the models. Through this, it explains the fact that the machine learning models' ability to develop along with the ever-changing threat landscape is of crucial importance for the maintenance of well-conditioned security systems (Wang and Liu at. al, 2022). Various examples and case studies with real-world context have been used to demonstrate applications of data science as well as machine learning in cyber security (Avgeris, M., 2020). Elgabli, A et al. (2022) present examples of the cases in which these technologies have been properly utilized in the process of detecting and mitigating cyber threats, and thus, provide tangible proof of their efficiency in real-life situations (Elgabli, A., Basu, K., & Hosein, P., 2022). According to the newly published studies, including the research by Han, S. et al., (2022), the topic of ethics and issues relating to the use of data science, machine learning for cyber security are addressed. Concepts such as

transparency, and interpretability, and monitoring of model performance are raised as key rationales for fair and ethical implementations of this technology (Han, S., Zhang, Y., & Xie, H., 2022).

2.1 Objectives of Study

1. To transform cyber security from an active to a proactive approach by employing predictive modelling and advanced analytics.
2. The goal is to discover potential vulnerabilities and flaws in the system before they are exploited, allowing for risk mitigation actions.
3. To develop robust systems using machine learning algorithms to identify unusual patterns that deviate from normal behaviour.
4. Involving updating models in real-time based on new data and threat intelligence, maintaining the effectiveness of the cyber security defence over time.
5. Improve incident response capabilities by integrating machine learning for rapid and accurate identification of incidents.
6. This involves prioritizing pitfalls predicated on their rigidness and possible impact, enabling associations to concentrate their expenditures and fund on the most critical areas of vulnerability.

3. Methodology

Data science methodology is the well-ordered stageaker/ image file set very one by one procedure of projects, with the whole process running all the way from problem specification to solution deployment (Doshi R, et al, 2018). Although there have been diversity in terms of successful ones in particular enterprises and individuals, a framework that many people have encouraged includes these followings steps:

3.1 Exploratory Data Analysis (EDA)

Conduct the research on information to figure out insights, discover trends and recognize the linkages between variables. Try to understand the data by visual visualizations and statistical techniques. Example: The retail company implements EDA by examining the churn rates among different demographic segments, viewing the associations between purchase frequency and satisfaction ratings, and analyzing customer behaviour through cohort analysis (Shone, N., et al, 2018).

3.2 Model Building

It is important to select one machine learning model or statistical model that matches the problem statement. Let's take a case where a retail company selects logistic regression in order to build its churn prediction model (Primartha R,& Tama B A,, 2017). This model was applied to the dataset, which consisted of 67 percent of the data, while the testing set is 30 percent. This systematic approach guarantees a step-by-step process through the data science project, thereby promoting successful problem solving and informed decision making at every stage. Design and execute machine learning solutions that can be scaled and are capable of handling large amounts of data without sacrificing performance. Automation has

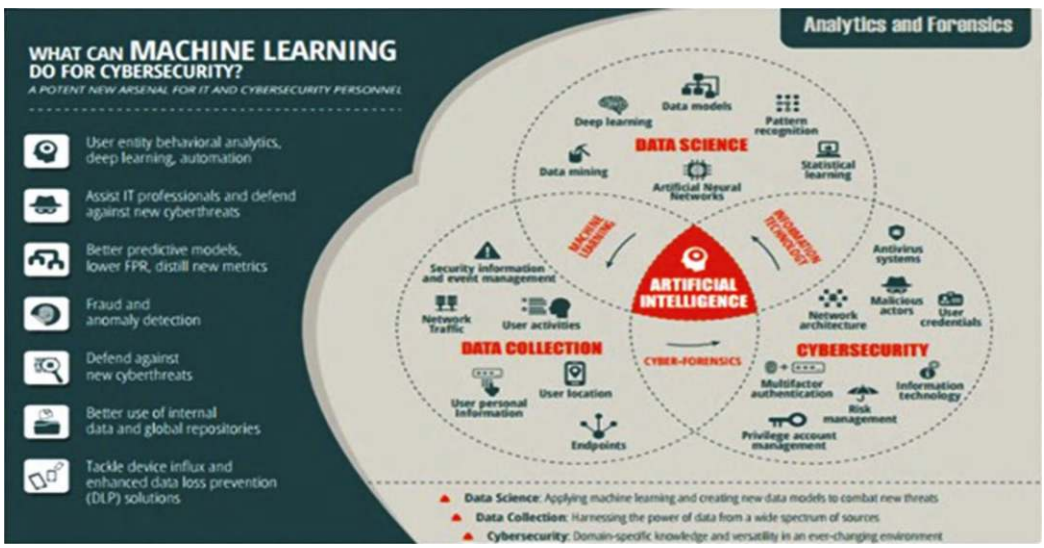

Fig. 101.1 Machine learning for cyber security

Source: https://infotechlead.com/security/can-machine-learning-cybersecurity-50357

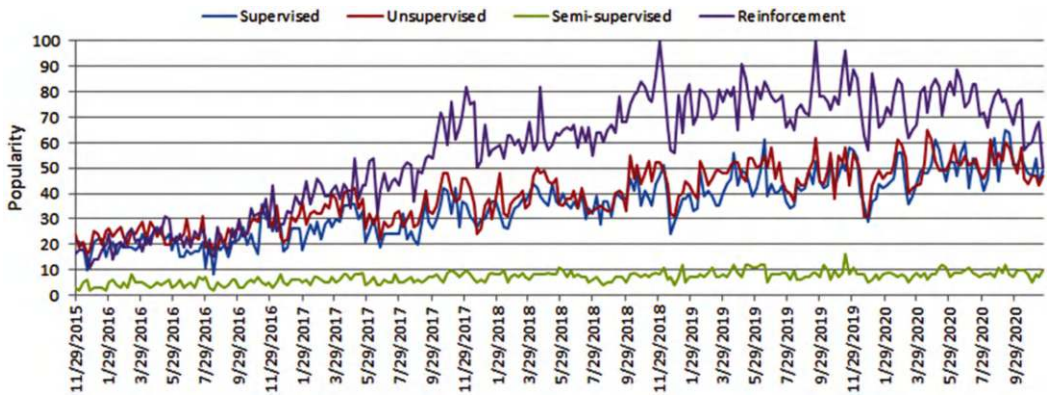

Fig. 101.2 Machine learning popularity across world

Source: https://www.researchgate.net/figure/The-worldwide-popularity-score-of-various-types-of-ML-algorithms-supervised_fig1_350297716 [accessed 9 Nov 2024)

turned out to be a key instrument for the overwhelmed workers who are struggling with the mounting prevalence, sophistication, and targeting of different cyber threats. The threats like phishing and malware are indeed prevalent. The imperfections in most defence measures are the main reason for the prevalence of these threats (Sekhar, B.V.D.S., Jagadev, A.K., 2023). It is also worth mentioning that the machine learning solution has become a popular technology, as evidenced by the below Fig. 101.2. Figure 101.2 helps to understand the changing trends of machine learning and cybercrime, thus, offering a complete perspective of their dynamics on a global scale (Buczak, A. L., & Guven, E., 2016).

4. Findings

4.1 Increased Accuracy of Threat

The use of data science as well as machine learning in advanced cyber security has greatly increased the accuracy of the threat. The models, especially the supervised learning ones, have a remarkable capability of assigning the known threats to the right class based on the rules when compared to the traditional systems (Doshi R, Apthorpe N, FeamsterN, 2018).

4.2 Identification of Novel Threats

Unsupervised learning methods, like clustering, are proven to be very successful in the detection of novel and previously unseen threats (Chang Y, Li W, Yang Z, 2017). The models, eloquently, prove to be flexible in the pattern recognition that could not be exhibited by rule-based systems; consequently, they are a good tool for the defence against developing cyber threats (Alcázar-Orteg et al, , 2019).

4.3 Reduced False Positives

The inclusion of AI has made a remarkable progress in solving one of the most serious problems of identifying false positive threats in security operations. This advancement provides security teams with the ability to focus their attention on the correct activities, thus avoiding unnecessary investigations and thereby improving the overall operational efficiency (Vasilomanolakis, E., 2015).

4.4 Proactive Risk Mitigation

The predictive modelling approach together with continuous model training allows the organizations to be preventive in terms of cyber security risk mitigation. Organizations can identify potential vulnerabilities and weaknesses that may be exploited in time and thus they can enact the preventive steps to strengthen their defence systems as well as keep the possible impact of cyber incidents at lower levels (Kliazovich, D.,et al, 2013).

4.5 Adaptive Defence Mechanisms

Adaptive mechanisms of model training and adaptation are highly important in keeping adaptive defence mechanisms. The models exhibit the ability to hit the ground running along with developing problems thus ensuring that the process of cyber security stays operational during the changing of tactics by bad actors (B.V.D.S.Sekhar, 2022).

4.6 Optimized Resource Allocation

Emphasis of the threat categorization based on the rigidity and potential impact ahead of the various entities, allows the strategy of distributing resources to be followed through by the company, thus, the most, exposed, areas and vulnerabilities are fixed (Matheu-Parrilla, A, et al, 2021).

This optimization makes the resources and budget more efficient.

5. Suggestions

While models consistently demonstrate high accuracy, a pressing need exists to further refine their explanatory capabilities and interpretability.

Continuous Evaluation and Validation: Implement continuous evaluation processes to assess the ongoing functioning of models. Regularly validate the models against new threat scenarios and evolving attack patterns to ensure that they remain effective and adaptive. This iterative approach proves indispensable in ensuring that cyber security solutions remain relevant (Alrashdi, I., et al, 2019).

Teamwork and Information Exchange: Encourage teamwork and information exchange among the cyber security community. This method allows professionals to collaboratively tackle new threats, exchange best practices, and utilize one another's strengths to remain proactive against potential risks. Establish weapons platform for sharing threat intelligence and best practices in implementing for cyber security (Mohamed, T., Otsuka, T., & Ito, T., 2018). Collaborative efforts can con- tribute to a collective defense against cyber threats.

Ethical Considerations and Compliance: Place a strong emphasis on ethical considerations in the deployment of cyber security. Ensure compliance with privacy regularization and address bias mitigation strategy to uphold ethical standards. An ethically sound approach is essential for the responsible use of these technologies (Resende, P. A. A., & Drummond, A. C. , 2018).

Investment in Training and Skill Development: Honoring the significance of investing in training and skill development for cyber security measures professionals. Building expertise in within cyber security teams see to it the effective implementation, monitoring, and adaptation of advanced technologies (B.V.D.S. Sekhar, 2023).

Scalability and Integration: Emphasize the importance of scalability, ensuring that solutions can efficiently expand to meet evolving needs. Furthermore, prioritize seamless integration with existing cyber security infrastructure, allowing for cohesive functionality and optimal performance. This harmonious alignment enables streamlined operations and enhances overall security posture. Ensure that the solutions can effectively manage escalating data volumes and seamlessly integrate with a diverse range of cyber security tools and frameworks that are commonly employed in operational environments (Mohamed, T., Otsuka, T., & Ito, T., 2018).

6. Conclusions

In conclusion, the escalating threat landscape in cyber security has prompted organizations to reassess and refine their methods for threat mitigation, risk reduction, and defense procedures. The findings from this study showcase the transformative potential of these applied sciences in enhancing the cyber security posture, addressing long standing challenges, and providing a proactive and adaptative defense against error develop landscape of cyber threats. The implementation of supervised learning models yields a notable enhancement in threat accuracy, thereby empowering organizations to classify known threats with heightened precision. This approach effectively minimizes false positives and, in turn, streamlines cyber security operations, enabling teams to concentrate on the most critical incidents. Unsupervised learning techniques prove invaluable in identifying novel threats, demonstrating a remarkable capacity to adapt and discern patterns that may elude traditional rule-based systems. Continuous model training and adaptation emerge as key factors in maintaining an adaptive defense mechanism. The forward-looking risk reduction abilities of predictive modeling underscore the vital need to recognize potential weaknesses prior to their exploitation. This, consequently, enhances a more robust cyber security framework, better prepared to endure new threats and protect sensitive data. Optimize resource allocation based on menace severity enhances operational efficiency, allowing governance to allocate resources strategically and maximize the impact of cyber security meter. The reduction of false positives and the ability to prioritize threats based on their potential impact give to a more efficient and in force cyber security strategy. However, to ensure the responsible and ethical deployment of in cyber security, it is imperative to enhance the explain ability and interpretability of the models. This transparency fosters trust among cyber security department professionals and facilitates a deeper understanding of the decision-making process. Continuous valuation, validation, and collaboration within the cyber security community are essential components for the sustained effectiveness of these technologies. Ethical condition, compliance with regulations, and investment in training and skill development promote contribute to a holistic and responsible approach to the integration of in sophisticated cyber security system. As organizations navigate an increasingly complex threat landscape, a key take away from this research is that certain elements must be integral to a modern cyber security strategy. The findings underscore the significance of embracing these components as fundamental to a comprehensive approach, one that effectively addresses the ever-evolving nature

of cyber threats. The future of cyber security depends on the seamless combination of human knowledge and the sophisticated abilities enabled by a stronger and more flexible defense. This strategic alliance is crucial in addressing the growingly advanced cyber threats that keep arising.

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A Comprehensive Review of Blockchain-Based E-Voting Systems: Security, Scalability, and Usability

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Abstract: In recent years, blockchain technology has emerged as a promising solution for enhancing the security and decentralization of electronic voting systems. When combined with biometric methods, such as facial recognition, blockchain offers potential remedies to longstanding security issues in e-voting, including identity fraud, ballot manipulation, and opacity. This paper presents a thorough examination of current research on e-voting systems that utilize blockchain, with an emphasis on their structure, the incorporation of facial recognition for robust authentication, data protection through cryptographic techniques, approaches to address scalability, and practical applications. We delve into the advantages and obstacles associated with this methodology, particularly focusing on privacy, user-friendliness, and regulatory considerations. The integration of blockchain and biometric technologies into e-voting systems presents a paradigm shift in electoral processes, offering enhanced security and transparency. However, challenges remain in terms of widespread adoption, including concerns about voter privacy, need for technological infrastructure, and public trust in these new systems. As research in this field progresses, it is crucial to address these challenges while maintaining the integrity and accessibility of the voting process to all citizens.

Keywords: Blockchain based voting, Voter privacy biometric authentication, Vote privacy, Cryptographic techniques, Decentralized elections

1. Introduction

The growing prevalence of digital technologies in society has necessitated the development of dependable and protected e-voting systems. While e-voting offers enhanced accessibility, speed, and transparency in elections, it also raises concerns about cyber security threats, fraudulent activities, and unauthorized entry. Blockchain technology has emerged as a promising remedy that offers an unalterable and distributed database for vote recording.

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Furthermore, the incorporation of facial recognition as an authentication method strengthens the verification of voter identities. Davies, P. (2020) explores the structure and essential elements of e-voting systems based on blockchain technology, with an emphasis on the integration of facial recognition for secure voter authentication. In addition, this study investigates the obstacles and potential future advancements in enhancing the security, confidentiality, and scalability of these systems. Feng, Z., & Zhao, L. (2020) explains the decentralized and immutable nature of blockchain provides a secure foundation for recording votes, ensuring transparency, and reducing the risk of tampering. Each vote is recorded as a transaction within a block, which is then added to the chain to create a permanent and verifiable record. Figure 102.1 explains architecture of e-voting system. This structure not only enhances the integrity of the voting process, but also allows for real-time auditing and verification, potentially increasing public trust in election outcomes. Facial recognition technology adds an additional security layer to the e-voting process by providing a robust method for voter authentication. This biometric approach significantly reduces the potential for identity fraud and ensures that only eligible voters participate. The system can compare a voter's live image with a pre-registered database to verify identity in real time. However, the implementation of facial recognition in voting systems also raises important concerns regarding privacy and data protection.

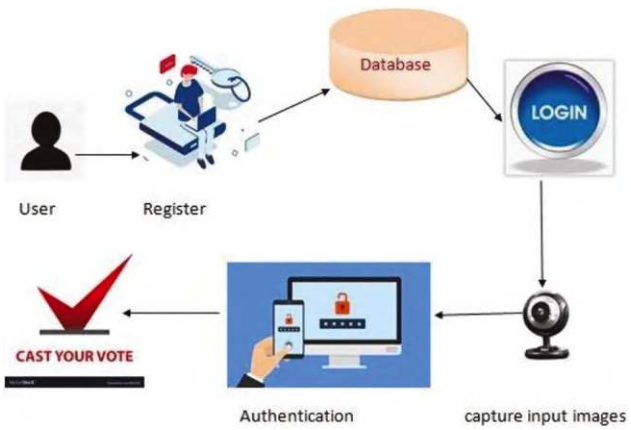

Fig. 102.1 Online voting system architecture

2. Literature Review

Cryptographic Techniques E-voting systems rely heavily on cryptographic methods to ensure vote confidentiality and integrity throughout the entire process, including transmission and storage. Asymmetric encryption, which uses public and private key pairs for secure data exchange, is a fundamental technique. Aitken, R., & Collins, J. (2022) defines the RSA (Rivest-Shamir-Adleman) and Elliptic Curve Cryptography (ECC) are widely used algorithms, with ECC gaining popularity due to its ability to provide equivalent security to RSA with smaller key sizes, resulting in faster processing and reduced computational demands.

Martinez, L., & Garcia, D. (2022) explains aadvanced cryptographic techniques are being investigated to address e-voting's unique challenges. Homomorphic encryption allows for computations, such as vote counting, to be performed on encrypted data without decryption. This preserves voter privacy throughout the entire process, including the tallying phase, while enabling election officials to verify result accuracy. Additionally, this approach minimizes the risk of tampering or manipulation by keeping data encrypted from the moment of casting until the final count is completed.

Blockchain technology offers a robust solution to many persistent e-voting system challenges through its decentralized structure. Olsen, T., & Eriksson, M. (2021) defines cconventional voting methods typically depend on a central authority for vote record management and storage, creating potential vulnerabilities for tampering, fraud, or unauthorized access to sensitive data. Blockchain effectively mitigates these risks by distributing control across a network of nodes, eliminating the need for a single, centralized authority. This decentralized approach enhances security and reduces the likelihood of any single entity manipulating or altering vote data.

El-Mahdi, A., & Hussein, M. (2021) proved that in blockchain-based e-voting systems, each vote is securely recorded as a transaction in a distributed ledger. This ledger is immutable, meaning once a vote is recorded, it cannot be modified or erased, safeguarding the voting process's integrity. This immutability fosters trust in the system, as any attempts to tamper with vote records would be immediately apparent to all network participants. Moreover, blockchain's transparency allows for vote traceability, enabling election auditors and potentially voters themselves to verify that their vote was accurately counted and remains unaltered.

Blockchain also offers the advantage of maintaining voter privacy while providing verifiability. Voters can confirm their votes are securely stored and included in the final tally without revealing their identity or voting choice, thanks to cryptographic methods like zero-knowledge proofs. This ensures the system upholds the principle of anonymity, a crucial requirement in any democratic election. Qureshi, F., & Ahmed, I. (2022) gives solution for cconsequently, blockchain's decentralized and tamper-resistant properties make it a promising solution for addressing critical security, transparency, and trust issues in modern e-voting systems.

In e-voting systems, smart contracts serve a vital function by boosting automation and transparency. These contracts, which are self-executing, incorporate predetermined rules and procedures directly into the blockchain. Green, J., & Walters, P. (2022) are designed to automatically perform tasks like gathering, authenticating, and counting votes based on the system's established conditions. By removing the need for human involvement, smart contracts minimize the possibility of errors and potential manipulation, ensuring the voting process unfolds as intended without any deviations or inconsistencies.The incorporation of smart contracts into e-voting platforms offers substantial advantages. For example, they can automatically initiate vote tallying once the voting period concludes, guaranteeing a quick and precise process. As the vote-counting rules are embedded within the blockchain, the procedure becomes transparent, enabling stakeholders to confirm that the results were generated in accordance with the predefined regulations. This transparency cultivates trust in the electoral system by eliminating the necessity for third-party intermediaries to validate or oversee the vote count.

Despite these benefits, implementing smart contracts in e-voting systems presents challenges. One of the most significant issues is ensuring that these contracts are devoid of bugs, vulnerabilities, or coding flaws that could be exploited by malicious entities. Given the immutable nature of smart contracts once deployed on the blockchain, any error or vulnerability in their design could potentially result in serious security problems or unintended consequences. Consequently, comprehensive testing, auditing, and validation of smart contracts are crucial to guarantee their reliability and security in the context of e-voting.

3. Voter Authentication and Identification

3.1 Biometric Authentication Methods

Ivanov, D., & Petrov, M. (2020) has proved that facial recognition, a form of biometric authentication, has emerged as a popular method for voter verification in electronic voting systems. This technology offers a more secure and user-friendly alternative to traditional password-based methods, which are vulnerable to hacking and phishing attacks. Singh, N., & Kumar, P. (2021) has introduced widespread adoption of facial recognition in consumer devices, such as smartphones, has led to its integration into several e-voting pilot programs due to its ease of use. However, concerns persist regarding the accuracy and fairness of biometric systems, with studies indicating potential biases in facial recognition technology, particularly in relation to age and race.

3.2 Multi-Factor Authentication (MFA)

Bhatia, S., & Kumar, R. (2021) define to enhance the security of e-voting systems, multi-factor authentication (MFA) is increasingly being recommended. MFA typically incorporates three elements: something the voter knows (such as a password), something they possess (like a mobile device or hardware token), and something inherent to them (such as biometric authentication). By implementing multiple layers of security, MFA substantially decreases the risk of unauthorized access to the voting system.

4. Security and Privacy Concerns

4.1 Transparency vs. Privacy

A key obstacle in e-voting system creation is striking an optimal equilibrium between openness and voter confidentiality. Nilsson, S. (2022) concluded ttransparency is crucial for fostering public confidence in elections, enabling verification of fair conduct and accurate vote counting. Open processes help prevent fraud, identify irregularities, and reinforce faith in electoral legitimacy. Equally vital is safeguarding voter privacy to uphold the principle of secret ballots, allowing individuals to vote without fear of intimidation or consequences.

Balancing transparency and privacy in e-voting systems is intricate, as these objectives may seem contradictory. However, cryptographic advancements offer promising solutions to this dilemma. For instance, homomorphic encryption enables vote tally computation on encrypted data, allowing result verification while keeping individual votes secure. This maintains voter privacy while providing verifiable outcomes.

Zero-knowledge proofs (ZKPs) are another powerful tool for preserving privacy and ensuring transparency. ZKPs allow voters to demonstrate their participation or vote validity without revealing specifics about their vote or identity. This enhances transparency by enabling verification of voter eligibility and involvement while fully protecting vote secrecy.

Despite these innovations, implementing such cryptographic solutions securely, efficiently, and practically for large-scale elections remains challenging. As elections grow in size and complexity, ensuring these technologies can scale while maintaining performance, usability, and accessibility is a significant hurdle. Moreover, thorough testing and validation are necessary to guarantee these systems' robustness against potential attacks or vulnerabilities.

4.2 Privacy-Preserving Techniques

Wang, X., & Li, B. (2020) introduced Further development of privacy-preserving cryptographic methods is essential

for protecting voter anonymity. Techniques such as mix networks, which shuffle votes to prevent tracking, and blind signatures, which allow voters to obtain anonymous signatures without disclosing vote details, are crucial for maintaining privacy. These approaches help ensure votes cannot be traced to individual voters while providing verifiable results. However, implementing these techniques requires sophisticated protocols and infrastructure, adding to the complexity of deploying blockchain-based e-voting systems at scale.

5. Scalability and Performance Issues

Huang, F., & Wang, Y. (2021) proved that facial recognition, a form of biometric authentication, has shown great potential for improving voter verification in the realm of e-voting systems. This method offers superior security compared to conventional authentication techniques, such as passwords or PINs, which are susceptible to various cyber threats. Biometrics leverage unique physical traits that are significantly more challenging for duplicates and pilfers. The widespread adoption of facial recognition technology in common devices, such as smartphones and tablets, has made it an increasingly popular choice because of its ease of use and accessibility for voters. Various e-voting trial programs have incorporated facial recognition, recognizing its ability to expedite and simplify the process of confirming voters' identities.

Nguyen, H., & Tran, K. (2023) developed some technology into everyday consumer electronics has resulted in high usage rates, as many individuals are already accustomed to employing facial recognition for device unlocking or payment authorization. This familiarity reduces the learning curve for voters, enabling e-voting systems to incorporate biometric authentication more seamlessly without causing significant user discomfort or bewilderment.

Research on blockchain-based e-voting systems examines alternative consensus mechanisms to overcome the limitations of proof-of-work (PoW) systems. Although PoW has been successful in securing decentralized networks for cryptocurrencies such as Bitcoin, its high energy consumption and reliance on extensive computational resources make it unsuitable for large-scale applications such as e-voting, where efficiency, speed, and environmental considerations are crucial.

Choi, M., & Li, H. (2023) developed two promising alternatives are the proof-of-stake (PoS) and delegated proof-of-stake (DPoS). PoS eliminates the need to solve complex mathematical problems to validate transactions. Instead, it selects validators based on the number of cryptocurrencies that they hold in the network. This approach significantly reduces energy requirements and improves system efficiency, making it more appropriate for large-scale e-voting applications. Tanaka, Y., & Kuroda, T. (2023) concluded that PoS also offers faster transaction processing, which is essential for swift and accurate vote tallying in elections.

DPoS builds on the PoS model by introducing a more democratic and scalable method. In this system, stakeholders elect a small group of trusted representatives to validate transactions on behalf of the network. This delegation process enhances scalability compared with both PoW and PoS by reducing the number of participants in the consensus process, resulting in quicker transaction times and improved energy efficiency. Furthermore, the accountability of delegates to their electors promotes transparency and trust, aligning well with the e-voting system requirements. Both PoS and DPoS offer promising solutions for blockchain-based e-voting by addressing key issues related to scalability, energy usage, and processing speed. However, additional research and testing are required to ensure that these consensus mechanisms deliver the necessary security, fairness, and decentralization for reliable and trustworthy large-scale voting systems.

5.1 Usability and Accessibility Challenges

One of the key barriers to the widespread adoption of e-voting systems is usability. If the system is overly complex or difficult to use, it risks alienating voters, especially those with limited technical expertise. Lee, J., & Choi, Y. (2021) are proved additionally accessibility features such as multi-language support, voice-guided instructions.

Ensuring accessibility for disabled voters is critical in achieving a fully inclusive electoral process. Research has explored the development of voice-activated systems for visually impaired voters, as well as text-to-speech and multilingual support for a diverse electorate. Efforts are also underway to create accessible voting platforms that cater to various disabilities, ensuring that e-voting systems do not inadvertently exclude vulnerable populations. Making e-voting accessible is not only a matter of equity but also a legal and ethical requirement in many jurisdictions, and future research will need to explore new ways to improve accessibility in digital voting systems.

6. Real World Implementations

Estonia is globally renowned for its pioneering role in blockchain-based electronic voting. Since 2005, the country has been utilizing its e-identity system for elections, which has been integrated with a secure blockchain infrastructure.

Table 102.1 Summary of blockchain technology

Country/ System	Blockchain Technology	Voter Authentication	Encryption Method	Consensus Mechanism	Scalability	Use Case
Estonia	Permissioned Blockchain	Digital ID	RSA	Proof of Stake (POS)	High (National elections)	National elections since 2005
Switzerland (Pilot)	Permissioned Blockchain	Digital Certificate	Homomor phic Encryption	Delegated Proof of Stake	Moder ate (Local elections)	Local referendu ms and pilots
Voatz (US pilot)	Permissioned Blockchain	Biometric (Facial, Fingerprint)	Elliptic Curve Cryptography (ECC)	Delegated Proof of Stake	Moderate (Military votes)	US military absentee voting pilot
Zug (Switzerland)	Public Blockchain	Digital ID	SHA-256	Proof of Work (PoW)	Low (Small-scale)	Local elections (pilot)

The system verifies voter identity using a national digital ID card, and votes are recorded on a blockchain ledger to ensure transparency and security. While Estonia's e-voting system is commended for its scalability, user-friendliness, and security, it also faces issues related to voter privacy and safeguarding elections from external interference.

This table summarizes the types of blockchain technology, voter authentication methods, crypto, and scalability for different e-voting systems implemented or piloted globally.

6.1 Blockchain Voting Pilots

Several countries have implemented blockchain voting pilots. In Switzerland, citizens participated in referendums using blockchain technology, whereas in the United States, military personnel used it for absentee voting. These real-world experiments serve as crucial testing grounds for assessing the viability of blockchain technology in elections. Although they have demonstrated promising outcomes in terms of secure and transparent voting, issues surrounding the technical infrastructure, voter confidence, and regulatory compliance have emerged.

7. Conclusion

Experts and policymakers have stressed the importance of international cooperation in developing regulatory frameworks that can guarantee the security and fairness of e-voting systems. Such frameworks would help establish common technical standards for election systems and provide voters with assurance regarding system integrity and transparency. Cutting-edge technologies such as artificial intelligence (AI) and quantum cryptography have the potential to further enhance the security and functionality of e-voting systems. AI can be employed to detect fraud in real-time, improve voter authentication processes, and streamline elections. Quantum cryptography offers the promise of unbreakable encryption, ensuring that even the most powerful adversaries cannot compromise the election integrity. However, these technologies are still in their early stages and require substantial research to be effectively integrated into existing block chain-based voting systems.

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Breast Cancer Early Detection and Diagnosis Through SHAP Analysis

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Abstract: Breast cancer detection is critical, particularly after symptoms manifest, and the interpretability of deep learning models is questioned because of their black-box character, which limits their applicability in real-world scenarios. The interpretation of a deep learning network trained to detect breast cancers using SHapley Additive exPlanations (SHAP) will be examined in this work. SHAP makes the model more transparent and credible by exposing the ways in which each variable influences the model's predictions. Using a game theoretic approach, SHAP links local explanations and optimal credit allocation using the standard Shapley values. The primary goal of employing image data sets for breast cancer is to identify the disease using SHAP analysis and discover it early. This paper explores the use of SHAP to comprehend a deep learning model for breast tumor classification, by linking local explanations with the best possible allocation of standard Shapley values of model correctness, transparency and trust are increased. Optimizers, like Adam, are robust and user-friendly, assessing SHAP model accuracy from Breast Cancer images.

Keywords: Adam optimizer, Breast cancer, Deep learning, Early detection, Shap analysis etc.

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1. Introduction

Breast cancer is usually detected by an emerging, solid, uneven, painful lump in the breast tissue[1]. Additional symptoms include edema, thinning, changes in size or shape, dimples, flaky skin, nipple soreness, nipple discharge, and enlarged lymph nodes. Other non-cancerous medical conditions may potentially cause similar alterations. Multiple breast sections are affected by the complex disease known as breast cancer. Early detection is essential. Lobular carcinoma in situ, invasive lobular carcinoma, ductal carcinoma in situ, and invasive ductal carcinoma are all prevalent varieties. Eighty percent of cases are invasive ductal carcinoma, making it the most prevalent type. Angiosarcoma, inflammatory, phyllodes, triple-negative, and Paget's disease are less prevalent varieties[2].

Males have small breast tissue that doesn't develop during puberty, potentially forming cancer. Men with breast cancer may experience lumps, swelling, nipple retraction, discharge, and rash. Pain, swelling, or lumps are examples of blood-related symptoms that may need medical attention or resolve on their own. Cysts, mastitis, hyperplasia, sclerosing adenosis, intraductal papillomas, fibrbroadenomas, radius scars, fat necrosis, and phyllodes tumors are a few benign breast disorders. These disorders, which a doctor may treat or control, can look like cancer on a mammogram. It is crucial to see a doctor if you are uncertain of the cause. The most common cancer diagnosed overall is now female breast cancer, surpassing lung cancer. Health systems aim to complete evaluation, imaging, and tissue diagnosis within 60 days, diagnose 60% of invasive breast cancers, and ensure 80% comprehensive treatment. Breast Cancer Early Detection is a comprehensive guide to breast cancer detection, including mammography, ultrasound, FNAC, and core biopsy. It includes 1000 annotated images and 186 case studies, making it a valuable resource for surgeons, gynaecologists, radiologists, pathologists, medical students, nurses, and paramedical staff. Breast imaging involves ultrasound and mammography to evaluate the normal appearance of the breast. It covers equipment, patient positioning, techniques, and common pitfalls for optimal results and minimizes repetition of procedures. Breast pathology involves the process of tissue samples for histological examination, emphasizing the importance of prompt fixation and transport. Cytology is a diagnostic tool for breast lumps, with diagnostic, prognostic, and predictive findings essential for multidisciplinary care[3].

Age, genetic mutations, thick breasts, family history, radiation therapy, obesity, insufficient physical activity, hormone replacement therapy, and alcohol use are risk factors for breast cancer. Moderate weight, regular exercise, abstaining from alcohol, and breastfeeding can lower the risk. Diagnosis involves breast inspection, medical history, and procedures like mammograms, ultrasounds, and biopsies. Treatment includes radiation therapy, chemotherapy, hormone therapy, lumpectomy, and mastectomy. A chance of survival is achieved with early detection and treatment of breast cancer, which necessitates mammograms, monthly self-examinations, and routine clinical examinations. When breast cancer is discovered before symptoms manifest, mammograms are essential for early detection, which lowers the chance of mortality and makes treatment easier. Early breast cancer prediction, cancer vulnerability, recurrent infections, survival, and medical outcomes can all be predicted by machine learning algorithms. They can also distinguish between benign and malignant tumors[4].

The six sections of the paper are as follows: The introductory section is shown in Section 1. The recommended work turns into Section 2.1. Shap Breast Cancer characteristics for image classification. 2.2. SHAP-Based Early Breast Cancer Detection. The experimental results are covered in section three. The conclusion is in Section 4. References are discussed in Section 5.

2. Projected Exertion

Interpreting physiological images from a variety of modalities, such as microscopes, X-rays, and mammograms, requires image processing. Through the extraction of target picture components and the description of shape properties such as size, perimeter, circularity, and compactness, it facilitates shape analysis. This paper explores develop a deep learning model for the categorization of breast tumors using SHAP, by utilizing traditional Shapley values to link local explanations with optimal credit allocation, transparency and trust are increased.

This work's objective is:

- Leveraging data sets for breast cancer images for early detection and making an identification using SHAP analysis.
- To obtain an MAbGENEx dataset that aids in the creation of the optimal model for forecasting the output of early breast cancer diagnosis based on input images.
- To determine the algorithm accuracy, train and test on the chosen dataset.
- Select a suitable algorithm to forecast the output based on the testing results.

2.1 Features of SHAP Breast Cancer for Classification of Images

Breast cancer occurs when uncontrolled breast cells proliferate, forming a tumor. It progresses to advanced, metastatic breast cancer, affecting the liver, lungs, bones, or brain, causing palpable bumps or visible x-rays. Early diagnosis and treatment for certain malignancies can lead to better prognosis and less severe treatment. Screening and early detection for malignancies may not always improve prognosis, prolong morbidity, or prevent excessive treatment. False-negative screening tests can lead to delayed diagnosis, increased costs, and increased risk, while false-positive tests may not. Explainable AI (XAI) uses SHAP for image analysis to understand the decision-making processes of machine learning models. SHAP helps identify key pixel groups that impact model predictions. The ImageNet dataset and pre-trained ResNet-50 model are used to demonstrate its application. The SHAP explainer visualizes the contributions of different pixel groups to the model's predictions. The quality of SHAP explanations depends on the number of evaluations [5]. They are valuable in interpretability-critical domains and can aid in model debugging and refinement. The paper outlines three crucial stages for early breast cancer airing, highlighting the effectiveness of these steps over a single exam or test:

- Breast self-exam (BSE) is to assess the health of the breast: It is advised that women perform monthly breast self-examinations to become acquainted with the feel and appearance of their breasts so they may notify their physician of any changes.
- The Clinical Breast Exam (CBE) is a diagnostic procedure used to assess the health of the breast tissue: A family doctor or gynaecologist will usually do the CBE, an in-office healthcare professional exam, as part of an annual examination to find different abnormalities and warning signals.
- Mammography: An X-ray called a mammography is used to look for suspicious spots in the breast tissue; it frequently identifies breast tumors before they are felt. In addition to routine mammograms, An MRI screening for breast cancer should be performed on women who have a genetic or familial background for the disease.

2.2 Early Detection of Breast Cancer Using SHAP

A game-theoretic method for dealing with SHAP values, enable patients understand the importance of each feature and give them an explanation of the machine knowledge algorithm's output by calculating the contribution of each feature to the model outcome. SHAP is used to calculate the Shapley, for value, which is a means of evaluating each actor's contribution to the result of a game. It calculates outcomes for 2^N combinations of group of actors, where "actors" are features and "outcome" is the model's prediction. However, for big amounts of N, it is not possible to calculate the contribution of each feature. Pixels of color increase the likelihood that a class would be predicted, while other color pixels decrease that likelihood. SHAP uses colors to explain attributions. Both the model's predictions and the explainer's approximation of the model's behaviour are examined in the feature analysis process. Meanwhile, these approximations might not fully capture the behaviour of the model, some attributions might not make sense [6].

2.3 Adam Optimizer

The Adam optimizer is a Python-based gradient-based optimization technique that uses AdaGrad and RMSprop extensions for adjustable learning rates. It improves machine learning model training by combining momentum and RMSprop, allowing for efficient sparse gradient navigation and faster convergence. This method offers improved solutions and faster convergence [7].

Adam Procedure for Optimization

Beginning:

- Model parameters, or θ, are the parameters.
- Learning Rate: α, which can be changed but is usually 0.001.
- The rates of exponential decay are β_1 (typically 0.9) and β_2 (typically 0.999).
- One small constant is ε, which is usually 10^-8 for numerical stability.
- Set up: t = 0 (timestep), m_0 = 0(first moment vector), and v_0 = 0(second moment vector).

Update Iteratively

For every time interval t: To compute the gradient, use the formula *$g_t = \nabla\theta\ J(\theta\{t-1\})$.

At the current timestep, calculate the gradient of the loss function J in relation to the parameters θ.

Estimates of Update Moments:

$m_t = \beta_1 * (-1 - \beta_1) + m_\{t-1\} * g_t$ (Update biased estimate of the first moment, such as momentum)

$v_t = \beta_2 * (g_t)^2 * v_{\{t-1\}} + (1 - \beta_2)$ (Use RMSprop or another biased second raw moment estimate.)

Adjust for bias in the first moment estimate by using the formula

$$m_t = m_t \big/ (1 - \beta_1^{\wedge} t)$$

Adjust for bias in the second-moment estimate

$$V_t = V_t / (1 - \beta_2^{\wedge} t)$$

Use corrected moment estimates to update parameters:

$$\theta_t = \theta_{\{t-1\}} - \alpha * \frac{m_t}{\sqrt{v_t + \in}}$$

Adam is a well-liked optimization method that combines momentum and RMSprop to train deep learning models with high-dimensional efficiency, fast convergence, and ease of use[8].

3. Experimental Result

This section examines features of Breast Cancer image from experiments, highlighting the need for further investigation into SHAP and other methods to better understand image features and SHAP's function. SHAP uses various explainers, with Deep Explainer being the foundation for image classification SHAP sample code, which is used in the notebook for early breast cancer features are displayed using SHAP Deep Explainer, these attributions are reviewed and annotated, and the procedure is repeated with a less accurate [9].

3.1 Breast Cancer MAbGENEx Data

This project will utilize the Breast Cancer MAbGENEx dataset, which includes breast mass images and a target column for binary classification of benign or malignant masses. The dataset will be loaded and pre-processed to conform to the expected shape and format for the learning model

3.2 Design of the Model

Python is utilized to build the deep neural network model for the assignment. A sigmoid activation function is used in the output layer, two dense hidden layers with 32 neurons each employing ReLU initiation, and an input layer. The Adam optimizer and binary cross-entropy loss are used to construct the model. This comparatively straightforward design would be used to illustrate the SHAP analysis and successfully learn to differentiate between benign and malignant tumors. However, the same method might also be used for more intricate structures.

3.3 Assessment of the Model

The model is trained for 100 epochs; the training and validation loss is presented below.

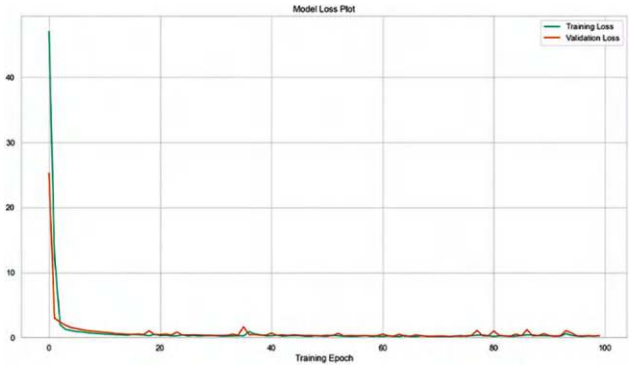

Fig. 103.1 Model loss against the number of training epochs

A separate test set has been employed to evaluate the model's performance, and Table 103.1 shows that it achieved an overall accuracy of 92%, exhibiting good precision and recall in the majority of cases.

Table 103.1 Performance metrics

	Precision	Recall	F1-Score	Support
Benign	0.99	0.89	0.94	75
Malignant	0.83	0.97	0.89	39
Accuracy			0.92	114
Macro Avg	0.91	0.93	0.92	114
Weighted Avg	0.93	0.92	0.92	114

3.4 SHAP Analysis

Our model's SHAP values, which indicate feature importance and impact results, are determined via the SHAP python module. For deep learning models, SHAP values are provided for every feature via the Deep Explainer tool[9].

Concave points and concavity have a significant impact on the yield of a model, especially when it comes to classifying breast cancer as benign or malignant, as the summary plot demonstrates. Although they have somewhat smaller effects than the top attributes, other characteristics like compactness and concavity are equally important.

3.5 SHAP Summary Plot

The process of a model's prediction is depicted by the SHAP waterfall plot, which begins with the baseline value and moves on to different features before arriving

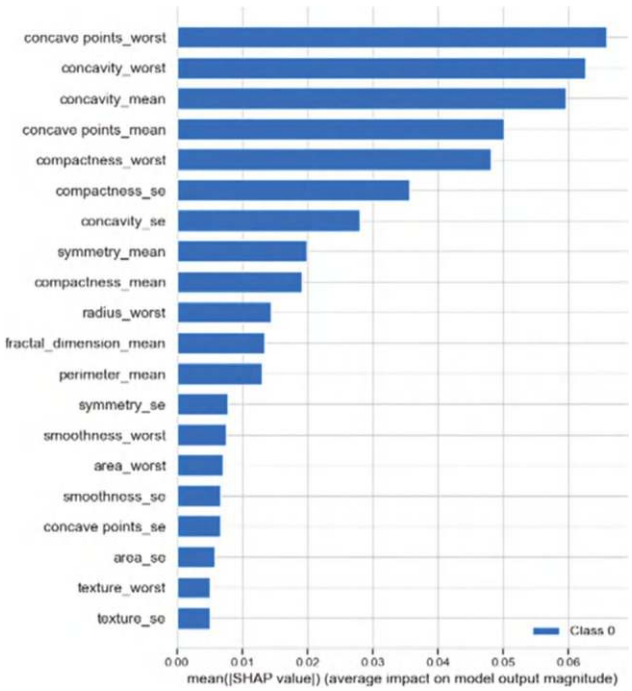

Fig. 103.2 Using a summary plot to visualize the significance of geographic features

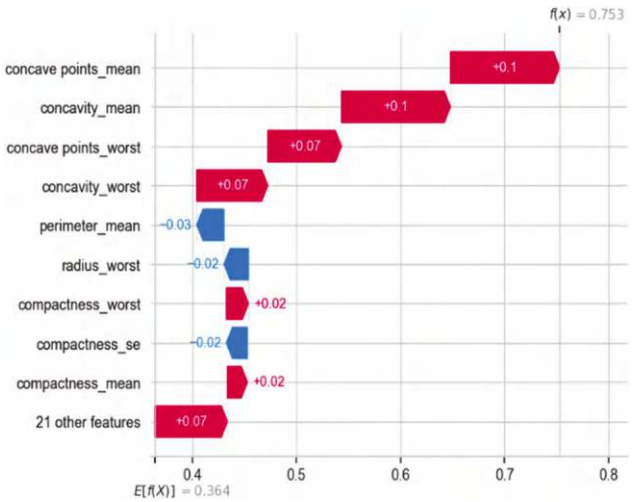

Fig. 103.3 SHAP waterfall plot

at the ultimate output of 0.75. This breakdown increases prediction trust by illuminating the model's decision-making process.

The SHAP force map offers a thorough illustration of how various features affect the model's predictions over a number of cases. It illustrates how the values of each component affect the decision-making process as a whole by displaying the cumulative effect of all features.

Finally, this research showed how to understand a deep learning model using SHAP. We may learn a lot and understand how each feature influences the forecasts made by the in order to boost the credibility of our prototypical. Complex models become more visible and intelligible with the help of SHAP's robust toolkit for model interpretability.

In order to identify the best parameters for the best model performance of a breast cancer image, optimizers are algorithms that modify neural network parameters such as weights and biases to minimize the loss function of breast cancer [10].

Optimizers, such as Adam, are essential for machine learning models, assessing predictive capacity from Breast Cancer images. They handle complexity, efficiency, and accuracy. Popular alternatives include SGD, Momentum, AdaGrad, RMSprop, and Adam, which aid in speedier convergence, accurate parameter adjustment, and automated manual tweaking. These techniques improve convergence in curvature situations and learning rate[10].

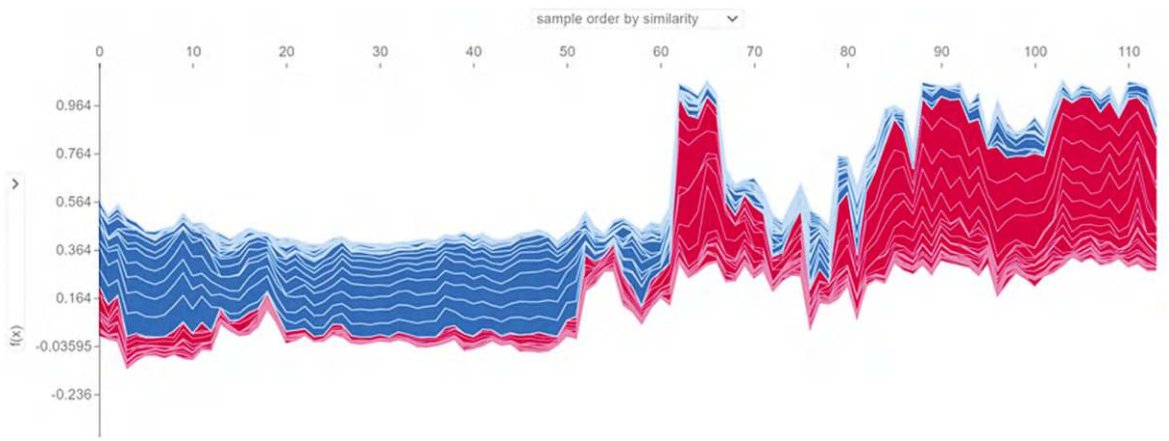

Fig. 103.4 Display every prediction from the training set

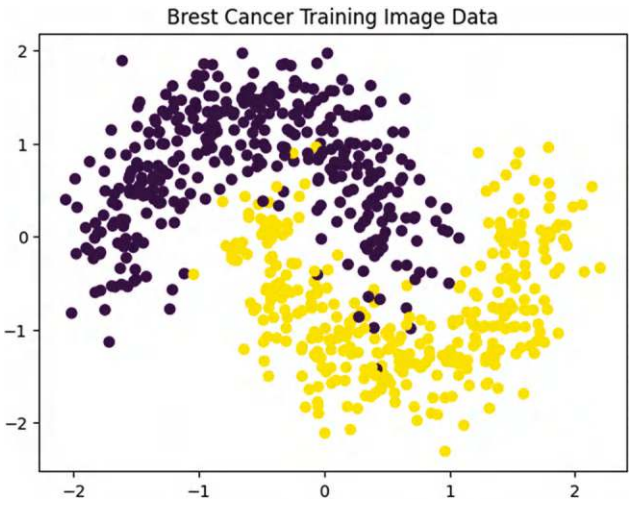

Fig. 103.5 Breast cancer training image data

4. Conclusion

Image processing is crucial for interpreting physiological images from various sources, enabling the extraction of target components and description of shape properties for shape analysis. Machine learning algorithms can predict early breast cancer, detect cancer vulnerability, and improve survival. This paper developed a deep learning model for breast tumor categorization using SHAP, enhancing transparency and trust by connecting optimal credit allocation with local explanations using classic Shapley values. Optimizers have unique strengths and weaknesses, making them suitable for different problems. Advanced methods like Adam are preferred for robustness and ease of use. Comparing performance on a dataset helps determine the best optimizer for a task. AdaGrad modifies the learning rate, whereas Momentum optimizer enhances

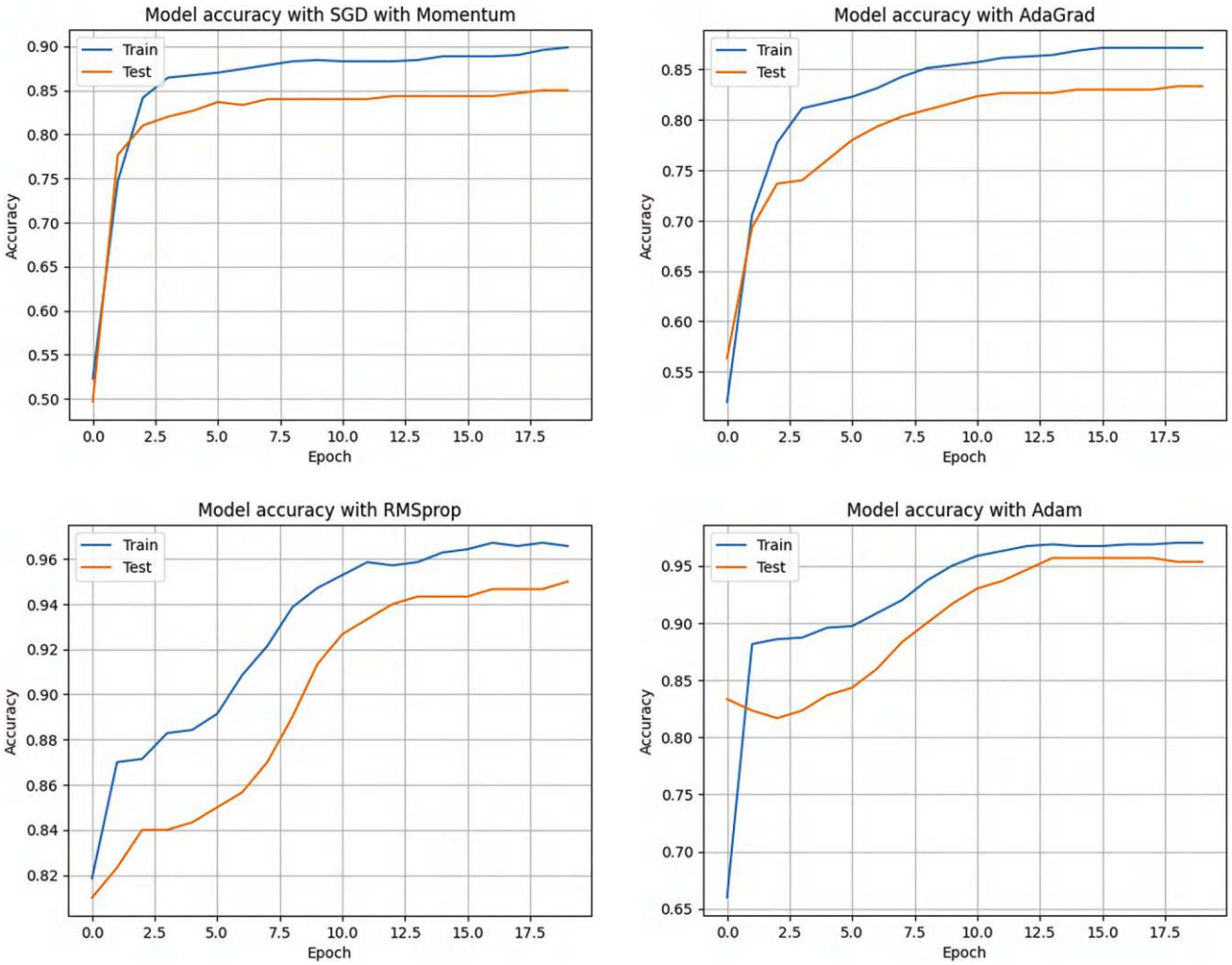

Fig. 103.6 Model accuracy of breast cancer image

convergence in curvature scenarios. Stochastic gradient descent (SGD) optimizes parameters based on the negative gradient of the loss function.

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Enhancing Accuracy in Cardiovascular Disease Prediction: A Novel Hybrid Machine Learning Framework

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Abstract: Cardiovascular disease (CVD) remains a main cause of mortality worldwide, necessitating accurate prediction replica for early detection and intervention. This study proposes a novel hybrid machine learning framework that combines LR and RF algorithms to enhance the accuracy of cardiovascular disease prediction. The framework leverages the strengths of both algorithms, with LR handling linear relationships and RF capturing non-linear patterns in the dataset. The work utilized a general available dataset containing clinical and demographic features such as age, bp, cholesterol levels, and electrocardiogram results. Data preprocessing involved handling missing values, normalizing features, and splitting the dataset into training and test sets. The hybrid model's performance was evaluated using standard metrics, including accuracy, sensitivity, specificity, F1-score, and area under the curve (AUC). The proposed hybrid model outperformed individual models, achieving an accuracy of 97% in forecasting cardiovascular illness. The results demonstrate that combining ML algorithms can significantly improve predictive accuracy, making this approach highly promising for the early diagnosis of heart disease. This study assists the advancement of healthcare data analytics by giving a robust and accurate hybrid machine learning framework for cardiovascular disease prediction.

Keywords: Cardiovascular disease prediction, Machine learning (ML), Clinical data analysis, Hybrid method

1. Introduction

Heart disease diagnosis is fraught with challenges due to fear factors such as diabetes, hypertension, high cholesterol levels, irregular pulse rates & many others. To measure the extent or advancement of heart disease, a variety of methods of algorithms from machine learning have been used. The severity of the disease is classified based on various algorithms like logistic regression algorithm and random forest algorithm. Heart disease is the major concern in the world, making early prediction crucial for reducing the global healthcare burden. This research paper proposes a hybrid machine learning model that integrates two or more number of algorithms to predict the likelihood of heart disease more accurately. By combining the strengths of various models, including logistic regression and random forest algorithms. In this study, publicly available datasets containing medical and demographic features, such as age, bp, cholesterol levels, and electrocardiogram (ECG) results, were utilized. Data preprocessing involved

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handling missing values, normalizing features, and it can be splitted into the training & testing data set.. The proposed hybrid model begins by utilizing random forest to handle non-linearity in the dataset and logistic regression to handle linearity in the dataset and detect patterns in the clinical variables. The intermediate results re sent to the meta model. Finally, we can capture the output from the meta model.

The performance evaluation was conducted using standard metrics namely accuracy, sensitivity, specificity, F1-Score, and AUC values. The hybrid model outperformed the individual models with an accuracy of 92%. The results indicate that combining ML models can significantly improve predictive accuracy, thus making this approach highly promising for the early curing of heart problems.

Still, conventional scoring mechanisms have dominated the current system, with the Framingham risk score being an example. These depend on elements like age, cholesterol levels, blood pressure, smoking habits, and diabetes(sugar) to assess the probability of cardiovascular diseases. Guidelines set by the American Heart Association, including these risk factors, similarly find applicability here. Statistical models like logistic regression are frequently used in medical studies and in cases involving binary classification forecast, like predicting heart disease through the analysis of input features to quantify probabilities. The dataset contains clinical measurements respectively used for assessing myocardial infarction risk-blood pressure, cholesterol level, and electrocardiographic results.So, proposed model for the forecast of heart problems makes up a hybrid model of the advanced ML algorithms that combine LR and RF, producing strengthened methodologies to reduce false results and thus better the confidence level in heart disease detection. The hybrid model has multiple algorithms that account for varying aspects of the data. Being a linear model, LR does well when there is an approximately linear relationship among the features and the predictor(target) variable, while RF an ensemble learning approach-works in more complex ways for non-linear relationships. This proposed system is capable of boosting the prediction accuracy.

1.1 Contribution

The principal offering of this work is building a novel hybrid machine learning framework with the following

- The research introduces a hybrid model that combines Logistic Regression and Random Forest algorithms to improve heart disease prediction.
- The hybrid model outperforms individual models, addressing limitations found in individual techniques.
- This approach enhances prediction accuracy, supporting more effective clinical decision-making in heart disease diagnosis.

2. Literature Review

In 2021, Alsharqi and colleagues reviewed, how ML techniques are applied to forecast the risk of cardiovascular disease. And discovered that ML techniques like LR, decision trees, and artificial neural networks can create perfect models for predicting cardiovascular disease.

In 2021, Abdi and others did a review and meta-analysis on using machine learning to predict cardiovascular disease risk based on electronic health record data. They confirm that machine learning algorithms can utilize the clinical data which is collected from the records and approximately it forecast the risk of cardiovascular disease.

In 2020, Abawajy and others, presented a deep learning technique of diagnosing heart disease on the basis of convolutional and recurrent neural networks. At the same time, reconcile them, and they found this method to possess very huge accuracy in diagnosing heart diseases with medical data. The Heart Disease Dataset holds plenty of vital information like age, gender, blood pressure, cholesterol level, an ECG + or - test and chest pain induced by exercise. The work offers great scope in providing an idea to researchers who can construct better policies for control and prevention of the disease.

The article "Forecasting Cardiovascular Disease Using ML Techniques: A Systematic Review" by A. M. Alsharqi et al. (2021), this study uses the ML methods for the forecasting of heart problems.

The article "ML for Predicting 10-Year Risk of Cardiovascular Disease Using Routine Clinical Data from the Electronic Health Record" by Abdi and colleagues (2021) illustrates the employment of ML pathway in predicting the cardiovascular disease risk, employing data found within electronic health records. This paper lays down the strength and weakness of various machine learning algorithms.

Another research has been conducted by the J. Abawajy and others, (2020), "A DL method for Heart Disease Diagnosis," explaining a Deep Learning-based approach to diagnosing heart disease. This study is about the hybrid of CNN and RNN.

M.N.R. Chowdary et al. gave their personal ideas on heart disease forecasting, which targets improved accuracy of predicting heart disease with the application of ML techniques for the determination of vital variables. Various learning techniques such as decision trees, logistic

regression, K-nearest neighbors, support vector machine, and Naive Bayes were utilized to train their model. However, SVM outperformed with an accuracy of 91% for threshold cases within the dataset. Accuracy generally fluctuates with these algorithms in accordance with the number of instances in the dataset, and this specific implementation tends heavily toward the performance of the SVM.

The authors P. Motarwarb and his colleagues introduced in their study of 2020 an ML method that estimates the risk for heart disease. The heart prediction framework contains five algorithms: NB, RF, Hoffding DT, LMT, and SVM. For both testing and training, the Cleveland dataset has been used. Random forest is the most accurate method, one could conclude.

3. METHODOLOGY

In this section, the hybrid model based on Logistic Regression and Random Forest is explained in detail. The idea behind combining these two models is to obtain the best of both worlds and to reduce the weaknesses of each method. LR is perfect for linear problems, while RF deals with the non-linearity of relationships and has a low tendency to overfit. A hybrid model combines two or more ML techniques for the performance gain. Here we used LR, which is very good for linear classification problems, to combine with Random Forest, which is quite competent at modeling highly complicated nonlinear relationships. Generally, the hybrid model has more power than the LR or RF alone, because it utilizes the complementary power of both.

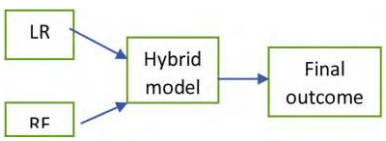

Fig. 104.1 Final outcome with hybrid model

3.1 Steps to Create a Hybrid Model

A LR model was trained on the data to get the probabilistic output $P_{LR}(y=1/x)$-how likely is the positive class predicted by Logistic regression. A Random Forest model was also built on the same training data to produce either class probabilities $P_{RF}(y=1/x)$. The simplest method for combining the two is through a weighted average or linear combination of the predictions.

$P_{LR}(y=1/x)$: the probability predicted by LR for the positive class.

$P_{RF}(y=1/x)$: the probability predicted by RF for the positive class.

For classification: Combine them with weights W_{LR}, W_{RF} where $\alpha + \beta = 1$.

$$P_{Hybrid}(y=1/x) = W_{LR} \cdot P_{LR}(y=1/x) + W_{RF} \cdot P_{RF}(y=1/x)$$

The final prediction is the class with the highest weighted probability: $\hat{F} = arg\ max_x(P_{Hybrid}(y=1/x))$ Which here means the final probability prediction for the positive class in the hybrid model.

For Regression: Final prediction becomes a weighted sum of the continuous prediction:

$$\hat{y}(x) = W_{LR} \cdot P_{LR}\left(y = \frac{1}{x}\right) + W_{RF} \cdot P_{RF}(y=1/x)$$

Where, W_{LR}, W_{RF} are, respectively, weights for LR and RF, based on performance measures. In a voting ensemble, we can combine Logistic Regression and Random Forest into a voting mechanism. Two kinds of voting are:

Hard Voting: Every model predicts a class label, and the final class label will be given the majority vote. If Logistic Regression predicts some label of y1 and Random Forest predicts some label of y1, then the final prediction will be y1, considering a majority vote. If Logistic Regression predicts a label of y1, while Random Forest makes a prediction of y0, majority voting will select the class with the highest votes.

Soft Voting: Each model assigns probabilities over the classes. The candidate for the final vote is the average of the probabilities-all probabilities across the models. That is, for class Cj: The final probability,

$$p(y_j/x) = \frac{1}{2}\left(P_{LR}(y_j/x) + P_{RF}(y_j/x)\right)$$

Final prediction is the class which has the more average probability. After calculating the combined probability P_{Hybrid} (Y=1/X), we find the final prediction using a decision boundary (0.5 for binary cation)$_{Hybrid}$

$$= \begin{cases} 1 \\ 0 \end{cases} \text{ if } P_{Hybrid}(y=1/x) > 0.5$$

3.2 Implementation Process

Data preprocessing involves the steps of data collection, data cleaning, and data splitting. We train the LR model and RF separately on the same training set. We combine the predictions of these base models using the hybrid. The predictions of two base models can be combined in two ways: "Average probabilities of both models" or "Weighting of model predictions based on performance, weighted average." The hybrid model should be compared against the individual models using the same evaluation metrics. The model is deployed for real-time predictions with continuous model performance monitoring.

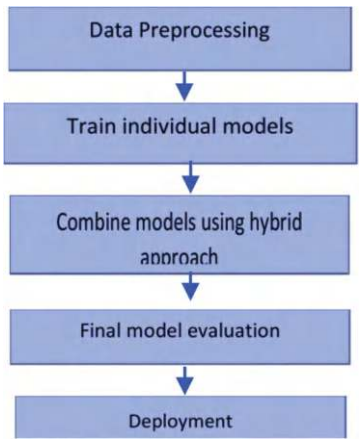

Fig. 104.2 Flow chart for the implementation

4. Result

This section includes illustration of performance metrics illustrations.

Performance Metrics of Machine Learning Models: In this section, performance metrics are evaluated for logistic regression, random forest, and hybrid model. Each of the metrics will give insight into the performance of the model in classifying heart illness patients. The performance of the various metrics shall now be explained, with their respective bar charts shown below.

Accuracy: Accuracy is the number of correct predictions to the total number of predictions in the dataset. It is a good first go to score, but if you have an imbalanced dataset this will be miss leading.

Fig. 104.3 Accuracy relation

F1 Score: Cardinal utility of the F1 Score is towards being the redressor of precision and recall for a true balance among the two. It lets little Hamlet in on the bandwagon where the class distribution is not so equal; because in repose, it internally checks for the minutiae of false positives and negatives.

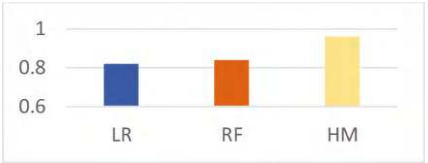

Fig. 104.4 F1 score relation

Precision: Precision measures the ratio of true positive observations to all predicted positive observations. It reflects the accuracy with which the model identifies the actual positive.

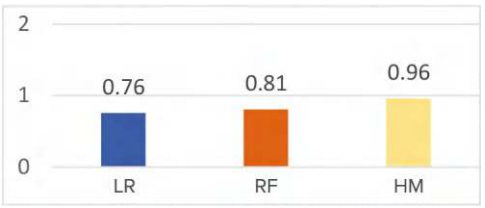

Fig. 104.5 Precision relation

Recall: Recall, also known as sensitivity, measures the proportion of real positive cases that had been effectively identified as positive by the model. This brings to attention the ability of the model to capture all positive instances.

Fig. 104.6 Recall considerations

On evaluating these models, it was clear that hybridization is better than machine learning in medical diagnosis. This indicates a growing understanding of the data through ensemble classifiers and subsequent improvement of predictive performance, particularly in important such as the diagnosis of coronary heart disease.

4.1 ROC

The ROC is an important graphical tool for evaluating binary classifiers. It graphically shows the diagnostics ability of any classifier for all threshold settings by displaying the true positive rate against the false positive rate.

Interpreting the ROC Curve

AUC is reflects how well a model has performed. As such, if a model's AUC is 1.0, it is said to be perfect; if the AUC is 0.5, it indicates chance performance. The nearer-to-1.0 the AUC, the more capable the model is in discriminating between its positive and negative classes.

Logistic Regression: The perceived ROC for LR was expected to yield a moderately-under-the-curve scoring, which indicated fair ability to distinguish between patients with heart disease and those without it.

Random Forest: The ROC curve for the RF is expected to yield higher AUC than LR. This is due to the characteristic

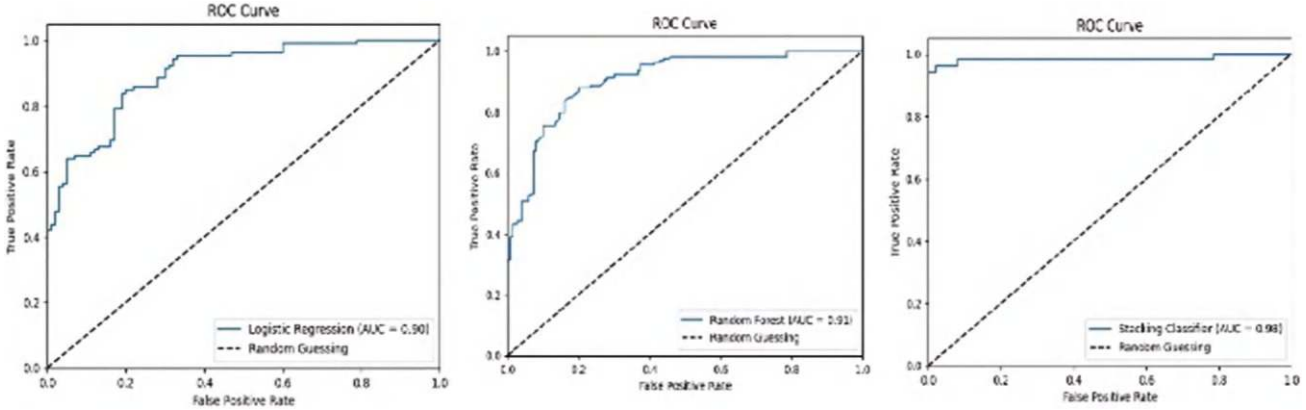

Fig. 104.7 ROC curve for all models

nature of RF that is enabled for ensemble learning capability, overriding a few hundred decision trees and reducing the overfitting problem.

Hybrid Model: The HM, which is based on combining the predictions from LR & RF, will outperform all the other models and, therefore, should show the highest AUC. The rationale for the AUC increases in this case is the simple ensemble principle, through which the model is able to take advantage of the best features of each model, developing a better discrimination potential.

5. Conclusion

The center of this work was the combination of different algorithms to exploit the strength of each of them to create a prediction model that is sturdy and reliable. Some of the findings are: Hybrid model has more accuracy than the base models Health care professionals easily cure the heart illness hybrid model provides the high stable and consistent performance of several datasets, S o it reduced the risk of over fitting and it very helpful to the patients to get the further treatment plans.

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Android Malware Detection Using Dynamic Analysis

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Abstract: This paper reviews recent studies on managing harmful mobile apps, focusing on the Android platform. It explores the main security challenges of these apps and examines methods to detect malware, which are primarily categorized into signature-based and heuristic-based approaches. Signature-based detection depends on known malware patterns but struggles with detecting new or developing threats. In the detection process, the heuristic approach requires detection materials, also known as features, which are classified into three types: static analysis (analyzing the app's code), dynamic analysis (monitoring the app's behavior during use), and hybrid analysis (a combination of both static and dynamic techniques). A key focus of this research is on analyzing network behavior as a critical factor in detecting malware activity. While hybrid approaches often work best, there are still challenges like poor detection on certain devices, reliance on outdated datasets, and difficulty in identifying rare or advanced attacks. This paper specifically aims to improve dynamic techniques for detecting malware, with an emphasis on network behavior.

Keywords: Malware detection, Machine learning, Dynamic analysis, Network behavior

1. Introduction

Android, developed by Google, is arguably the most widely used operating system for mobile in the world. Today, billions of devices, from handsets and tablets to wearables, are powered by Android. The number of Android users has consistently grown each year, exceeding 3 billion by 2022[1]. In fact, since it came out in 2008, the version is

[1]kvkraju@srkrec.ac.in, [2]dileep.akula2003@gmail.com, [3]sanjanaareti8919@gmail.com, [4]bharath79019@gmail.com, [5]sivabhupathiraju67@gmail.com

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quite easy to identify what really made it so mainstream early on in its very existence-that was the fact that it was open-source, which means that manufacturers can use the platform free in their devices. This flexibility managed to attract a wide variety of manufacturers and most notably, industry giants Samsung, Huawei, Xiaomi, and others. It gave Android quick impetus to become one of the most key mobile platforms in the world.

IOS, by Apple, is an operating system meant for use in an Apple device, such as iPhones, iPads, and iPods[2]. It was developed in 2007 and is appreciated by many for its great performance with an emphasis on data protection as well as security. The App Store is a kind of download center, downloading only from that and trying to minimize chances of deleterious downloads. iOS generally receives more updates through Apple itself, and this ensures that the best features and security fixes reach the hands of users always. Being less customizable than Android, iOS has an interfacing that is simple and reliable. However, being high in value, iOS devices are much costlier.

When comparing Android and iOS, several key differences stand out. As highlighted in the analysis, Android holds a slight lead in overall users, but iOS is ahead as far as design, security, timely software updates, and ecosystem integration go, making it a favourite among many [3]. Android, being open-source, offers more customization and flexibility, with a wide variety of devices available at different price points. In contrast, iOS is a closed-source platform that prioritizes security, performance, and seamless integration within the Apple ecosystem. While Android provides users with more freedom to modify their devices and install apps from outside the Google Play Store, this openness also increases the risk of malware. On the other hand, iOS's strict control over app distribution and frequent updates provide a more secure environment, but limit customization options and device choices.

Malware detection techniques include signature-based and heuristic-based methods [4]. The signature-based detection identifies known malwares by matching files with their database of known signatures, while The heuristic-based detection analyses the behavior and characteristics of files to identify potential malwares, meaning that it can detect new or unknown threats. Signature and heuristic methods are two of the primary malware detection techniques used in Android security. Figure 105.1 shows the block diagram of malware detection techniques in the Android environment. Additionally, there are three other important methods: behavior-based detection, which analyzes how apps behave during usage; cloud-based detection, which utilizes external servers to enhance detection capabilities; and machine learning-based detection, which employs algorithms to identify patterns and anomalies in app behavior. Together, these approaches help improve the overall security of Android devices. Heuristic detection can be further categorized into static, dynamic, and hybrid approaches. Each of these methods has its strengths and weaknesses, and often, a combination of techniques is used to achieve more accurate and comprehensive malware detection.

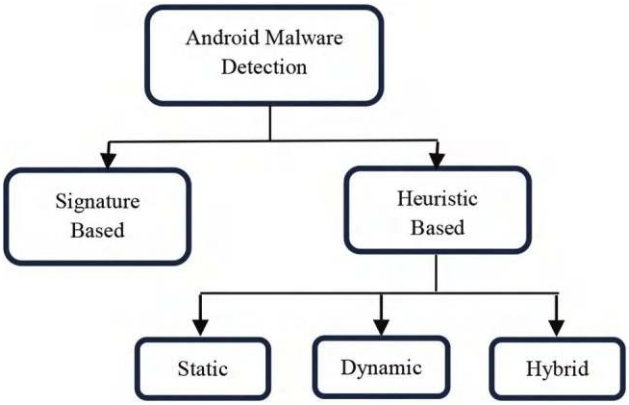

Fig. 105.1 Android malware detection techniques

Source: https://ieeexplore.ieee.org/abstract/document/10473005

1.1 Static Analysis

Static analysis involves analyzing the app or examining the code and structure of a file without executing it. This method checks for known signatures, patterns, and irregularities, such as suspicious access permissions or system calls that might allow unauthorized actions. It is fast and efficient, allowing for quick scanning of files. Although static analysis in Android malware detection has made progress, it continues to face significant challenges [5].

1.2 Dynamic Analysis

Dynamic analysis monitors a file's behavior while it is executed in a controlled environment, such as a sandbox [6]. This method observes how the file interacts with the system, including its use of system resources and network activity. Examples of irregular behavior include unexpected network connections, where the file tries to connect to unauthorized servers or download harmful files, and suspicious API calls, which may show attempts to access sensitive information or change system settings without permission.

1.3 Hybrid Analysis

Hybrid analysis combines both static and dynamic methods [7]. It checks the code for known malware and then runs the file to observe its behavior. This approach offers better protection against both known and new threats. In this

research paper, as we review network behavior, dynamic analysis proves to be the most effective method alongside hybrid analysis.

Android malware detection can be strengthened through multiple approaches, including deep learning and machine learning techniques, along with signature-based and heuristic methods. Techniques such as CNN-BiLSTM [8] and Factorization Machines [9] utilize deep learning and feature extraction to accurately identify malware, even when it's concealed within legitimate applications. Signature-based detection works by matching known malware patterns within app code, while heuristic detection applies dynamic analysis to observe and flag suspicious behaviors, providing an additional layer of protection against unknown threats. Together, these combined methods create a powerful system capable of identifying both existing and new forms of malware on Android devices.

In this research, we focus on dynamic analysis of network behaviour for a few key reasons. First, it allows us to spot suspicious activity in real-time, like unauthorized connections or unusual traffic patterns, which could be signs of malware. Second, dynamic analysis helps us avoid malware that tries to hide its intentions through code obfuscation. Instead of looking at the code itself, we track the app's behaviour, revealing malicious actions like connections to shady servers or attempts to download harmful files. Finally, since many Android malware rely on network communication to steal data or fetch additional malicious files, monitoring network traffic is an effective way to catch these threats. Together, these points make dynamic analysis a powerful tool for improving network security.

In this research, we propose a dynamic network behavior analysis approach to detect malware. By focusing on how apps interact with the network, rather than simply examining their code, we can uncover suspicious activities that may signal malware. This method allows us to detect unauthorized connections, unusual traffic patterns, and other behaviors that could indicate malicious intent. Importantly, tracking behavior rather than code also helps us bypass malware techniques like code obfuscation, which try to mask harmful actions.

To enhance detection accuracy, we classify incoming network traffic into four categories:

1. **Scareware** – Applications that generate false warnings or alerts, pressuring users into purchasing unnecessary security products.
2. **Adware** – Apps that trigger frequent network requests to display ads, leading to abnormal traffic volume from various ad servers.
3. **SMS Malware** – Malware that misuses SMS functionality to send unauthorized messages, potentially leading to unapproved charges or data exposure.
4. **Benign Apps** – Regular applications that communicate with trusted services for standard operations like syncing or updating.

By categorizing network traffic in this manner, the legitimate activity is isolated from suspicious behaviour and allowing to concentrate on traffic patterns associated with potential malware. This methodology provides an effective means to improve malware detection and bolster network security, particularly in environments where Android malware relies on network communication to steal data or retrieve additional malicious files.

2. Literature Review

2.1 Android Usage

Naveen Kumar [1] highlights that Android has a huge global presence in 2024, with around 3.3 billion users, making up 71.85% of the mobile OS market. In the U.S., it holds 42.34% of the market, just behind iOS at 57.39%. Samsung leads the Android market with a 22.91% share. Android 14 is quickly gaining traction, running on 33.67% of devices. The OS is especially dominant in countries like Brazil, India, and Indonesia, where it has over 85% market share. Overall, Android's ecosystem remains crucial in mobile tech and security.

2.2 IOS Usage

Shivi Garg and Niyati Baliyan's [2] research points out that while iOS is generally more secure than Android, it's not without its vulnerabilities. They compare iOS and Android on various security fronts like system architecture, encryption, and app permissions. The paper also sheds light on the common vulnerabilities and malware attacks targeting iOS from 2015 to 2019. Even though iOS has more robust security features, it still faces new threats, which is why ongoing research to tackle these issues is so important.

2.3 Analysis of IOS and Android

Lazarela Lazareska and Kire Jakimoski [3] compare Android and iOS, noting Android's strength in customization and device variety, while iOS stands out for its sleek design, security, and privacy features. Even though Android scores a bit higher (9 to 8), many users still prefer iOS because of its regular updates and focus on privacy. They also discuss how apps can be transferred between platforms, with key elements like images and audio staying the same, which

helps improve the user experience and reduce development costs.

2.4 Malware Detection Approaches

Rajif Agung Yunmar [4] and his team highlighted two methods for detecting Android malware: static analysis, which is quick but can miss hidden threats, and dynamic analysis, which is more thorough but resource-heavy. They recommend combining both for better accuracy and emphasize the need for efficient, real-time protection, regular updates, and strategies to detect new threats.

2.5 Malware Detection using Static Analysis

Ya Pan et al. [5] conducted a systematic review of Android malware detection techniques that rely on static code analysis, noting that neural network models are particularly effective for identifying threats. However, they point out that further improvements are necessary to boost detection accuracy, suggesting that ongoing advancements in this area could make static analysis even more reliable for Android security.

2.6 Malware Detection using Dynamic Analysis

Taniya Bhatia and Rishabh Kausha [6] explore dynamic malware detection using system call analysis. They track the behavior of applications during runtime to identify whether they are benign or malicious. Their approach works well, even with malware that uses complex obfuscation techniques, showing how system call analysis can be a powerful tool for detecting and monitoring harmful applications.

2.7 Malware Detection using Hybrid Analysis

Yus Kamalrul Bin Mohamed Yunus and Syahrulanuar Bin Ngah [7] highlighted the benefits of using a hybrid analysis approach for malware detection, which combines static and dynamic methods for greater effectiveness. They emphasize the importance of incorporating memory analysis to enhance accuracy, especially for identifying sophisticated malware threats.

2.8 Robust DL Model for Android Malware Detection

Ikram Ul Haq et al. [8] created a smart deep learning system to spot complex malware on Android devices, helping to tackle the rising security threats from advanced mobile attacks. Their method uses CNN and BiLSTM models to reliably detect malware, even when it's hidden inside legitimate apps. After testing with public datasets, their system proved to be fast and accurate, making it a good fit for the growing Android market. The team also plans to improve their system by trying out more advanced deep learning methods and better feature selection to boost its detection power and overall performance.

2.9 Detection Based on Factorization Machine

Chenglin Li et al. [9] developed a new method for detecting Android malware using a Factorization Machine model. They focused on extracting features from app manifest files and source code to identify malicious behavior. Their approach handles the challenges of sparse data by using one-hot encoding and capturing the interactions between different features. The results showed that their system performs extremely well, achieving near-perfect precision on two major datasets, DREBIN and AMD, and is much faster to train than other methods, making it a promising solution for malware detection.

2.10 Android System Architecture

Chao Wang et al. [10] emphasize the layered structure of Android's architecture, explaining how components like the Application Framework, Libraries, and Android Runtime collaborate to support app functionality. They also discuss the flexibility of Android's open-source platform, which allows developers to create versatile applications using the Android SDK.

2.11 Understanding Android Security

William Enck et al. [11] explain Android's security architecture, which relies on a combination of mandatory access control and permission labels to protect application data and interactions. They detail how Android isolates applications by assigning each a unique user identity, which helps to contain vulnerabilities within individual apps. Additionally, they highlight the role of intents in enabling inter-application communication while maintaining security through permission-based restrictions. This approach aims to balance functionality with security, though it requires careful management to prevent unintended data exposure.

2.12 MADAM: Efficient Behavior-based Android Malware Detection

Andrea Saracino et al. [12] introduce MADAM, a multi-level host-based malware detector for Android that analyzes features across kernel, app, user, and package levels. By detecting and blocking threats from 125 malware families using two classifiers and a behavioral signature detector, MADAM successfully blocks over 96% of malicious apps. With low false alarms, minimal performance impact, and reduced battery drain, MADAM provides an efficient solution for protecting Android devices from diverse malware threats.

3. Android Architecture

Android is built on a layered structure, with each layer playing a specific role to keep apps running smoothly and securely [10]. Figure 105.2 shows the architecture. Here's a breakdown of the main parts:

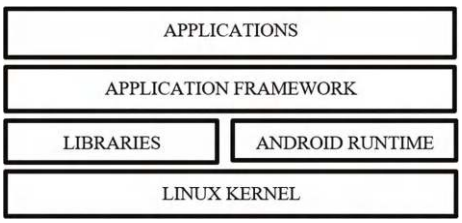

Fig. 105.2 Android architecture

Source: https://ieeexplore.ieee.org/document/6182081

1. **Applications**

   At the top, we have the Applications layer, which includes both Android's built-in apps (like email, SMS, calendar, maps, and contacts) and apps that developers create. The built-in apps cover essential functions that people need every day. Developers can also create their own apps using the same tools, making it easy to add new features to Android devices.

2. **Application Framework**

   This layer is what developers use to build their apps. It's a set of tools and services that Android provides to make app development easier. For example:

   Activity Manager manages the lifecycle of apps (like when they open, close, or switch).

   Content Providers allow apps to share data with each other.

   Resource Manager manages non-code resources, like images and layout files.

   Notification Manager lets apps show notifications.

   And **View System** helps create user interfaces. This framework allows developers to build apps that work smoothly with other Android apps and to customize or even replace built-in apps if they want.

3. **Libraries**

   Underneath the framework are Libraries collections of code written in C and C++ that handle specific functions. These libraries make things like graphics, databases, and web browsing possible. Some key ones include:

   Media Libraries for handling audio and video.

   SQLite for storing app data.

   OpenGL for graphics.

   And **FreeType** for fonts. These libraries do the heavy lifting in the background so apps can perform complex tasks.

4. **Android Runtime**

   Each app runs in its own environment, using the Android Runtime. This includes a set of core libraries that provide most of the basic functionality of Java. Each app has its own Dalvik Virtual Machine (or DVM), which is optimized to make Android apps run efficiently on mobile devices. The DVM uses the Linux kernel to manage memory and run tasks smoothly.

5. **Linux Kernel**

   At the bottom of everything is the Linux Kernel, which acts as the bridge between Android and the actual hardware. It manages things like memory, processes, and security, and makes sure apps can work with the phone's hardware (like the camera, screen, or sensors) without needing to worry about the details.

4. Data Set

This dataset analyzes Android app behavior by capturing network flow characteristics across four categories: scareware, adware, SMS malware, and benign apps. It has 355,630 rows and 86 columns, with features like IP addresses, ports, packet stats, flow duration, and inter-arrival times. By examining traffic patterns like packet length variance and flow rates, the dataset helps distinguish between benign and malicious apps. It's imbalanced, with some categories having more data than others, which may impact model performance and require techniques like resampling or class weighting.

5. Algorithm and Methodology

Algorithm

Input: DataFrame df with features and target column Label.

Output: Filtered DataFrame df_filtered1 with low-correlation and high-correlation attributes removed.

1: **Low-Correlation Feature Elimination** (Correlation Between Independent and Dependent Features)

2: **Input:** DataFrame df, target_column

3: **Initialize** correlation_matrix as the correlation matrix of df.

4: **Extract** correlation values of all features with target_column as correlation_with_target.

5: **Identify** *features with absolute correlation <0.005*:

For *each feature in correlation_with_target*:

If *correlation_with_target[feature] < 0.005* **then:**

Add feature to low_correlation_cols

6: **If** *target_column* **in** *low_correlation_cols*, **then** *remove it.*
7: **Drop** *low_correlation_cols from df to get df_filtered.*
8: **High Inter-Feature Correlation Elimination** (Correlation Between Independent Features)
9: **Input:** DataFrame df_filtered, Exclude target_column
10: **Initialize** correlation_matrix for df_filtered.
11: **Extract** independent columns as independent_columns (excluding target_column).
12: **Initialize** to_drop as an empty set.
13: **For** *each pair (col1, col2) in independent_columns*:
    If *correlation_matrix.loc[col1, col2] >= 0.99* **then:**
    Add *col2 to to_drop*
14: **Drop** *to_drop columns from df_filtered to get df_filtered1.*
15: **Return:**df_filtered1

Data Loading and Exploration

- Import necessary libraries.
- Load the dataset using pandas.read_csv() from the actual file path.
- Generate a profiling report for initial data analysis using ProfileReport() function from ydata_profiling.

Data Preprocessing

Handling Missing Data

- KNN imputation for missing Numerical Columns.
- Simple imputation for missing Categorical Columns.

Remove Duplicates

- Drop duplicates and reset the Dataframe index.

Data Cleaning

- Strip the whitespace from string columns
- Validate Source and Destination IP addresses using the regular expressions.
- Remove invalid rows based on protocol and IP validation.

Type Consistency and Label Encoding

- Ensure type consistency by checking and converting mixed types in columns.
- Convert categorical features to numerical using LabelEncoder.

Outlier Detection and Removal

- Remove the extreme Outliers based on 0.1 and 99.9 Percentiles.

Correlation Analysis

- Calculate correlation matrix for all the features.
- Remove the features with a correlation value less than 0.005 with the target (Label).
- Identify and remove features with high multicollinearity (correlation>=0.99).

Data Splitting & Oversampling

- Split the dataset into training and testing sets using train_test_split() with a stratified approach.
- Apply SMOTE (Synthetic Minority Oversampling Technique) to balance the training data.
- Normalize the feature values using MinMax Scaler to scale between 0 and 1.

Model Training & Evaluation

- Define multiple machine learning models (e.g., Decision Tree, Random Forest, Gradient Boosting, Naive Bayes, MLP).
- Train each model using the training set and evaluate its performance on the test set.
- Compute evaluation metrics such as accuracy, precision, recall, and F1 score.

Model Performance Comparison

- Collect performance metrics for each model and store them in a DataFrame.
- Save the performance results to a CSV file for further analysis.

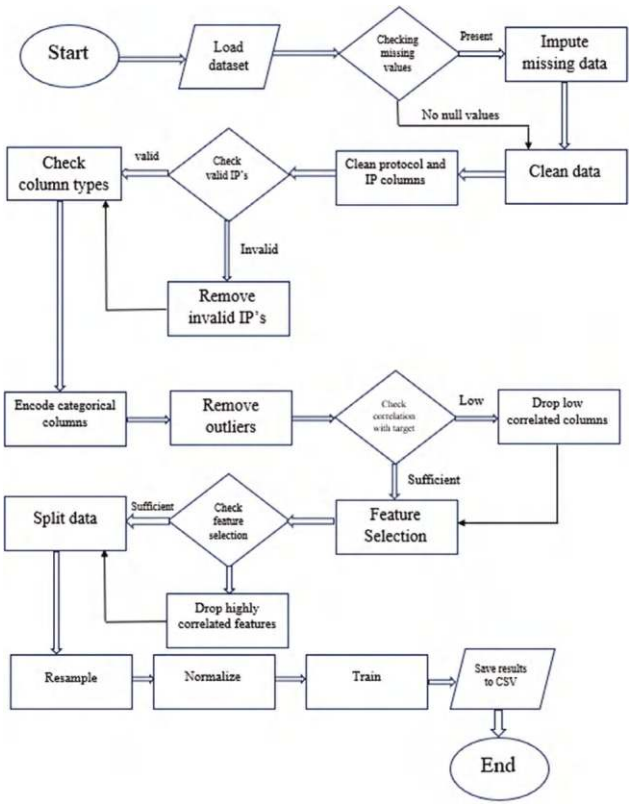

Fig. 105.3 Flowchart of algorithm

Source: Authors

6. Results

The results show that Gradient Boosting is the best model, achieving the highest accuracy (97.4%) with strong precision, recall, and F1 scores, making it the most reliable choice for this task. Bagging and Random Forest are also strong alternatives, performing well across metrics. Other models like Decision Tree and MLP perform reasonably, while Naive Bayes, AdaBoost, LDA, and QDA show much lower accuracy (59-67%) and may not be suitable. Overall, Gradient Boosting stands out as the ideal model for this classification problem.

Below is the Table 105.2 showing the Accuracy, Precision, Recall, and F1 scores for each model, along with a graph Fig. 105.1 for visual comparison.

7. Conclusion and Future Work

In this research, we successfully explored various machine learning models to predict our target variable. Among all the models evaluated, Gradient Boosting demonstrated exceptional performance, achieving an accuracy of 0.974. This outcome highlights the effectiveness of our approach and the significance of the selected features in enhancing model performance.

Looking ahead, there are opportunities to further improve this accuracy through advanced techniques such as feature engineering, hyperparameter tuning, and the exploration of alternative models. Additionally, expanding the dataset and evaluating the model in real-world scenarios could provide further insights into its applicability and robustness. By

Table 105.1 Model scores for accuracy, precision, recall, and F1

Model	Accuracy	Precision	Recall	F1 Score
MLP	0.933602847	0.94244188	0.933602847	0.934855974
Decision Tree	0.945350149	0.947869773	0.945350149	0.946203931
Random Forest	0.94710785	0.947280435	0.94710785	0.947189768
Bagging	0.959279929	0.95949722	0.959279929	0.959372051
Extra Tree	0.919643773	0.919757292	0.919643773	0.919497884
Naive Bayes	0.677901305	0.675429728	0.677901305	0.675962765
AdaBoost	0.599786146	0.474496341	0.599786146	0.521314376
Gradient Boosting	0.974249681	0.976864178	0.974249681	0.974554585
LDA	0.611313735	0.60210885	0.611313735	0.601527882
QDA	0.670138126	0.623720866	0.670138126	0.635371313

Source: Authors

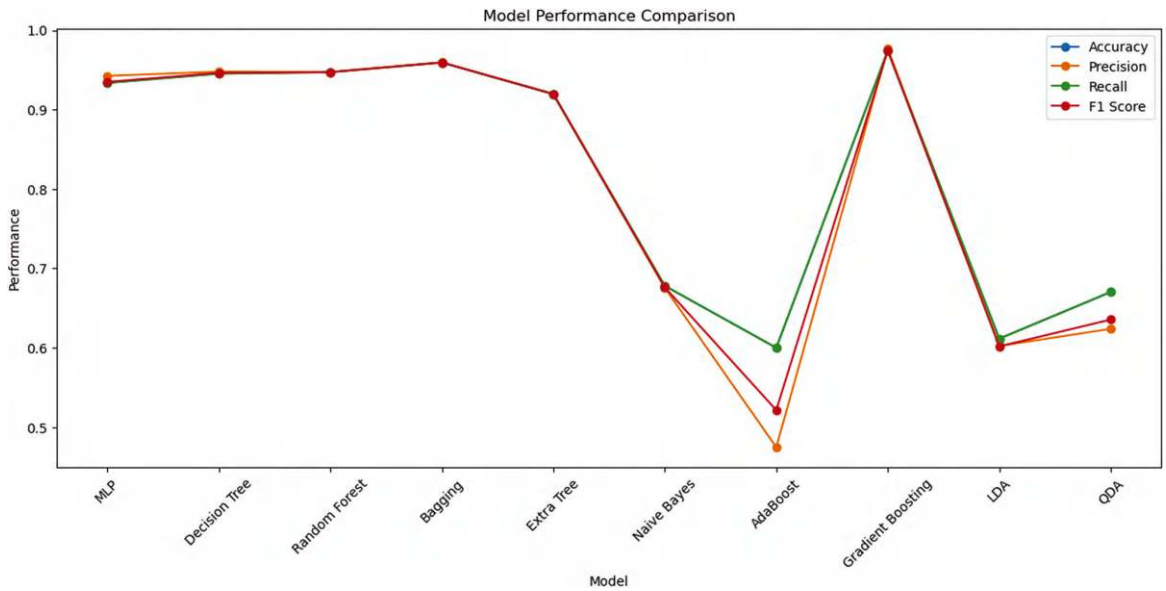

Fig. 105.4 Model scores distribution for accuracy, precision, recall, and F1

Source: Authors

exploring these options, we can improve our model's performance and gain a better understanding of machine learning in this area.

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State of Health Forecasting for Lithium-Ion Batteries Using Data-Driven Methods in Sustainable Transportation

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Abstract: Lithium-ion batteries are essential to modern technology in the growing adoption of electric vehicles (EVs) for sustainable transportation. Accurate prediction of the monitoring the State of Health (SOH) of these batteries is crucial for optimizing battery performance, minimizing maintenance costs, and ensuring vehicle safety. Traditional SOH estimation methods often rely on precise measurements and have limitations in terms of accuracy, scalability, and cost-effectiveness. This paper presents a data-driven approach leveraging Long Short-Term Memory (LSTM) networks to forecast the SOH of rechargeable lithium-ion cells in hybrid vehicles. The proposed system leverages historical battery data, including temperature, charge/discharge cycles, and other relevant measurements, to train the LSTM model. By capturing complex battery behavior and long-term dependencies, the LSTM-based approach aims to provide accurate and timely SOH predictions. The system architecture incorporates data preprocessing, model training, and real-time implementation, with a focus on scalability and adaptability to different battery types and configurations. The effectiveness of the proposed system is assessed using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The successful implementation of this data-driven SOH forecasting system has the potential to optimize battery usage, extend battery life, reduce operational costs, and supporting broader sustainability efforts. and safety of electric and hybrid vehicles. Future research directions include the integration of hybrid models, federated learning, and addressing challenges related to data availability, model interpretability, and validation in real-world scenarios.

Keywords: Electric vehicles, Sustainable transportation, Reduce carbon emissions, Long short term memory (LSTM), Optimized battery performance, State of health

1. Introduction

As these Electric Vehicles continues to grow in high demand, it is most necessary for us to forecast health of Lithium ion batteries. These batteries are highly valued due to their long life span, high energy density and its efficiency. However the performance of Electric vehicles mainly depends on Lithium ion battery, it is crucial for us to

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maintain a stable battery health and observing its remaining life span of battery. Accurate SOH forecasting is critical for optimizing battery usage, minimizing maintenance costs, and ensuring the safety and longevity of electric vehicles.

By examining big datasets and uncovering hidden patterns, machine learning is a potential technique for calculating SoH.

In this paper, we used historical battery performance and charge cycle data to construct an LSTM model for predicting the improved health of lithium ion batteries. The aim is to design predictive models that can not only track battery degradation over time but also provide accurate and timely SOH forecasts.

The successful implementation of this project could lead to several benefits, including efficient battery management systems, cost effective, and improvement in vehicle safety. Further implementation of this project leads to early prediction of battery failures which contributes to extended life span of batteries ensuring more vehicle safety.

2. Contributions

In this paper, Machine Learning based forecasting Lithium-ion battery state of health in hybrid vehicles the contributions include the following:

- Data Driven Estimation of SOH
- High Accuracy and Efficiency
- Cost Effective
- Optimizing performance of battery
- Large scale usage
- Sustainability &safe Transportation
- No physical/hardware requirements

3. Literature Review

Based upon some literature survey We have gained some knowledge from some journals to work on this project. We have collected many journals that are applicable to our project that will be more useful to us in the preparation part of our design. Here is the appraisal of the journals that we have gone through.

From the last decade, the usage of Electric Vehicles has a rapid growth. Since this, the Lithium ion batteries are widely recognized for its advantages and well known for hybrid vehicles. However it has gradual degradation of its performance due to various reasons, the LI batteries remains as a significant challenge for vehicle's safety. Accurate prediction of battery SOH is crucial for optimizing battery performance.

3.1 Traditional SOH Estimation Methods

Before emergence of Machine Learning approaches the traditional methods were high in range. These methods often require precise measurements such as capacity, battery condition etc.. In these traditional methods there are less accurate predictions and also high cost with low scalability.

Irrespective of prediction results Traditional methods ensures high complexity in maintaining proper data which leads to difficulty in obtaining predictions for real world problems. It also not appropriate method for large datasets. Since this reason the Machine Learning approaches overcomes the usage of these traditional methods.

3.2 Data Driven SOH Prediction

Data Driven methods delivers more key features and benefits than traditional methods. Machine Learning approaches also supports data driven SOH Prediction. They allow for the use of historical battery data, which is often readily available from vehicle operations, making it possible to build accurate models without the need for physical measurements. These data driven methods not only supports a single type of battery it can works with various kinds of batteries. These methods secures continuous performance with the availability of data through retraining.

The main challenge we should focus while training the model is to make sure about the quality and quantity of the data that we input for the model. Li et al emphasize the importance of diverse datasets that is having a wide range of operational conditions to ensure the generalization of the model across different use cases. The techniques like feature selection, setting up of environment conditions are employed to enhance the performance and evaluation of the model.

3.3 Hybrid Models

Hybrid Models combines the Machine Learning models with electro chemical models which gains attention. Hu et al propose a hybrid method which is used to train machine learning models for improved SOH prediction in hybrid vehicles. Hybrid models have predictive power of data driven approaches. The use of federated learning, where decentralized data is used to train models without compromising data privacy, could further expand the scalability of ML-based SOH estimation across industries.

Finally, this literature review includes the different approaches for predicting SOH of Lithium-ion batteries in hybrid vehicles. Among them, the advantages of Long Short Term Memory algorithm makes us to select this approach for the better accurate results. It also outlines the

key advancements in both traditional and machine learning approaches of SOH estimation, showcasing the growing importance of data-driven models. It also highlights emerging trends and future directions for battery health forecasting.

4. Challenges

4.1 Availability and Quality of Data

For effective results the quality of the data should be high and it should be labeled. Accessing large dataset among all battery types may be difficult. Batteries which can be used in different environments may have different degradation levels makes it more challenging. It leads to inconsistency in data.

4.2 Model Accuracy

The accuracy of the model may be reduced due to the ML model which overfit to some datasets. The accuracy may also depends on the type of battery that can be used.

4.3 Complex Battery Behavior

Degradation levels of battery is often nonlinear and complex affected by factors like temperature, voltage, life cycle etc this are interdependent which makes complex for training the model.

4.4 Real-Time Implementation

Machine learning models may require significant high computational power which can pose challenges for the real time SOH prediction in hybrid vehicles. Integration of ML models with BMS is a highly technical challenge.

4.5 Uncertainty in Predictions

The primary aim of the machine learning is to deal with certain and consistent high accurate prediction as the outcome. The prediction of SOH of battery inherits many uncertainties especially with large datasets. Accurately estimating the SOH is the critical to avoid erroneous predictions.

4.6 Model Interpretability

The internal working of Long Short Term Memory is not easily interpretable. When predicting battery SOH, LSTM models relies on intricate relationships between features but these are not directly accessible. When LSTM model provides predictions with less accuracy there is inefficient battery management.

1) **Validation and Testing**

   Machine learning models can be developed using data generated through simulations, enabling flexible training, real-world conditions introduce factors that simulations may not account for, leading to discrepancies between predicted and actual SOH Testing machine learning models on real-world battery systems over long periods to validate their predictions is time-consuming and expensive.

2) **Sustainability and Life cycle Management**

   Predicting when a battery will reach the end of its useful life with high accuracy remains a challenge, as battery degradation accelerates unpredictably in its final stages.

   Addressing these challenges will be crucial for successfully implementing machine learning models in real-world battery state of health forecasting and management.

5. Proposed System

To address all the mentioned challenges a proposed system is designed. The goal of proposed system is to enhance the prediction of SOH for Lithium ion batteries in hybrid vehicles based on machine learning models(LSTM). The system aims to increase accuracy of the predictions in real time applications. All the inputs that required are collected from Battery Management System of the vehicle. Initially, the data will be preprocessed and normalized for ensuring quality of the data. The predictions are developed based on historical data.

The reason behind choosing LSTM is its ability to hold time series data and acquiring long term dependencies which makes ideal for SOH of battery. The system is trained based on LSTM model which encloses labeled datasets including information of battery SOH. Its performance is calculated on the metrics Mean Absolute Error(MAE) and Root Mean Square Error(RMSE). this will be ensure the reliable predictions that can be used in real world applications.

By continuously monitoring the battery SOH, the system will alert the vehicle when the degradation level is high and there is no more battery energy. It notifies the users when the battery level is below critical threshold value which allows to take preventive measures. The system will also ensures the Remaining useful life (RUL) of battery which offers valuable perceptions to battery replacement. This approach will help to extend the battery life and reduce operational costs.

Finally, the proposed system is designed to be scalable and adaptable for different type of batteries systems and configurations. The updates will ensure the battery to remain optimized always which will increase the battery performance.

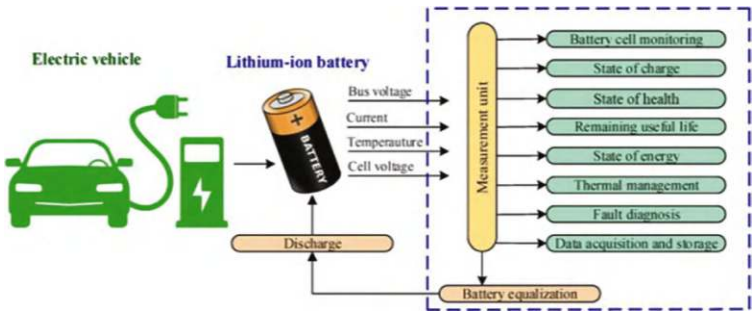

Fig. 106.1 Lithium-ion battery system architecture for electric vehicles [19]

6. System Architecture

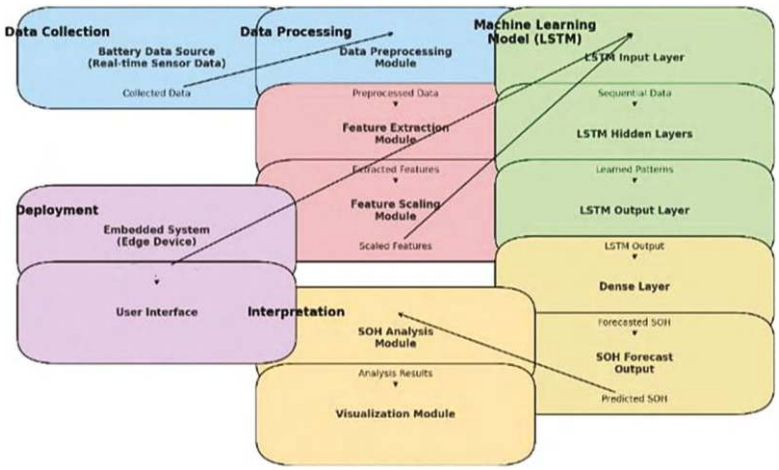

Fig. 106.2 Workflow for SoH prediction using LSTM models

Source: Author

7. Results

The input data i.e the dataset has been collected from NASA Prognostic Center, Experiments on Li-ion Batteries. This dataset contains the historical data based on which the predictions are made. The dataset contains the values of voltage, charge, SoH, temperature etc

7.1 Analyzing and Plotting State of Health (SoH) Using 7 Li-ion Battery

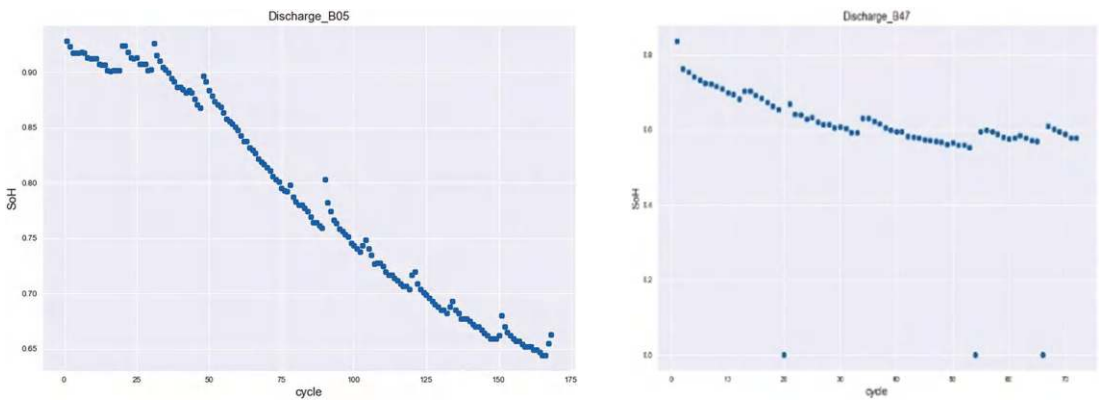

Fig. 106.3 SoH degradation with charging cycles

Source: Author

7.2 Removing Outliers with Quantile

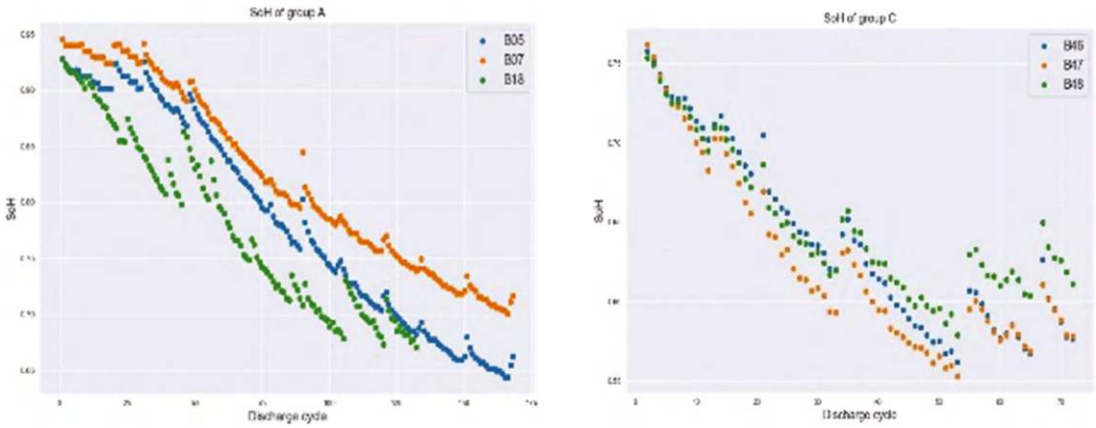

Fig. 106.4 Removal of outliers from dataset

Source: Author

7.3 Applying Linear Regression on the Dataset

- **Begin at the halfway point of the cycle**

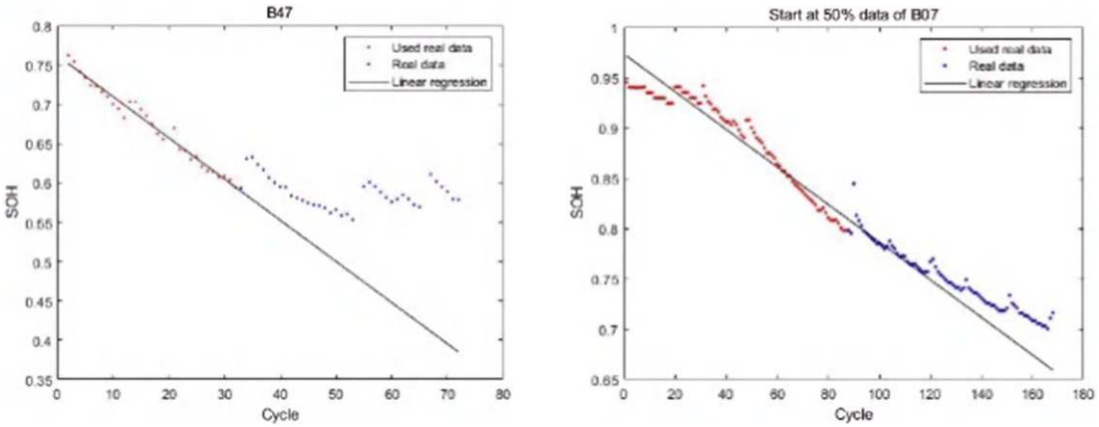

Fig. 106.5 SoH vs charging cycle using linear regression (50% data)

Source: Author

- **Begin at 70 percent of the cycle**

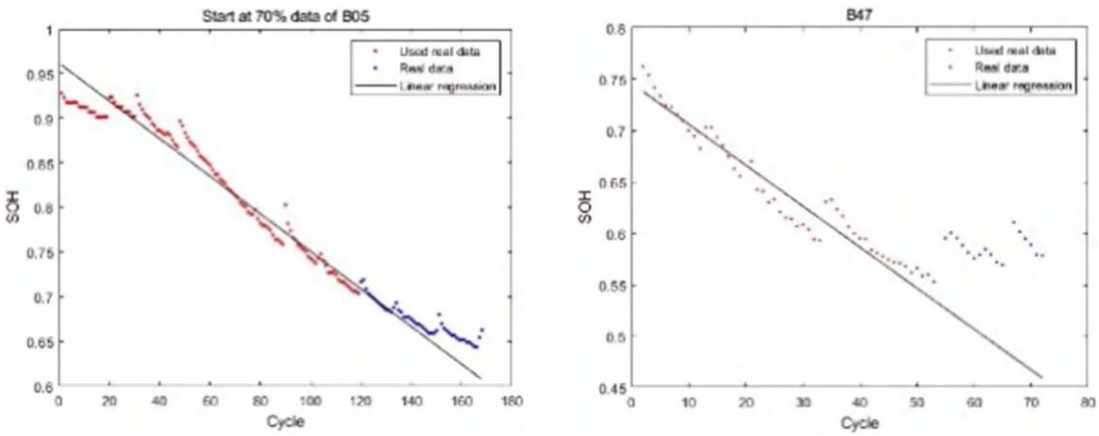

Fig. 106.6 SoH vs charging cycle using linear regression (70% data)

Source: Author

7.4 Applying Long Short Term Memory Algorithm on the dataset

- **Begin at the halfway point of the cycle**

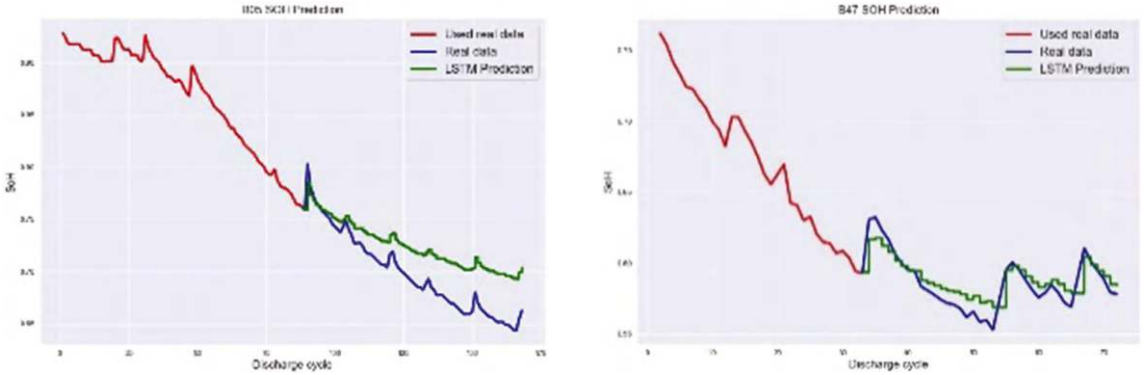

Fig. 106.7 SoH vs discharge cycle using LSTM (50% data)

Source: Author

- **Begin at 70 percent of the cycle**

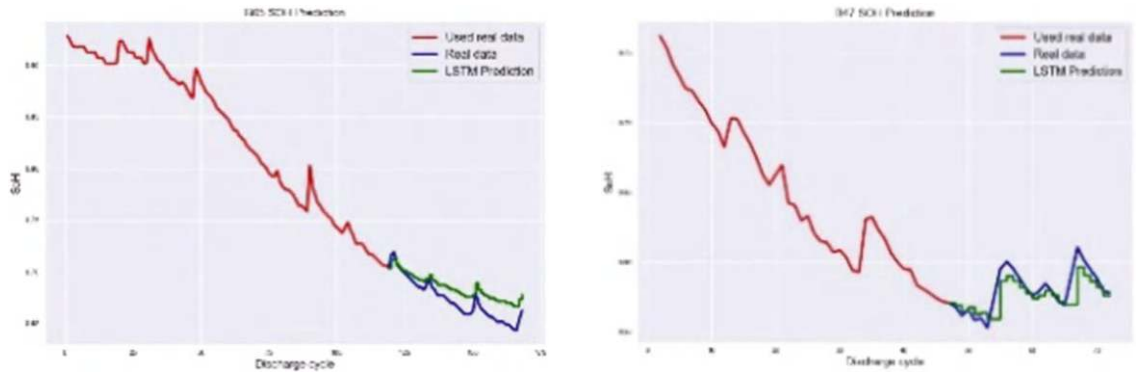

Fig. 106.8 SoH vs discharge cycle using LSTM (70% data)

Source: Author

Observed Results

RMSE

	A						B				C					
	B05		B07		B18		B33		B34		B46		B47		B48	
	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%
Linear regression	0.1599	0.1431	0.1190	0.1315	0.1389	0.1231	0.0303	0.0351	0.0255	0.0273	0.0654	0.0385	0.1129	0.0543	0.0973	0.0470
LSTM	0.030	0.014	0.026	0.015	0.056	0.009	0.024	0.016	0.008	0.011	0.018	0.007	0.008	0.006	0.009	0.009

MAE

	A						B				C					
	B05		B07		B18		B33		B34		B46		B47		B48	
	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%
Linear regression	0.1595	0.0934	0.0777	0.1307	0.1380	0.0803	0.0258	0.0202	0.0196	0.0154	0.0524	0.0207	0.0979	0.0314	0.0839	0.0266
LSTM	0.026	0.012	0.023	0.013	0.053	0.007	0.020	0.012	0.006	0.008	0.016	0.005	0.007	0.005	0.008	0.007

Fig. 106.9 RMSE, MAE values for linear regression and LSTM model

Source: Author

8. Conclusion

This paper proposes a machine learning system to forecast the State of Health (SOH) of lithium-ion batteries in hybrid vehicles. Utilizing the capabilities of Long Short-Term Memory (LSTM) networks, the system accurately predicts battery degradation based on both real-time and historical data. This idealogy enhance the accuracy of the prediction compared to traditional battery management system by including complex time series data and large datasets. Through this prediction the system aims to prolong the battery life and also optimization.

The proposed solution can be effortlessly integrated with existing vehicle systems and scaled across different battery types and configurations, making it highly flexible to a vast range of hybrid and electric vehicles. Over all, the machine learning approach can influence advantages and improvements in BMS. As battery technologies and machine learning models continue to evolve, the system can be further improved to better support the evolving needs of electric and hybrid vehicle collections, ensuring it keeps flow with their growing demands.

9. Declaration

I hereby declare that the paper report named "Data-Driven State of Health Forecasting for Lithium-Ion Batteries in Sustainable Transportation" is my original work that has been carried out under assistance of Dr.V.S.NARESH sir. The content of this report is based on my research and complete understanding of the project and subject, using various literature sources, tools, and techniques.

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Effective Disaster Management in India Using Twitter Data Analytics

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Abstract: Natural disasters in India have resulted in significant loss of lives and properties. The existing disaster management system has several drawbacks, including untimely warning systems and inadequate supervision. This study proposes using Twitter data to communicate information on natural calamities and hasten relief operations. The objectives of this study include identifying key entities in disaster management and developing systems for early prediction of natural disasters. The proposed system utilizes big data analytics and Twitter API to retrieve tweets and analyse data. The study aims to develop a database for natural disasters in India and estimate the social impact of natural hazards. The proposed system uses Twitter data to provide location information, enabling disaster management teams to respond more effectively. The system has a narrower gap between the occurrence of a natural disaster and the implementation of remedial measures. The study recommends adopting the proposed system for reporting natural disasters and suggests future work to improve the system's accuracy. The proposed system can improve response time and effectiveness for disaster management efforts.

Keywords: Natural disasters, Disaster management, Twitter data, Big data analytics, Early prediction, Relief operations, Social media, R-studio, R packages, Data analysis

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1. Introduction

Natural hazards are events triggered by the Earth's natural forces, including earthquakes, cyclones, hurricanes, floods, volcanic eruptions, and tsunamis. These events can lead to significant loss of life and substantial disruption to communities. Defined by their atmospheric or geological origins, natural hazards result in social upheaval, extensive damage, and fatalities. Estimates suggest that the world experiences between 500 and 1,000 natural hazards each year.

Social media, particularly Twitter, has become a crucial source of real-time information during crises. Its vast user base and user-friendly interface make it an ideal platform for monitoring public sentiment, emotions, and reactions after disasters. This information enables emergency responders, governments, and humanitarian organizations to prioritize needs and allocate resources more effectively [1].

During catastrophic events, millions of individuals turn to social media platforms to stay informed and share their experiences and insights. Research has shown that social media data can serve as a valuable resource for various humanitarian goals, including "crisis monitoring"

[2]. A significant amount of information shared on social media platforms is not accessible through traditional news outlets such as television and print media. These findings suggest that leveraging social media content during disasters has the potential to facilitate rapid response, minimize damage, and improve emergency preparedness strategies [3].

Social media can provide valuable information for disaster response teams, but handling the large volume and fast pace of data can be challenging [4]. Disaster management consists of three main phases: preparedness and early warning, impact assessment and response, and mitigation along with modeling risk and vulnerability [5]. Data collected during these phases' falls into two categories: user-generated content (i.e., posts and messages from individuals on social media), and visual data (i.e., images and videos from sources like satellites and drones. Analyzing this data effectively is essential for managing disaster impacts. Big data analytics can help process these datasets quickly, ensuring a timely response in all disaster management phases [6].

An analysis of several significant studies that contribute to the field of disaster response research. The studies span various datasets, techniques, and results, showcasing the diversity of approaches in analyzing social media data for disaster management. Pranckevičius et al [7] utilized Amazon Reviews related to unlocked mobile phones, employing multiple classification techniques, including Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Logistic Regression (LR). Their findings indicated that Logistic Regression achieved the highest classification accuracy at 56%, highlighting the potential of traditional machine learning methods in processing user-generated content.

In another study, Ramadhani et al [8] focused on analyzing tweets, using a dataset of 2,000 tweets for both training and testing. They applied deep learning techniques, specifically an MLP, which yielded a notable accuracy of 75%. This demonstrates the efficacy of deep learning in extracting meaningful insights from social media data. Shandilya et al. (2019) [9] conducted a comparative analysis using Twitter data from the Italy and Nepal earthquakes. They implemented both unsupervised and supervised techniques, combining pattern matching, Information Retrieval, Gradient Boosted Decision Trees, SVM, Naive Bayes, and CNN. Their results indicated that the unsupervised methods achieved the highest F-scores for the Nepal dataset, while supervised methods excelled for the Italy dataset, showcasing the effectiveness of combining different approaches in analyzing social media data.

Numerous researchers have leveraged Twitter to extract crisis-relevant information during natural disasters by employing relevant keywords and geo-tagged tweets [10]. For instance, social media data analysis has been conducted during various natural disasters, including floods, earthquakes, and wildfires. Identifying the locations of information extracted from tweets is crucial for effective disaster and risk management. However, a significant limitation is that less than 1% of tweets are geo-tagged [11]. To address this limitation, researchers have employed a phased approach to examine how people respond to disasters at various stages of the event. Sentiment analysis has been used to determine whether social media content during disasters is positive, negative, or neutral [12].

Although earlier research on social media use during natural disasters offers valuable insights into social response and disaster management, sentiment analysis in conjunction with topic classification can yield more valuable information on social response and crisis management. To assist emergency response and aid organizations in making more informed decisions and optimizing resource allocation during disasters, this study seeks to advance the field of social media analytics. Specifically, it aims to develop a sophisticated sentiment analysis model that is tailored to Twitter data within the context of disaster management. Twitter has become an essential tool for disaster response and management, providing a platform

for real-time information sharing, communication, and coordination [13, 14]. This model will enhance the ability of organizations to interpret public sentiment and respond effectively in crises, thereby improving overall disaster response efforts [15].

Based on social media platforms, particularly Twitter, have become vital sources of information during crises, offering real-time updates and user-generated content. This study aims to develop a sophisticated sentiment analysis model tailored to Twitter data within the context of disaster management. The proposed system has the potential to improve the response time and effectiveness of disaster management efforts. This study aims to identify key entities in disaster management to improve response strategies, develop early prediction systems for natural disasters, and estimate the social impact of such events. Additionally, it plans to create a comprehensive database for natural disasters in India and utilize Twitter data for location information to enhance disaster response efforts. By achieving these objectives, the study seeks to improve disaster management outcomes significantly.

2. Methodology of Proposed System

The proposed system for Twitter analysis is designed to collect, process, and analyze Twitter data to gain insights into natural disasters. The system consists of seven steps, which are shown below.

1. **Creation of Twitter Application:** Begin by creating a Twitter application to obtain the necessary API keys and access tokens. This involves registering the application on the Twitter Developer website, which will allow you to access Twitter's API.
2. **Twitter API Code Execution through R-Studio:** Utilize R-Studio to execute the Twitter API code. First, ensure that you have installed the required R packages, such as Twitter and ROAuth. Then, use the R console to run the Twitter search API code to interact with the Twitter data.
3. **Import Tweets through Twitter API:** Employ the searchTwitter() function to retrieve tweets that are based on a specific keyword. Focus on retrieving the latest tweets related to the area of interest. After collecting the tweets, convert the list of tweets into a data frame (DF) and subsequently save it in a .csv format file for further analysis.
4. **Standardizing the Data:** Apply functions to convert the collected tweets into a uniform format that is useful for analysis. This includes removing extra symbols and characters that do not contribute meaningful information to the tweets. Standardizing the data helps reduce complexity and prepares it for classification.
5. **Classification of the Data:** Conduct sentiment analysis by calculating the combinations of words present in the tweets. Download and save a word list to your working directory that will be used for sentiment scoring. Additionally, utilize packages such as dplyr and stringr to manipulate strings effectively during the sentiment analysis process.
6. **Getting Scores:** Assign scores to each individual tweet by using the sentiment function. This involves comparing the words in the tweets against the previously compiled word list to generate a sentiment score that reflects the overall tone of the tweet.
7. **Establishing R Maps to View Results:** Finally, use R packages such as ggplot2 and RColorBrewer to create visual maps that display the results of your analysis. This step is crucial for interpreting the data in a meaningful way, allowing stakeholders to visualize the public sentiment and response during disaster situations.

The Twitter sentiment analysis algorithm is a 7-step process that takes in Twitter data as input and outputs a sentiment score for each tweet. The algorithm can be represented as follows:

Input: Twitter data (tweets)

Def twitter_sentiment_analysis (tweets):

Step 1: Data Pre-processing: tweets = [preprocess_tweet (tweet) for tweet in tweets]

Step 2: Feature Extraction: features = [extract_ features(tweet) for tweet in tweets]

Step 3: Sentiment Analysis: sentiment_scores = [calculate_ sentiment_score (tweet) for tweet in tweets]

Step 4: Classification: classifications = [classify_ tweet(tweet) for tweet in tweets]

Step 5: Score Calculation: scores = [calculate_score(tweet) for tweet in tweets]

Step 6: Visualization: visualize_results(scores)

Step 7: Output: return scores, classifications

3. Tools and Libraries

The architecture of the Twitter sentiment analysis system can be represented as follows:

- **Twitter API:** The Twitter API is used to collect tweets based on a specific keyword or hashtag.
- **R-Studio:** R-Studio is used to execute the Twitter API code and collect tweets.

- **R-Packages:** R-Packages such as TwitteR, ROAuth, plyr, stringr, ggplot2, and RColorBrewer are used to process and analyze the tweets.
- **Database:** A database is used to store the collected tweets and sentiment analysis results.
- **Sentiment Analysis Module:** The sentiment analysis module is used to analyze the tweets and calculate the sentiment scores.
- **Visualization Module:** The visualization module is used to visualize the sentiment analysis results.

4. Result Analysis

Visualizing public opinion on natural disasters using Twitter data and R involves several steps. First, you need to collect Twitter data related to natural disasters using the Twitter API and R packages such as TwitteR and ROAuth. Then, you need to preprocess the tweets by removing stop words, punctuation, and converting all text to lower case. The process begins with identifying relevant keywords related to natural disasters, such as "flood," "earthquake," "disaster," and specific geographic locations (e.g., "India"). Using the Twitter API, developers can execute a search query to fetch the latest tweets containing these keywords. This can be done using the search_tweets function, which allows for filtering tweets based on various parameters like date, language, and geolocation. Once the tweets are retrieved, they are typically in a raw JSON format. This data includes various attributes such as: Tweet text, Creation date, User information (e.g., screen name, user ID), Retweet status, Geographic coordinates (longitude and latitude) if available. The relevant attributes are extracted and organized into a structured format, commonly a DataFrame (DF) using libraries like pandas in Python.

After structuring the data, it is common practice to save it in a CSV (Comma-Separated Values) format. This format is widely used for data analysis and can be easily imported into various data analysis tools and software. The conversion can be done using the to_csv() method provided by the pandas library, which allows for specifying the output file name, delimiter, and other parameters. After that, you can perform sentiment analysis on the tweets using R packages such as sentiment and syuzhet. This structured approach allows researchers and analysts to effectively study the impact of natural disasters through public sentiment and information shared on social media.

The tables (Table 107.1 and Table 107.2) provide a clear and organized view of the geographic coordinates of disasters and the corresponding tweets, facilitating better understanding and analysis.

Table 107.1 Natural disasters in india imported tweets data frame

Sl. No	Text	Created	Status Source	Screen Name	Tweet Count	Retweeted
1	RT @alertnetclimate: India's "Diamond City" finds ways to keep its sparkle in the face of economic shocks and	03-05-2017 15:29	Twitter for Android	naman climate	6	TRUE
2	Morning Update	13 Dead in Java Flash Floods; India Postpones May 25 Kashmir Polls Amid Fears of Uprising	03-05-2017 02:59	Mail Chimp	GlobalMom Info	56
3	Social Entrepreneurs help Chennai in India to better manage flooding	01-05-2017 13:22	Twitter Web Client	GWFWater	90	TRUE
4	Fire chief among 14 dead in devastating tornadoes, floods and thunderstorms	01-05-2017 13:12	dlvr.it	India_ travel_s	134	TRUE
5	@ndtv It has become imperative to nationalise all rivers in India what with drought/floods on one side	01-05-2017 10:44	Twitter for Android	sridhar 160954	56	TRUE
6	Incessant rains in Arunachal floods capital, causes landslides.	28-04-2017 16:31	NewsBoss. in	NewsBoss India	66	TRUE
7	Pharakka due to the flood situation in India is causing. Farakka because of the recent floods in Bihar state.	28-04-2017 15:44	Twitter Web Client	parvenbd	34	TRUE
8	Grand Idea. That will save lot of floods and water to many. In fact many Rivers in India can be liked and water	28-04-2017 14:04	Twitter for Android	greatgod 2014	152	TRUE
9	India - Evacuations After Floods in Meghalaya	27-04-2017 16:13	Twitter Web Client	Bagalue Sunab	88	TRUE
10	Incessant #Rains Arunachal #Floods #Capital:	27-04-2017 15:20	AsiaNews	AsiaNewsEye	163	TRUE

Table 107.2 Longitude and latitude information in india

SL. No	Longitude	Latitude
1	–70.25	52.99
2	67.39	32.66
3	82.18	32.51
4	67.88	31.8
5	88.96	23.7
6	98.86	32.9
7	–104.10	23.8
8	3.89	45.17
9	77.21	28.61
10	2.17	41.39
11	–0.13	51.51
12	73.02	26.24
13	78.96	20.59
14	–61.22	10.69
15	100.62	34.05
16	22.94	–30.56
17	78.49	17.39
18	95.33	28.06
19	78.96	20.59
20	78.96	20.59
21	78.07	20.66

The existing system for reporting natural disasters has several limitations. Firstly, it does not provide the location of the natural disaster-affected area, making it difficult for disaster management teams to respond effectively. Secondly, the existing system relies on print media and electronic media, which can be slow in reporting natural disasters. As a result, there is a significant gap between the occurrence of a natural disaster and the implementation of remedial measures. In contrast, the proposed system using Twitter has several advantages. Twitter is a faster medium for reporting natural disasters, allowing for quicker dissemination of information. Additionally, Twitter provides location information, enabling disaster management teams to respond more effectively. The proposed system has a narrower gap between the occurrence of a natural disaster and the implementation of remedial measures.

A graphical representation shown in Fig. 107.1 is the relation between impact efforts over time reveals that 50% of disasters occur within 2 hours, and the efforts to remedy them reach the affected area within 3 hours. In contrast, the existing system takes around 5 hours to respond to natural disasters, resulting in a significant gap between the disaster occurrence and remedial measures. Overall,

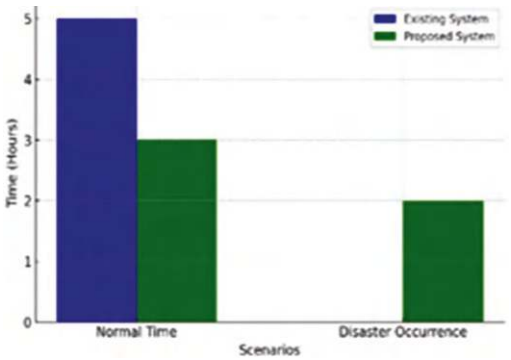

Fig. 107.1 Comparison of existing vs proposed systems timeline

the proposed system using Twitter is more effective than the existing system in reporting natural disasters and responding to them in a timely manner. The faster reporting and location information provided by Twitter enable disaster management teams to respond more effectively, reducing the gap between disaster occurrence and remedial measures.

5. Conclusion and Future Scope

The proposed system using Twitter for reporting natural disasters has several advantages over the existing system. One of the key benefits is that it provides location information, which enables disaster management teams to respond more effectively. This is particularly important in the immediate aftermath of a disaster, when every minute counts. By having access to accurate location information, disaster management teams can quickly identify the areas that need assistance and deploy resources accordingly.

Furthermore, the proposed system can reduce the gap between disaster occurrence and remedial measures, enabling disaster management teams to respond more effectively. This is because Twitter provides a platform for people to share information about natural disasters in real-time, which can help disaster management teams to identify the areas that need assistance and deploy resources accordingly. Overall, the proposed system using Twitter for reporting natural disasters has several advantages over the existing system, and it has the potential to improve the response time and effectiveness of disaster management efforts.

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Accurate Vitamin Deficiency Detection for Personalized Health Care Using Deep Learning

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Abstract: One important part of preventative healthcare is finding people with vitamin deficits. This job has made use of current machine learning models, although these models frequently fail to achieve the required degree of classification accuracy. Incorporating state-of-the-art neural network designs like MobileNet, Artificial Neural Networks (ANNs), and Convolutional Neural Networks (CNNs) is the goal of this suggested model to overcome this constraint and diagnose vitamin insufficiency. This app allows users to self-diagnose possible vitamin deficiencies without blood testing by evaluating photos of the nails, skin, and teeth. Feature extraction is an area where CNNs and MobileNet really shine, making them ideal for image-based jobs. They can learn to recognise key features in photos automatically, doing away with the requirement for human feature engineers. With this feature, the model can diagnose vitamin deficiencies more accurately and prescribe dietary changes more effectively.

Keywords: Vitamin deficiency, Diet recommendation, Healthcare, Real-time inference, MobileNet

1. Introduction

Vitamin deficiencies are a common yet often overlooked health issue that can seriously impact wellbeing. Symptoms can vary widely from fatigue and weakened immunity to more severe conditions due to low intake or poor absorption of essential vitamins. Quick and accurate detection of these deficiencies is key for proactive health care, but current methods like blood tests, though effective, are often slow, invasive, and inconvenient.

Emerging Machine Learning techniques offer a more accessible and efficient way to screen for vitamin deficiencies [1]. To overcome the shortcomings of conventional testing methods, this research delves into cutting-edge deep learning techniques, such as MobileNet, Convolutional Neural Networks (CNNs), and Artificial

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Neural Networks (ANNs). By leveraging the power of these neural networks, it may soon be possible to identify potential deficiencies without requiring blood samples, making the process simpler and more comfortable. Additionally, this approach includes tailored dietary guidance to help individuals meet their nutritional needs and counteract deficiencies. Integrating deep learning into health assessments is transforming our ability to manage and understand nutritional gaps, ultimately promoting better health and reducing the risks associated with vitamin deficiency. This article goes beyond identifying deficiencies, offering actionable food recommendations to support balanced nutrition and overall wellness [2].

2. Literature Review

T. K. Chaithanya, J. Gupta and M. S. Roobini, "Vitamin Deficiency Detection Using Neural Networks," the platform furnishes tailored dietary suggestions to tackle pinpointed inadequacies, thus alleviating health hazards linked with insufficient nourishment with accuracy of 83.5% [3].

Indian Tamil 'Micronutrient Deficiency Detection with Fingernail Images Using Deep Learning Techniques.' The article was published by Selvi, K., Thamilselvan, R., Aarthi, R., Priyadarsini, P.S., and Ranjani, T. By training a deep learning model with real-time photos and then validating it with sample photographs, the researchers were able to achieve an accuracy of around 94% [4].

K.Sneha Reddy et.al The forecast is shown utilizing a flagon web application that identifies lack of nutrient and prescribes the sort of food to be devoured in various blends. It gives by the perception that the precision is 98% for the fabricated model and considered informational index. Review midpoints 98%. The f1 score additionally midpoints 98% [5].

'Prediction of Vitamin D Deficiency in Older Adults: The Role of Machine Learning Models.' was the title of a 2022 study by John D. Sluyter, Yoshihiko Raita, Kohei Hasegawa, Ian R. Reid, Robert Scragg, and Carlos A. Camargo. I Results showed that ML models outperformed other methods across all thresholds, with an accuracy of almost 95%. [6]

3. Existing Methodology

This framework underlines a current technique that which was planned utilizing a portion of the algorithms of machine learning here this existed system isn't sufficient and furthermore it didn't perform accurately with the calculations that were utilized and grouping no longer doesn't depend fair and square of anticipated precision [7].

Disadvantages:

1. Less Accuracy.
2. Time consuming.
3. Lesser prediction.

4. Proposed Methodology

The proposed technique gives a way for identifying the lack of vitamins and providing a healthy food plan. In this system, it uses the methods of deep learning, like MobileNet, Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) to produce the result in an efficient manner with more accuracy.

4.1 Image-Based Assessment of Vitamin Deficiencies

Users can use mobile to give the pictures of their nails, skin and teeth. These photos are the main sources for identifying the probability of deficit vitamins [8].

4.2 Food Plan

To address the inadequacies discovered, the proposed system provides personalized dietary suggestions [9] [10]. It recommends foods high in vitamins that may be deficient, as well as quick and practical meal plans based on the user's dietary preferences and limits.

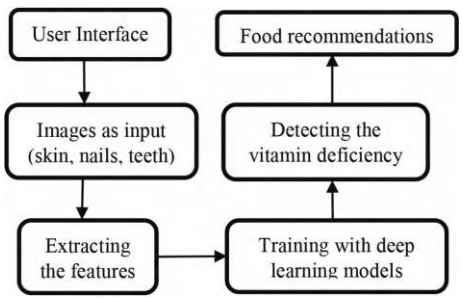

Fig. 108.1 Architecture of proposed system

4.3 Algorithms

CNN means "Convolutional Neural Network". This approach consists of algorithm for processing the images that are given as input [11]. Mainly in this procedure the pictures like skin, nails and teeth are taken from the users as input. So, this algorithm gives the clear-cut information about the expected data from the images.

CNN algorithm process on these images and extract the percentage or the probability of the deficit present in it. And so, by getting the probability it will check the number if it is having the probability more than 90% then it is said to be vitamin lacking in that respected user's body [12].

The below pictures resemble the symptoms of your respective body parts like skin if user is having a dry patches or flaky skin then the user is having vitamin B lacking and in the same way if they are having bleeding gums or oral issues suffering from vitamin C deficit and if the nails are becoming brittle like cracking symptoms, then they are deficit in B12 [13].

Fig. 108.2 Flaky skin

Fig. 108.3 Bleeding gums

Fig. 108.4 Brittle nails

MOBILENET is another algorithm used in the proposed system it is also used for performing image related process. This algorithm plays a vital role in enhancing the efficient extraction of vital image features while maintaining a compact model size. In the context of vitamin deficiency detection and the analysis of the images that are taken from the user, MobileNet proves to be an invaluable tool [14].

It mainly plays a key role from extraction of information from these images, including identifying skin conditions and other. This MobileNet supports all mobile applications. Its lightweight design allows it to be seamlessly integrated into a variety of platforms, including mobile phones, tablets, and small embedded devices.

ANN means "Artificial Neural Network". The role of ANN is to offer to the precise finding of vitamin deficiencies. ANN is a important component in this proposed solution and plays a vital role in the overall system [15].

4.4 Data Processing

ANN is used for data processing and analyzes large sets of health data, medical images, and other information. They assist in extracting required patterns and features from the data that are crucial for precision vitamin level monitoring.

4.5 Classification

ANNs can classify the input data into various categories, which, in this context, would involve identifying different vitamin deficiency states. For instance, ANN can categorize individuals into "deficient" or "non-deficient" based on their health data.

4.6 Personalized Health Care

ANN can also contribute to personalized health care by tailoring recommendations and interventions based on an individual's specific vitamin deficiency profile. This personalization ensures that the healthcare approach is optimized for each patient's unique needs [16].

4.7 Model Integration

ANNs can be integrated with other machine learning techniques, such as CNN (Convolutional Neural Networks) and MobileNet, to create a comprehensive system for vitamin deficiency detection. The collective efforts of these neural networks can provide a more accurate and robust solution [17].

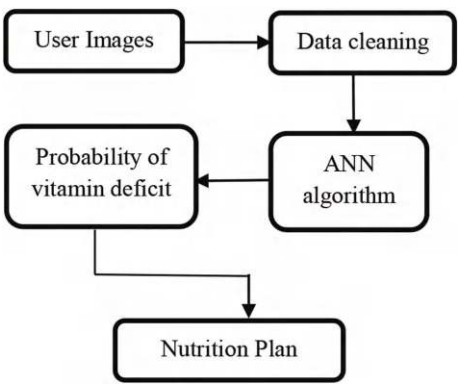

Fig. 108.5 Block diagram of ANN algorithm

5. Results

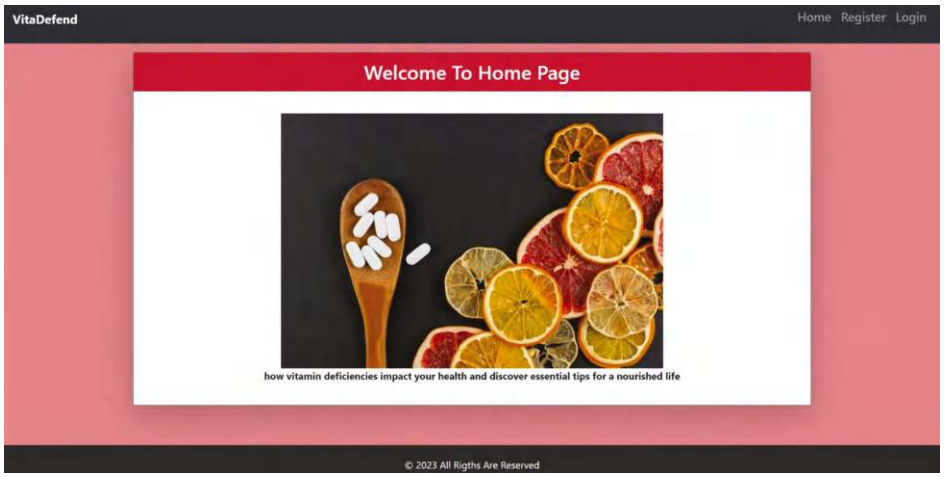

Fig. 108.6 Home page for the user

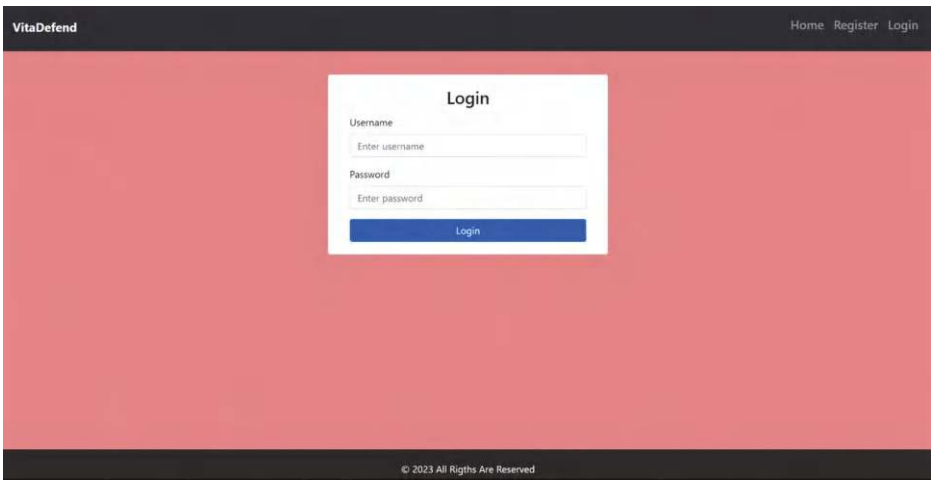

Fig. 108.7 Login page for the user

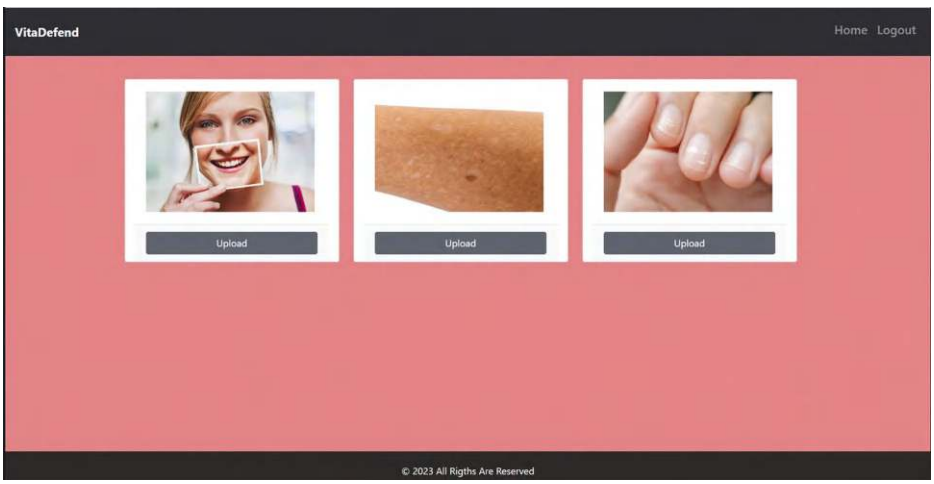

Fig. 108.8 Detecting the vitamin deficiency

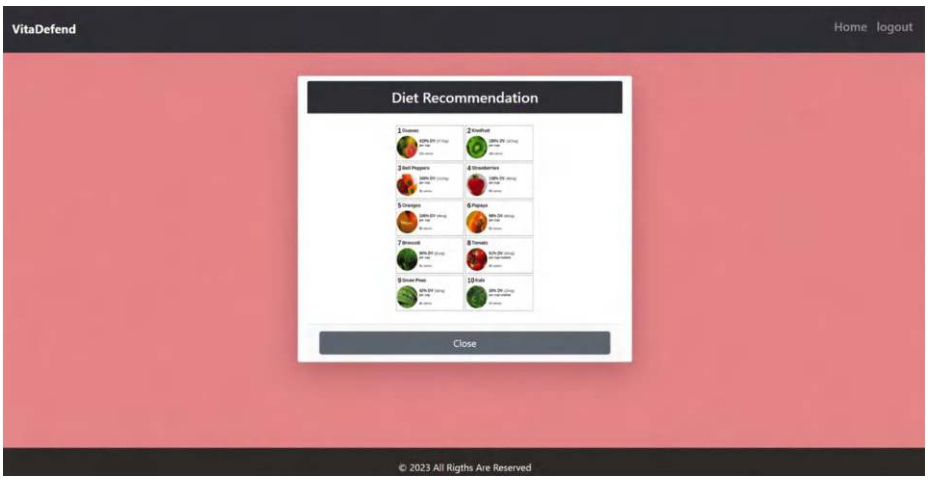

Fig. 108.9 Recommended diet plan

Accuracy:

Accuracy of Support Vector Machine 93.3333333333333

Table 108.1 Estimated values of accuracy for vitamin deficiency

Outcomes	Precision	Recall	FI_score	Support
0	1.00	0.90	0.95	21
1	0.82	1.00	0.90	9
Accuracy	0.85	1.25	0.93	30
Macro avg	0.91	0.95	0.93	30
Weighted avg	0.95	0.93	0.540.94	30

6. Conclusion and Future Scope

By collecting the data from the respective user. The accuracy and reliability of these models depend on the high-quality datasets, robust features. By including the algorithms like ANN, CNN and MobileNet the accuracy of this method will and will impact more effectively. ANN algorithm mainly focuses on well-defined and structured data. While CNN and MobileNet algorithms mainly focuses on images-based data for detecting process. So, this technique conclude that which vitamins are lacking in their body by finding the percentage of the deficiency of vitamins and providing food recommendation diet, based on their needed vitamin to maintain the user health respectively [18]. These algorithms are mainly useful in medical sector to give or to find the expected results.

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Weather Image Classification Using Ensemble Deep Learning Model

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Abstract: Turbid media like haze, smoke, fog, rain, and snow impair outdoor image data, affecting systems such as ADAS and vision-based surveillance. Defeathering, or removing weather effects from images, is vital to address this challenge. Accurate identification of weather conditions in images is essential, yet no existing model achieves consistently accurate predictions. This research proposes an ensemble deep learning model for recognizing hazy, rainy, and snowy conditions in images. The model assigns images to one of three weather categories or none (e.g., sunny). Using the Jehan Bhathena weather dataset for training, the ensemble model, combining VGG-19 and Inception V3, achieved 96.87% accuracy, outperforming individual models and demonstrating its effectiveness in extensive experiments.

Keywords: Jehanbhathena dataset, Weather image classification, Deweathering, Advanced driving assistance system, Vision assisted transportation

1. Introduction

Tropical cyclones (TCs), along with gales, rainstorms, and storm surges, are extreme weather phenomena causing significant damage in coastal areas. Meteorologists and warning organizations have made progress in studying atmospheric environments, particularly air-sea interactions, yet accurately estimating TC intensity under high wind speeds remains challenging due to poor representation of air-sea energy exchange. The upper ocean significantly influences TCs, necessitating focused research in this region to mitigate effects and improve forecasting performance. Statistical models often yield inaccurate predictions due to unstructured data, where missing or overlooked information hampers outcomes. Enhanced attention to such datasets is critical to improving weather predictions. According to the World Meteorological Organization (WMO), weather forecasting is increasingly vital for crisis management and risk reduction, though it remains complex. Small-scale convective weather events, in particular, pose significant challenges. Users face difficulty predicting weather by analyzing numerous parameters and

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cross-checking for severe weather warnings, complicating disaster preparedness.

Meteorological institutes worldwide aim to forecast extreme weather, such as heavy rainfall, in advance to mitigate disasters. Achieving this requires employing feature selection methods to eliminate irrelevant attributes, improving task efficiency and model accuracy. Clustering algorithms can classify sample datasets into groups, enabling recognition of patterns in input data. By addressing these challenges, meteorologists can enhance prediction accuracy and better prepare for climate changes and extreme weather events..

From the above Fig. 109.1, we can see several classes related to weather prediction. Almost most of the images are very complex to identify manually the type of weather occurrence and hence we try to develop the proposed application by using deep learning model to identify the weather occurrences from the input images.

Fig. 109.1 Represent the several classes of weather prediction

2. Literature Survey

Here, we mainly discuss about some important articles which are related to weather predictions and we are going to take some important articles into consideration and further extend our work.

Difficult Vision in Bad Weather

Authors: S.K. Nayar et.all [7] analyze weather effects like haze, fog, and rain on vision systems, improving performance under adverse conditions. They address outdoor challenges, including false alarms in video-based incident detection.

This paper [7] highlights the need for vision systems to handle haze, fog, rain, and snow, analyzing weather effects and improving performance. It also addresses false alarms in video-based incident detection for smart roads..

Authors: M. S. Shehata, et al.

This article [8] discusses video-based automated incident detection in intelligent transport systems, addressing challenges from environmental factors like shadows, snow, rain, brightness, and interactive deweathering using physical models.

Authors: S. G. Narasimhan, et al.

This article [9] highlights the importance of weather effects in photographs, emphasizing interactive deweathering across regions to reveal similarities.

4. Single image haze removal using dark channel prior.

Authors: K. He, J. Sun and X. Tang, et al.

This article [10] presents a single-image haze removal technique, enhancing blurry images and producing high-quality depth maps from non-hazed images.

2.1 Primitive Method

The existing system has no proper method to classify the weather images collected from satellite or high resolution cameras. As there is no method to classify the weather images they failed to label the weather images into several categories.

The limitations are as follows:

1) More time delay to find out the weather image and label it.
2) All the primitive approaches are manually done.
3) There is huge dimensionality problem when we try to classify the weather images.
4) Camera lighting conditions are more important in existing system to figure out the appropriate weather condition

2.2 Current System

This study leverages CNNs and deep neural networks for weather photo classification, achieving near-100% accuracy. Advantages include faster, more accurate classification and insights from reviewed papers employing data mining for improved categorization.

3. PROPOSED ALGORITHMS

In this section we try to discuss the proposed algorithms which are used for our proposed application. Here we try to check the performance of ensemble model which is formed by collecting two different deep learning models to achieve more accuracy. They are as follows:

1) VGG-19 Model
2) Inception V3 Model

Now let us discuss the overview.

3.1 Figure 1

The VGG-19 Model is used to predict weather types using satellite or high-resolution camera images. The model consists of 19 layers, including 16 convolution layers, 3 fully connected layers, 5 Maxpool layers, and 1 Softmax layer.

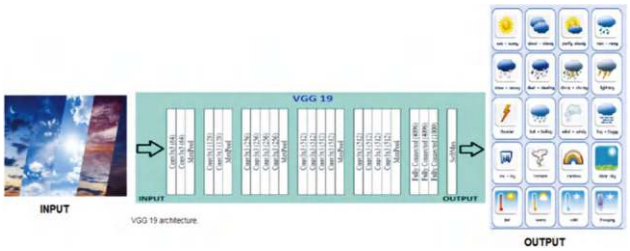

Fig. 109.2 Figure 1

Procedure:

1. VGG-19 receives a fixed-size (224x224) RGB weather image as input.
2. Mean RGB values of each pixel are calculated during preprocessing.
3. Kernels (3x3) with a stride of 1 pixel cover the entire image.
4. Spatial padding maintains the resolution of the input image.
5. Max pooling is performed over a 2x2 pixel window with stride 2.
6. Rectified Linear Unit (ReLU) enhances classification accuracy.
7. Three fully connected layers are implemented.

VGG-19 achieves only 63.56% accuracy on the weather dataset, proving insufficient for precise weather condition prediction.

3.2 Inception V3 Model

We use the VGG-19 and Inception V3 models to predict weather types from satellite or high-resolution images. The CNN is trained on labeled weather datasets to classify images accurately based on extracted features.

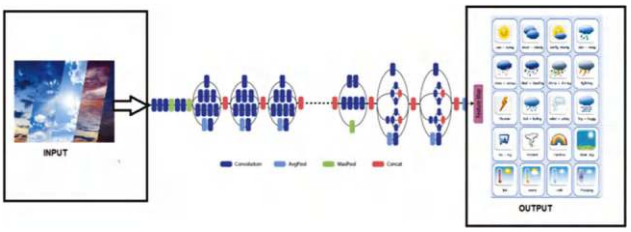

Fig. 109.3 Inception V3

The inception v3 model was launched in middle of 2015,which contains almost of forty two layers with very less error rate compared with other preceding models.

TYPE	PATCH / STRIDE SIZE	INPUT SIZE
Conv	3×3/2	299×299×3
Conv	3×3/1	149×149×32
Conv padded	3×3/1	147×147×32
Pool	3×3/2	147×147×64
Conv	3×3/1	73×73×64
Conv	3×3/2	71×71×80
Conv	3×3/1	35×35×192
3 × Inception	Module 1	35×35×288
5 × Inception	Module 2	17×17×768
2 × Inception	Module 3	8×8×1280
Pool	8 × 8	8 × 8 × 2048
Linear	Logits	1 × 1 × 2048
Softmax	Classifier	1 × 1 × 1000

Fig. 109.4 Inception poolings

Inception V3 applies Avgpool, Maxpool, and Concat operations to classify input weather images, achieving only 87.01% accuracy on the sample dataset. This limitation highlights its inability to predict weather conditions with higher accuracy. Motivated by this, I developed an Ensemble Deep Learning model combining multiple architectures to improve accuracy compared to individual models, enabling more precise weather classification from images.

3.3 Ensemble Deep Learning Model

Here by using the ensemble model, we try to integrate Inception V3 and VGG-19 and then check the efficiency of our model. The ensemble model greatly achieved an accuracy of **96.87** % by performing 86 epochs on weather dataset. Hence this clearly state that ensemble model can accurately predict the weather condition and label the images from sample weather image.

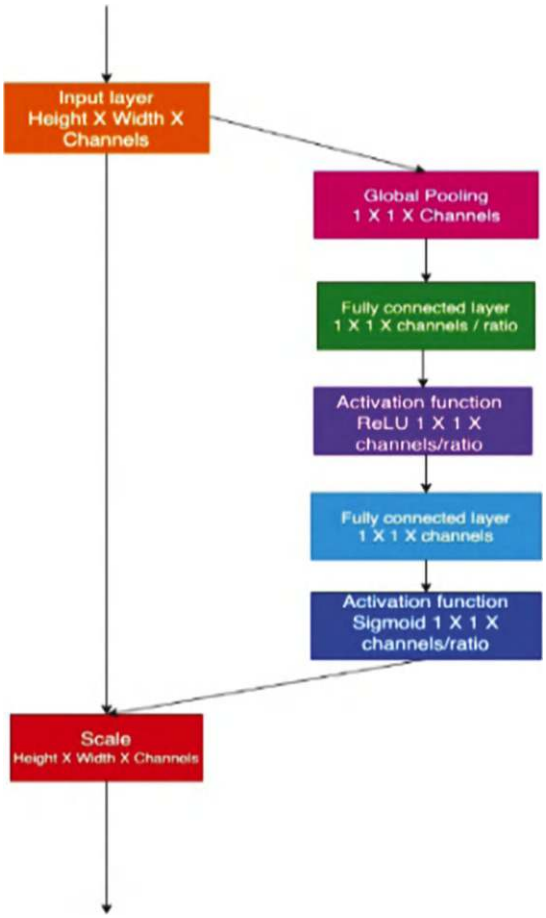

Fig. 109.5 Deep learning model

The ensemble model combines the two pre-trained classifiers and then applies the input image in order to predict the weather occurrences based on several weather classes present in the dataset.

4. Experimental Results

Here, we are using Python as programming language for implementing the application and for this we use google collab platform to store the information and execute the project.

4.1 Load Dataset

Here, we try to load the dataset from kaggle and the following data is downloaded.

!kaggle datasets download-d jehanbhathena/ weather-dataset

4.2 Unzip the Dataset

Here we can see dataset is unzipped in order to extract the information.

Display Category Names

Plot Sample Image from the Dataset

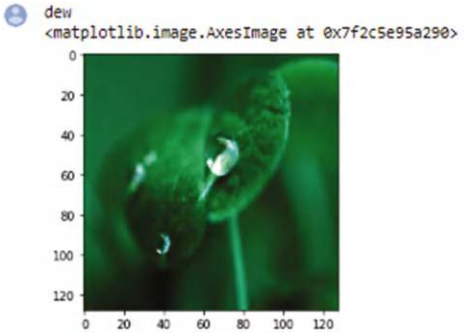

Fig. 109.6 Plot sample image

From the above window we can clearly see the sample image is related to some rainy season image.

Apply VGG-19 Model

Fig. 109.7 VGG-19 model

From the above window we can clearly see Vgg-19 Model is applied on Weather Image Dataset.

Apply Inception V3 Model

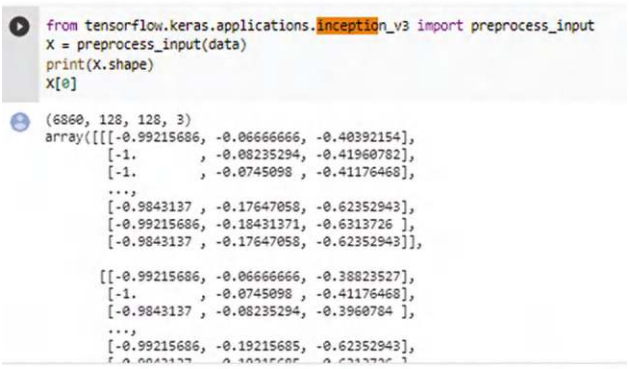

Fig. 109.8 Inception V3 model

From the above window we can clearly see Inception V3 Model is applied on Weather Images Dataset.

Performance of Ensemble Model

From the above window we can clearly see Ensemble Model is applied and now we can see the accuracy of our given model is 96.87 %.

Training and Testing Accuracy

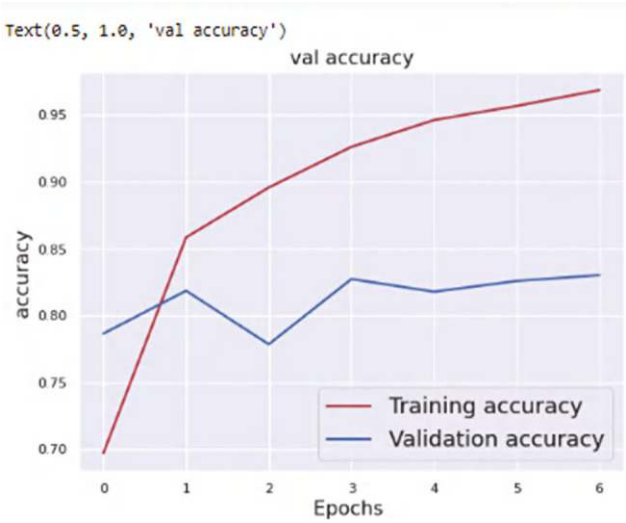

Fig. 109.9 Training and testing accuracy

From the above window we can clearly see Ensemble model is achieved an accuracy of 96.87 % at 86 epochs. We can see the same in validation graph corresponding to training accuracy

4.3 Test Input Image

Fig. 109.10 Test input image

From the above window we can see the user selected one sample weather image for the system and he is expecting the result.

5. Result Analysis

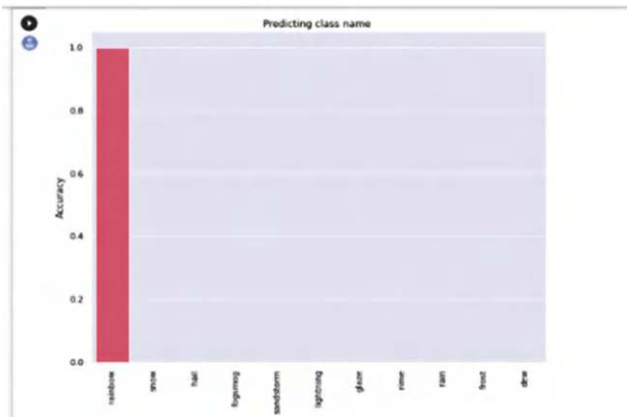

Fig. 109.11 Result analysis

From the above window we can see the user input image matched with Rainbow Category and the same we can see in above window.

6. Conclusion

Tropical cyclones have long posed challenges for meteorologists. While early machine learning models could predict weather from statistical data, they failed with image-based predictions. This limitation highlights the need for deep learning models capable of accurately analyzing weather images. Inspired by this, I developed an application using an ensemble deep learning model to improve the precision of weather image classification, surpassing individual CNN models. Future advancements will focus on enhancing accuracy while reducing time complexity, paving the way for more reliable and efficient weather prediction systems.

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Self-Attention-Based Classification of Satellite Images: Unlocking the Potential of Vision Transformers for Land Use Analysis

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Abstract: The study explores the use of Vision Transformers for identifying land locations using satellite images. The Vision Transformer (ViT) model, a novel design that varies from the traditional Convolutional Neural Networks (CNNs), is used in this study to classify satellite photos from the LandSat dataset. The ViT model makes use of the self-attention mechanism, which has proven widely effective in Natural Language Processing (NLP), to focus on different parts of the image. This might lead to a more effective land identification image classification method. By examining ViT's capacity to distinguish between various land use and land cover categories, this work contributes to the increasing cultivation field of studies on the agriculture application of transformer models in computer vision.

Keywords: Convolutional neural network, Natural language processing, Land location identification, Satellite images, Vision transformers

1. Introduction

Agriculture, a significant global economy contributor, is often traditional in India due to lack of knowledge, high costs, or ignorance of emerging technologies like IoT, Machine Learning, and Deep Learning, which can provide valuable insights. Satellite imagery and other technologies can be utilized to create remote sensing applications that assist farmers in monitoring and analyzing their farms' growth [1].The use of technologies in improving agriculture, focusing on monitoring farms by separating agricultural land from other types using unsupervised machine learning classification and grouping them into a single class. Soil is undervalued and underutilized, causing unsustainable land usage in globally, affecting life on land and changing landscapes due to human activities. Intensive farming, utilizing synthetic fertilizers and plant protection, is causing soil pressure, abandoning remote agricultural land, and affecting rural communities with limited economic prospects and younger generations moving to urban areas. Land use, particularly food production and resource extraction, is influenced by global market forces, such as demand for fodder, food, and bioenergy [2], [3], [4]. Droughts and production shortages affect global prices

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of staple foods like rice. Global policies aim to tackle land loss, pollution, and soil protection, but lack binding targets and commitments in some areas and fail to achieve their objectives in others. Land use is also linked to climate change, as soil contains carbon and nitrogen, which can be released into the atmosphere [5], [6].

Land encompasses the planet's surface, including continents and islands, and can be covered by various types of vegetation, such as grassland, cropland, and wetlands, and artificial surfaces like roads and buildings.Land that is either arable, planted with permanent crops, or used for pastures is referred to as agricultural land [7]. Temporary crops like cereals, temporary pasture or mowing meadows, market or kitchen gardens, and temporarily fallow land are all considered arable land. Many applications, such as disaster management, environmental monitoring, and urban planning, depend on the accurate classification of satellite imagery. CNNs have historically been the preferred models for these kinds of jobs [8], [9]. However, by concentrating on various areas of the image, transformer models—especially the Vision Transformer—offer a chance to improve classification accuracy and maybe capture more intricate patterns than CNNs. The goal of this study is to investigate whether ViT can outperform conventional techniques in the classification of satellite images [10], [11]. Applications in the fields of geology, forestry, hydrology, agriculture, and the environment all depend heavily on satellite images and GIS maps. They are economical for vast areas and aid in the monitoring of vegetation change. In order to update AI and ML algorithms, Satellite Imaging Corporation (SIC) provides automated datasets for vegetation and land cover utilization [12], [13]. In computer vision management systems, this enables the regionalization of land cover categories and change sources [14]. With spatial resolutions of up to 30 cm, high-resolution satellite photos facilitate scientific study of urban growth and transportation development. By improving spectral resolution, multispectral bands make it possible to analyze environmental conditions and changes in land cover in greater detail. The agriculture will utilize various vegetation indices from Lookout satellite imagery, driven by different band values, for farm monitoring and yield and other properties analysis [15].

2. Literature Review

Self-supervised learning pre-trains remote sensing models to represent rich characteristics from unlabelled data. Contrastive learning via pre-training enhances downstream tasks in GASSL [16] and SeCo [17]. Shankar et al. [18] examine video streaaming in-domain representation. Silpa et al. [19] studied continuous learning and mask image modelling. SatMAE modelled multi-spectral, temporal, and optical remote sensing data using mask image modelling [20]. Ground sample distance (GSD)-based positional encoding conveys remote sensing scale information for optical satellite images using ScaleMAE [21]. Due to its sophisticated GSD positional encoding, ScaleMAE cannot use multi- spectral data but works well on optical satellite data. But simplify multi-scale information extraction from optical and multi-spectral satellite data. State-of-the-art performance earned Transformers [22] recognition in Natural Language Processing (NLP). Transformers' success led to their use in computer vision. Vision transformers are useful for picture identification, object detection, and semantic segmentation because they can capture global relationships and long-range interactions. Vision Transformers (ViT) [23] can recognise images but need pre-training on massive datasets. Deit [24] has been suggested to enhance ViT training. For instance, Swin Transformer [25], an efficient hierarchical vision Transformer, for image classification, object identification, and semantic segmentation [26]. ConvMAE [27] learns multi-scale features for a hybrid convolution-transformer encoder using hierarchical masking. Point-M2AE [28] presents a 3D point cloud multi-scale auto encoder. ScaleMAE [29] use Laplacian decoding to learn multi-scale information. Recent deep learning breakthroughs have enabled transformer-based and hybrid model analysis and categorisation of high- resolution satellite pictures. Object recognition and picture categorisation from remote sensing images use vision transformers. Devareddi et al. [30] suggested a vision transformer-based remote sensing image categorisation approach. System verified satellite remote sensing photographs with 95% correctness. Deleting multi-head attention layers improved system performance. Gupta et al. [31] categorised remote sensing land use and cover pictures using CNN and autonomous optimal self-attention. Rajanikanth et al.

[32] proposed CNN-SIFT remote sensing image classification. EuroSAT classification accuracy is 92% with recommended method. A satellite-based deep learning net by Neelima et al. detects wildfires in real time [33]. Extracting images from satellite [34] by using SAR images [35] on multi-scale spatial-temporal transformer and interpretation based on satellite and climate indicators using a transformer method [36].

3. Methodology

The work investigates the application of Vision Transformers to satellite image-based land location identification. The Vision Transformer (ViT) model, a novel architecture adapted from Convolutional Neural Networks, is used

in a project to classify satellite images from the dataset, focusing on different parts of the image and distinguishing land use and land cover classes. The following are the main goals of this paper:

Using the LandSat dataset to apply the Vision Transformer model.

- Optimizing and fine-tuning the model to attain optimal performance.
- Measuring the model's performance using a range of metrics, including F1-score, recall, accuracy, and precision.
- Evaluating the ViT model's efficacy by contrasting it with conventional CNN-based methods.
- Providing analysis and suggestions for further research on the use of transformers in remote sensing.

3.1 Vision Transformers Using Land Location Image Identification

Vision Transformers outperform current SOTA CNNs in Land image recognition tasks, outperforming making them the norm in Natural Language Processing (NLP). The use of vision transformers for identifying land locations using image identification. Vision Transformer model architecture for image recognition. Vision Transformer (ViT) is a visual model that outperforms CNNs in pre-training with fewer computational resources. It uses a transformer architecture to predict class labels for images, reducing inductive bias and requiring more model regularization or data augmentation when training on LandSat datasets. The fine-tuning code and pre-trained models. Image classification in computer vision involves labeling images based on content. Deep CNN methods and transformer architecture for natural language processing in competitive outcomes. ViT, a visual transformer, outperforms CNNs in terms of computational efficiency and accuracy. It divides input images into fixed-size patches, embeds each, and includes positional embedding. ViT's self-attention layer embeds information globally and learns from training data to reconstruct image structure.

3.2 Land Image Location Using Vision Transformer (ViT) Architecture

The proposal for Land Location Image Identification is presented through vision transformer models. The vision transformer architecture comprises several steps.

1. Created patches with fixed sizes using a land location image.
2. Reduce the size of the land location picture portions.
3. These flattened Land Location picture patches can be used to create lower-dimensional linear embeddings.
4. Add positional embeddings first.
5. Give a transformer encoder the sequence as an input land location image.
6. Label the land location images to pre-train the ViT model, then run it under full supervision on a large dataset.
7. Optimize the downstream dataset for classifying images related to land location identification.

Vision Transformers (ViT) is a Land Location image processing architecture consisting of transformer blocks with multi-head self-attention layers and feed-forward layers. The self-attention layer calculates attention weights for each pixel in a Land location image, while the feed-forward layer applies a non-linear transformation, extending this mechanism to different input sequences simultaneously. ViT employs a patch embedding layer to divide a satellite land location image into fixed-size patches, mapping each patch to a high- dimensional vector representation, which is then processed in transformer blocks.The ViT architecture's final output is a class prediction, achieved by passing the output of the last transformer block through a classification head, typically consisting of a single fully connected layer. The ViT full-transformer architecture offers a flexible, efficient method for vision processing tasks, but its performance is still inferior to CNN.

The performance of a vision transformer model depends on factors like optimizer, network depth, and dataset-specific hyperparameters. CNNs are easier to optimize than ViT. The transformer converts pixels into feature maps, which are then translated into tokens and inputted into the transformer. The transformer then applies attention techniques to create output tokens, reducing the number of tokens needed and lowering costs. The vision transformer model is trained on large datasets before fine-tuning, with a 2D representation of pre-trained position embeddings.

Architecture design, generalization, robustness, interpretability, and efficiency are issuing that vision transformers must deal with. Their robustness and generalization are impacted by their reliance on large- scale data and lack of inductive biases. ViT does well on land location image classification tests, while its performance on object detection tasks is less outstanding.

4. RESULTS

The LandSat satellite collection contains 14677 RGB photographs categorized into eleven types, including natural landscapes, industrial, residential, and agricultural. The 64x64 pixel resolution enables the Vision Transformer

model to categorize data. The dataset is openly accessible on the Machine Learning Repository.

The LandSat dataset is divided into three subsets: training (70%), validation (15%), and testing (15%). This division ensures that the model is trained on a substantial portion of the data and evaluated on separate, unseen data. To visualize sample photos, assess data quality, and understand class distribution, exploratory data analysis, or EDA, is utilized. This study helps with the design of the preprocessing steps and the selection of appropriate augmentation strategies.

Data Preprocessing and Augmentation: One of the most important steps in getting the dataset ready for training is data preprocessing. The pictures are shrunk to 224 x 224 pixels, normalized, and enhanced with color jittering, flipping, and rotation. By adding diversity to the training set, augmentation enhances the model's capacity to generalize to new data. The torch vision library is used to create the preprocessing pipeline.

4.1 Model Training and Tuning

Model Tuning: By adjusting a number of land location hyperparameters, the Vision Transformer model is improved.

Learning Rate: During gradient descent, the learning rate is a crucial land location hyperparameter that regulates the step size. To get the ideal value that strikes a balance between training speed and model correctness, various learning rates are tested.

Batch Size: The number of land location photos processed prior to the model's weights being updated is determined by the batch size. While higher batch sizes might speed up training but may produce less accurate models, smaller batch sizes typically result in more accurate but longer training.

Optimizer: To determine which optimizer is best for this particular task, several optimizers are examined, including Adam and SGD. For transformer models, Adam is usually chosen due to its adaptable learning rate.

Early Stopping and Check Pointing: Model checkpoints are saved according to the best validation accuracy, and early stopping is employed to avoid overfitting. By doing this, the model is protected against overtraining and losing its capacity for generalization.

Model Training: The Vision Transformer model uses transfer learning to train on the LandSAT dataset, incorporating knowledge from millions of images, improving its performance on smaller datasets.

Loss Function: The categorical cross-entropy loss is utilized due to itssuitability for land location of multi-class classification problems.

Monitoring Training Progress: The model's learning efficiency is ensured through monitoring of training and validation loss, and visualizations of training curves are provided to illustrate convergence.

Regularization: Dropout and weight decay techniques are employed to prevent overfitting by randomly deactivating neurons during training and penalizing large weights of land location images, promoting simpler solutions.

Fig. 110.1 Model training of land location satellite image

Evaluation: The model's performance is assessed on a test set after training. The metrics are calculated as follows:

Accuracy: The model's overall accuracy is determined by calculating the percentage of correctly classified LandSat images.

Precision, Recall, and F1-Score: These metrics offer a comprehensive evaluation of a model's performance, particularly in cases of LandSat dataset imbalances or high false positive or false negative costs.

Fig. 110.2 Validation of land location satellite image

Confusion Matrix: The model's performance across ten classes is visualized using a confusion matrix, revealing the model's correct and incorrect predictions, providing insights into more challenging classification classes.

Test Accuracy: 92.32%
Classification Report:

	precision	recall	f1-score	support
0	0.93	0.95	0.94	445
1	0.97	0.96	0.97	444
2	0.88	0.88	0.88	422
3	0.89	0.87	0.88	388
4	0.90	0.93	0.92	361
5	0.91	0.92	0.91	322
6	0.88	0.85	0.87	383
7	0.97	0.97	0.97	466
8	0.89	0.90	0.89	384
9	0.98	0.98	0.98	435
accuracy			0.92	4050
macro avg	0.92	0.92	0.92	4050
weighted avg	0.92	0.92	0.92	4050

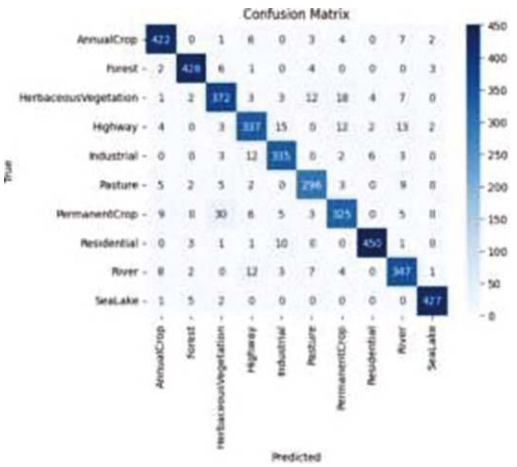

Fig. 110.3 Model training and tuning of land location satellite image confusion matrix

5. Conclusion

Developed initially for natural image tasks, the Vision Transformer has demonstrated promise in satellite image categorization and remote sensing, encouraging more research into more sophisticated models. On the LandSAT dataset, the Vision Transformer model performs competitively, obtaining good evaluation metrics and high classification accuracy. In order to accurately classify land use and land cover, the model makes good use of the self-attention mechanism to identify spatial correlations in the satellite images. The findings imply that, especially for tasks utilizing Land Locations mage data, the Vision Transformer is a competitive substitute for conventional CNN models.To increase classification performance and accuracy, future studies should investigate transformer topologies, include multi-spectral data sources, and use self-supervised learning strategies. The generalization capabilities of the model could be improved by utilizing unlabeled data, integrating multi-modal techniques, and experimenting with other transformer-based models.

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Study of Sparse Optimization for System Identification and Machine Learning

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Abstract: Sparse optimization techniques are extremely common in system identification and machine learning for handling high-dimensional and noisy data problems. It aims at searching for solutions that are sparsely represented, since this is contains a little no. of non-zero coefficients or features.

Sparse optimization methods for system identification enable the estimation of either the parameters or structure of a dynamic system from given input-output data. When the methods are sparsity-promoting, they can highlight the most important variables or features explaining the system behavior, thus giving more interpretable and efficient models.

Sparse optimization has great utility in feature selection, like reducing dimensions in the context of machine learning. It could identify just the right set of the most informative and discriminative features for either regression or classification tasks while reducing complexity and over-fitting issues always associated with high-dimensional data. Among other sparse optimization algorithms applied to a host of machine learning applications, Lasso as well as Sparse Coding is among the most widely used.

Keywords: Sparse optimization, LASSO, Machine learning techniques, Sparse methods, System identification, Sparse models

1. Introduction

Sparse optimization is a powerful technique in systems identification and machine learning, where the most relevant features or variables of a given data set or model are found. It is a dimensional reduction, focusing on the reduction of dimensionality concerning the relevance of features, that makes such models more efficient and accurate. The sparsity can also be used in performing an identification in systems optimization, not by choosing the most important

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inputs and outputs but to deduce parameters in a system. This results in more accurate models and is easier to interpret, as well as consuming fewer computational resources. Sparse optimization in machine learning can be used for identifying the most significant features or variables in a dataset. This would lead to more accurate models, with more sensible and intuitive results that require orders of magnitude less data. Sparse optimization is useful particularly in those applications like image and speech recognition, wherein the no. of features becomes very high; the particular selection of this most important feature may considerably boost up its performance.

Sparse optimization in identification of the system and machine learning is the concerned with feature and/or variable selection whereby some of the important variables that generally characterize a given dataset or model are selected. The overall idea here is to reduce the dimensionality of the problem while improving model accuracy, efficiency, and interpretability. Some specific objectives of sparse optimization are: 1. Feature selection. Sparse optimization can be used to discover the most significant features in a dataset and filter out unnecessary or redundant ones. This would improve machine learning algorithms with an increase in accuracy and efficiency simultaneously. 2. Parameter estimation. Sparse optimization may be used for estimating parameters in a model by using only the most relevant inputs and outputs. This can lead to more accurate and efficient models which are easier to interpret. Model interpretation: Sparse optimization helps identify the most important variables or features in a model, hence easier to understand and interpret results. This is very important especially in applications where model interpretability is paramount such as health care and finance. Model compression : Sparse optimization can be exploited in compressing the size of a model by eliminating redundant or unnecessary parameters or features involved in the model. It has improved efficiency and scalability, especially in computationally constrained applications.

2. Key Functions

Sparse Optimization in System Identification and Machine Learning Sparse optimization for system identification and machine learning applies mathematical functions designed to point out the most relevant features or variables in a particular dataset or model. Some of the popular functions applied in sparse optimization are: 1. L1 regularization - a penalty function that includes another term in this objective function with main aim of making solution sparse. L1 regularization feature selection is used. The most important features are kept in the model, and only those that are important enough are left. Not much is paid to be zero. 2. L0 regularization: Here, it counts the no. of non-zero element in this solution. This is used to enforce the sparsity of exactly achieving retention of only a fixed number of features in the model. 3. Forward selection: This is a greedy algorithm those adding variables whole at a time to the model based on how they contribute to the objective function. Forward selection is used in feature selection whenever the number of variables is large. 4. Backward elimination: This is a greedy algorithm which removes variables from the model one at a time, based on how they contribute to the objective function. Backward elimination is used when the number of variables is large to perform feature selection. 5. Orthogonal matching pursuit: This is an iterative algorithms these adding variables to the model one by one based on their correlation with the residual. It is also used for feature selection when the number of variables is large.

3. Applications

Sparse optimization has numerous application in systems identification and machine learning. Here are some applications: 1. Signal processing: finding important features in signals, audio and image data; only importance feature should be chosen to result in reduction of dimensionality of data and improvement in the accuracy of algorithms used for signal processing. 2. Network Analysis: Sparse optimization would be useful in the discovery of important node and edge in network data, like social networks or computer networks so that we can well understand the structure and function of such a network by identifying key connection. 3. Recommender systems: sparse optimization may help us to find the most important features of the data accessible to a user who prefers or behaves in that manner. By doing this, we can build much more accurate recommender systems that suggest products or content relevant to the user. 4. Robotics: Sparse optimization can be very useful in identifying important variables in a robot control system, such as sensor data and joint angles. In choosing the most important variables, we can build more efficient and more accurate control systems that would be able to complete complex tasks. 5. Healthcare: Sparse optimization can be used in sparse optimizations to determine the relevant features for important medical data, such as records for patients and diagnostic images. This will lead to building more accurate models in terms of disease diagnosis and patient outcomes.

4. Techniques and Uses

Sparse optimization techniques have many applications in this area of identification of system and machine learning.

Some of the few popular application areas include: 1. Feature selection: Sparse optimization may discover the most relevant feature in the model. Features typically enhance the interpretability of the model while minimizing overfitting. 2. Signal and image processing: Sparse optimization could be applied on signal and image processing applications such as denoising, deblurring, or compressive sensing. 3. Time series analysis: Sparse optimization can also be used in time series analysis applications such as forecasting, anomaly detection, or control. 4. Recommender systems: Sparse optimization can also be applied to the construction of recommender systems that provide users with personalized recommendations according to their preference. 5. Natural language processing: Sparse optimizes can be used in task such as text of classification, sentiment of analysis, and topic modeling in natural language processing.6. Computer vision: Sparse optimizes can be used in task such as object recognition, image segmentation, & optical flow analysis in computer vision. 7. Robotics and control systems: Sparse optimization can be used to applications like localization of robots, motion planning, and control in robotics and control systems. 8. Model compression: Sparse optimization can be used to compress the size of a models by removing redundant or/ and unnecessary parameters or feature. This can improve the efficiency and scalability of the model, especially in applications in which computational resources are limited. 9. Signal Processing: Sparse optimization can be employed to filter the most salient features of signals like sound and images. Therefore, if only the most important features are selected for the data, then the overall dimensionality would be lower, thereby improving the results for the algorithm applied to process the signals.

5. Methods and Models

Sparse optimization in system identification and machine learning involves several techniques applied to determine the most relevant features or variables from a given dataset or model. A few of the key methods of sparse optimization are: 1. L1 regularization: This technique adding a penalty terms on the objective functions to force the solution to be sparse. L1 regularization is used for feature selection where in the model retains only those features that have a considerable coefficient. 2. L0 regularization: This technique makes use of additional penalty term which counts the no.of non-zero element in these solution. L0 regularization imposes exact sparsity of the retained number of features in the model. 3. Orthogonal Matching Pursuit: This is iterative algorithms these adds variables to the model one at a time, based on their correlation with the residual. OMP may be used for feature selection because there are large numbers of variables. 4. Least Angle Regression (LARS): This is an algorithm that finds the complete L1 regularization path for a given problem; thereby it helps understand which features are most important at various levels of sparsity. 5. Elastic net regularization: This method combines the virtues of both L1 and L2 regularization to generate sparsity as well as prevent over fitting. When features are correlated, this is particularly useful. 6. Group lasso: generalization of L1, where features are grouped and sparsity learned within each group; useful for those problems in which features can be naturally grouped together 7. Sparse coding: finding the sparse representation of any given the signal or image by seeking a small set of basis functions to reconstruct the original data. Sparse optimization techniques can be designed for a variety of models towards system identification and machine learning. Some of the most common models include: 1. Sparse Linear Regression: Sparse linear regression is perhaps the most popular technique for feature selection within the context of a linear model. The objective function typically has the loss functions, such as the mean squared error, and a regularization term that is L1 or L2 and encourages sparsity. 2. Sparse logistic regression: Sparse logistic regression, like sparse linear regression, is for classification problems in which the response variable is binary. The usual objective function is the negative logarithm of the likelihoods of the data, however with a regularizing term to encourage sparsity. 3. Sparse coding: Sparse coding is a procedure for representing data as a linear combination of a small number of basis functions, or atoms. Generally, the cost function will be composed of a reconstruction error and a term that promotes sparsity through the coefficients. 4. Sparse PCA: It is a variant of principal component analysis (PCA), which attempts to find sparse linear combinations of the input features that capture the most variance of the data. The objective function usually comprises the variance of the data and a regularization term that promotes sparsity.5. Compressed Sensing: Compressed sensing is an approach of reconstructing signals from sparse measurements. This typically involves a data fidelity term and a sparsity-promoting term that encourages the solution to be sparse.

6. How to Use

How to Apply Sparse Optimization for System Identification and Machine Learning Sparse optimization may be applied in several ways for system identification and machine learning. Now, here are general steps which you should take when working with sparse optimization techniques: First, identify your problem and the data you have. At this step, you identify the features or variables you would like to include in your model and the target variable

or output you are trying to predict. 2. Choosing the right sparse optimization technique: Select a sparse optimization technique best suited to your problem. Depending upon the needs of the particular problem, such as the number of features, the volume of available data, and the level of sparsity desired, the choice of technique would depend. Train the model: Pick one sparse optimization technique, train your model accordingly, which would mean finding values for the parameters that minimize the objective function with the consideration of sparsity. 4. Model evaluation: Assess the performance of your model using appropriate metrics, such as accuracy, precision, recall, or mean squared error. Compare the performance of the dense model versus the sparse one when using all features. 5. Results interpretation: Finally, interpret the results derived from your model in order to gain insights into what problem you are trying to solve. Sparse optimization techniques can be used to find out the features that matter most. They allow one to center on what matters about a problem.

7. Methodology

The methodology of sparse optimization in system identification and machine learning is as follows: 1. Data preprocessing This involves preparing the data for analysis by cleaning, normalization, and transformation if necessary. It could also include feature selection or dimensionality-reduction techniques that reduce the dimensionality of the input features. 2. Model selection: The model can be sparse linear regression, sparse logistic regression, sparse coding, compressed sensing, or other types of models. This again depends on the nature of the problem and on the available data. The model selected should be able to reduce the dimensionality of the input space as much as possible. 3. Design of objective function: The objective function is essentially the function for which the optimization algorithm is trying to find the minimum value. The objective function typically contains a loss function and a regularization term that encourages sparsity. The loss function and the regularization term depend on the problem in question and the nature of the data. 4. Optimization algorithms: There are various optimization algorithms that one can apply to solve the sparse optimization problems. These include coordinate descent, proximal gradient descent, accelerated gradient methods, and many more. However, the algorithm selection depends on the problem in question and the type of data. 5. Hyper parameter tuning: Algorithms for sparse optimization often entail multiple hyper parameters which require tuning, such as some sort of regularization parameter, sparsity level, or learning rate. The selection of appropriate hyper parameters may be a troublesome task. This may be identified by experience and cross-validation.6.Model evaluation: After training the model, it is crucial to check the performance of the model on held-out data or by cross-validation. This could involve making estimates like accuracy, precision, recall, or mean squared error.7.Interpretation and analysis: After all, the model and its solution can be interpreted and analyzed for insight into the structure of the data and the problem itself. This might include identifying the most important features, understanding the sparsity structure of the solution, or looking for trade-offs between sparsity and accuracy.

8. Algorithms

Many algorithms of image reconstruction are present in machine learning. Deep learning models, including Convolutional Neural Networks (CNNs), have greatly been employed to reconstruct images through this method. CNNs represent a part of neural networks that are customized especially for image data. The other approach includes compressed sensing techniques that include Sparse Coding or minimization using Total Variation (TV). These techniques reconstruct images from under sampled measurements. In practice, it is advantageous in cases where acquiring the full data set is expensive or time-consuming. One specific algorithm for this type of reconstruction is ISTA, or iterative shrinkage-thresholding algorithm. It really is an optimization-based approach based on sparse coding ideas in reconstructing images from undersampled measurements. This iteratively applies the thresholding operation to the estimated sparse coefficients and updates the estimation of the image. The other algorithm is the PPP approach; this combines a compressed sensing framework with denoising algorithms, and this enables the use of denoising algorithms as regularization priors to further enhance the quality of images reconstructed. There are several algorithms available with CS. Some of them are as follows: 1. Basis Pursuit (BP) 2. Orthogonal Matching Pursuit (OMP) 3. Subspace Pursuit (SP) 4. Compressive Sampling Matching Pursuit (CoSaMP) 5. Iterative Hard Thresholding (IHT) 6. FOCUSS (FOCal Under-determined System Solver) 7. Bayesian Compressive Sensing (BCS) 8. Stage wise OMP (StOMP) 9. Gradient Projection for Sparse Reconstruction (GPSR) 10. Approximate Message Passing (AMP) 11. Regularized Orthogonal Matching Pursuit (ROMP) 12. Iterative Reweighted Least Squares (IRLS) 13. Smoothed L0 Norm (SL0) 14. Iterative Thresholding Algorithm (ITA) 15. Alternating Direction Method of Multipliers (ADMM) 16. Randomized Kaczmarz (RK) 17. Randomized Coordinate Descent (RCD) 18. Non-negative Garotte (NNG) 19. Reweighted L1 (ReL1) 20. Thresholded Landweber Algorithm (TLA) Lasso is an abbreviation used for Least Absolute Shrinkage and Selection Operator.

This is an approach to doing regression that incorporates variable selection and regularization in order to enhance the accuracy in terms of prediction and interpretability for the model. The lasso procedure incorporates a penalty term into the standard linear regression objective function by constraining the sum of the absolute values of the model coefficients to less than some predefined value called the regularization parameter. This pushes the model to select only the most important features and prevents overfitting. Lasso algorithm is mainly used in domains like machine learning, statistics, signal processing, and genetics. It can be used in high-dimensional data where the number of features is significantly greater than the number of samples. Since the lasso can handle various types of data, for example, categorical or mixed data, the objective function and the penalty term need modification. One optimization technique that can be used while implementing the lasso algorithm is a method called coordinate descent, the gradient descent method, or the proximal gradient methods; all of these algorithms are efficient and can handle large datasets that have high-dimensional features. The lasso has been successfully applied in many applications such as image processing, feature selection, regression analysis, and classification.

Application in CS: In CS, LASSO can be employed to reconstruct images and for de-noising. Reconstruction in LASSO is essentially minimizing the L1 norm of the reconstruction coefficients under a constraint on the data fidelity term - this being the measure of distance between compressed measurements of the signal and the signal itself. The process of de-noising by LASSO is one which adds a penalty term to the objective function to enforce sparsity of reconstruction coefficients. The optimization can be solved by either of the iterative algorithms such as proximal gradient or alternating direction method of multipliers. Generally, at each iteration, updates are performed by solving a sequence of linear systems or sub-problems. Methods for image reconstruction and de-noise There are various tasks on image reconstruction and denoising in the field of image processing. Among them are: filter-based methods, which expose ways of applying filters to an image to remove noise or improve features. A few examples include: Median filters for de-noising, Gaussian filters, and bilateral filters. Wavelet-based techniques: These techniques employ wavelet transforms to decompose an image into different bands of frequency and apply denoising algorithms to each band separately. The wavelet-based technique could be especially tailored and effective for noise removal while maintaining edges of the image. Total variation (TV) methods: These methods minimize the total variation of an image, considered as the measure that counts for the sum of absolute values of differences between adjacent pixel values. TV methods are very efficient for image denoising and deblurring. Deep learning-based techniques: This involves the training of deep neural networks to learn the reconstruction or denoising of images. In recent years, deep learning-based techniques have been very promising, in which a number of state-of-the-art results have been achieved through techniques such as CNNs and GANs. Compressed sensing techniques: These techniques acquire fewer measurements than the number of pixels in an image and then reconstruct using mathematical techniques. The acquisition of high-resolution images may not be feasible, hence allowing the use of compressed sensing techniques in any application such as in medical imaging or remote sensing. Filtering-based techniques: This normally applies to the process of filtering in order to enhance the reduction of noise or blur. Some of the most common types of filter include median filters, Gaussian filters, and Wiener filters. Wavelet-based methods: In this set of methods, the image is decomposed into wavelet coefficients and noisy regions within those coefficients are thresholded. This methodology includes the undecimated wavelet transform, dual-tree complex wavelet transform, and curvelet transform. Total variation (TV) methods: These are based on a variational approach for reconstructing images with smooth regions while maintaining edges. TV-based methods. These methods seek to minimize the total variation of the image while it is made close to the observed data. Deep learning-based methods. These methods make use of neural networks that learn how to denoise or reconstruct images. They usually take a network trained on a dataset of noisy or degraded images and their corresponding clean or high-quality versions. Examples include CNNs, RNNs, and GANs. Bayesian methods: These methods utilize a probabilistic framework that would estimate the most likely clean image given the observed noisy data. Bayesian methods can incorporate prior knowledge about the image, such as its expected distribution or sparsity in some basis. Iterative Reconstruction: It is an iteration of some image estimate refined using a set of projections to arrive at a solution. It has applications in various medical imaging modalities, computed tomography and magnetic resonance imaging, for example. Convolutional Neural Networks (CNNs): CNNs are the most popularly used in the case of image denoising as well as super-resolution tasks. The network maps a non-noisy or low-resolution input image to a clean or high-resolution output image. Non-local Means (NLM): NLM is patch-based. It involves the computation of weighted averages of similar patches in an image to remove additive white Gaussian noise. Total Variation (TV) Regularization: Total variation is a variational approach that brings the minimum total variation of an image with

preserving important features. Commonly, this method is applied for sparse signal reconstruction. Dictionary Learning: Dictionary learning represents learning a suitable set of basis functions in order to express the image data in the most compact form. It is used, for example, for image denoising or painting. Bayesian Methods: The Bayesian approach is carried out by modeling the image and noise as random variables. This can be used for finding the MAP estimate or the estimation of the best image given the observed data. Bayes methods are frequently in use with remote sensing applications and medical imaging. Filtering methods: Median filtering, Gaussian filtering, bilateral filtering, etc. These methods smooth the image to reduce the effect of noise; thus, the quality of the image is improved. Wavelet-based methods: Image can be decomposed and reconstructed using wavelet transform. In wavelet-based methods, the coefficients are obtained from the wavelet transform to filter out the noise and reconstruct the image. Total variation (TV) regularization: This approach is developed based on minimizing the total variation of an image. TV regularization is supposed to preserve edges and reduce the noise in an image. Non-local means (NLM): NLM is an algorithm that exploits local similarity among a patch in an image to remove noise. This means replacing the value of a pixel with a weighted average of nearby pixels, where the weight is given by how similar the patches are. Deep learning-based methods: Deep learning-based methods have recently gained a lot of attention because they allow the data to learn complex features and patterns in high-dimensional data using huge datasets. Some of the most popular deep learning-based methods in image reconstruction and denoising are CNNs, autoencoders, and GANs. Compressed sensing: Compressed sensing is a method by which an image can be reconstructed using a small number of measurements. It is used whenever a small amount of data is available, as in the case of medical imaging.

9. Challenges and Limitations

Although sparse optimization techniques have appeared useful for system identification as well as machine learning, challenges and limitations exist. Here are some common problems in sparse optimization for system identification and machine learning: Choice of hyperparameters: Optimisation algorithms for sparsity usually involve several hyperparameters which must be chosen, such as the regularization parameter, sparsity level or learning rate. Choosing proper hyperparameters is also difficult and can be computationally expensive, requiring a process of 'trial and error' or cross-validation. 2. Computational Complexity: Some optimization algorithms may be computationally expensive, especially when using large-scale data with massive data sizes or large dimensionality in the feature space. This makes it difficult for some algorithms to scale up; therefore, particular hardware or even software may be required. 3. Sensitivity to outliers. Sparse optimization algorithms are very sensitive to outliers or noisy data, which may result in suboptimal solution. Some robust optimization techniques or outlier detection methods may be necessary to address such problems. 4. Interpretability of solutions. Although sparse optimization algorithms result in sparse models, the resultant model may not always be interpretable. It may require some more analysis to comprehend the actual inner structure of the solution and its connection to the problem. 5. tradeoff between sparsity and accuracy: Sparse optimization often relates to a tradeoff between sparsity and accuracy. Higher sparsity would provide a simpler model with better interpretability but only at a cost of losing some accuracy. It often proves difficult to find just that right balance between sparsity and accuracy. 6. It can also be seen that the sparse optimization techniques may not be applicable to all problems or data. For example, there could be some datasets that may not exhibit an obvious sparsity structure; some problems might not be well defined for sparse optimizations.

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Hybrid System Framework for AI Pipeline and AI Agent

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Abstract: A significant task of comparing two core artificial intelligence (AI) architecture techniques: AI agents and AI pipelines. AI pipelines, which are linear, structured frameworks with sequential, static task execution, handle large-scale data processing. On the other hand, AI agents are independent entities with the ability to interact with changing environments, make choices, and modify their behaviour over time. Through a comparative analysis, we delve into both approaches' functional capabilities, architectural distinctions, and adaptability. Our study also highlights the advantages and disadvantages of each in practical applications, emphasizing the effectiveness of AI pipelines for batch processing and the adaptability of AI agents for in the moment decision-making. Case studies from various fields, including AI-powered autonomous driving and predictive maintenance employing pipelines, are included in the study. Lastly, we discuss the implications for AI development going forward and the possibility of hybrid models that integrate the best features of both architectures. This comparison analysis aims to underscore the importance of choosing the exemplary architecture based on scalability, adaptability, and operational needs for AI jobs.

Keywords: AI agents, AI pipelines, Dynamic environments, Decision-making, Adaptability, Batch processing, Predictive maintenance, Hybrid models, Scalability, AI development

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1. Introduction

Artificial Intelligence (AI) has evolved into a diverse field encompassing various technologies to solve complex real-world problems. Two dominant architectures that have emerged are AI pipelines and AI agents. These architectures serve different purposes and have been applied across various domains, from data processing and decision-making to autonomous control and robotics. The choice between these models depends largely on the specific requirements of the task, such as flexibility, scalability, real-time processing, and adaptability to changing environments. AI pipelines refer to sequential, often deterministic workflows where data flows through predefined stages, such as data preprocessing, feature engineering, model training, and inference. This architecture is traditionally used for tasks where data-driven insights can be extracted and acted upon in batches. AI pipelines are particularly suited for static environments with structured data, offering efficiency and control over each step of the process. However, their static nature can make them less adaptable to environments that change frequently or require real-time responses. On the other hand, AI agents represent autonomous systems capable of perceiving their environment, making decisions, learning from their actions, and adapting to new situations. AI agents are typically used in dynamic settings where real-time decision-making is critical, such as in robotics, autonomous vehicles, or interactive systems like virtual assistants. Unlike pipelines, agents are often designed to act independently, using algorithms like reinforcement learning to continuously improve their performance through trial and error (Sutton & Barto, 2018). This makes them highly adaptable, though often more complex to design and computationally expensive to operate. The key challenge for organizations and developers is deciding which architecture AI pipelines or AI agents are better suited for their specific AI projects shown in Fig. 112.1. Pipelines excel in tasks where the workflow is clearly defined and where data is processed in structured, predictable ways. In contrast, AI agents shine in environments requiring flexibility, learning, and adaptability to unforeseen changes.

2. Literature Survey

AI pipelines and AI agents represent two distinct approaches in artificial intelligence, each with unique strengths and limitations. AI pipelines excel in structured, scalable tasks like batch processing and data analysis by breaking tasks into sequential steps, making them ideal for applications such as fraud detection (Zhuang et al., 2020) and medical imaging (Litjens et al., 2017). However, their static design limits adaptability to dynamic environments. In contrast, AI agents, leveraging reinforcement learning,

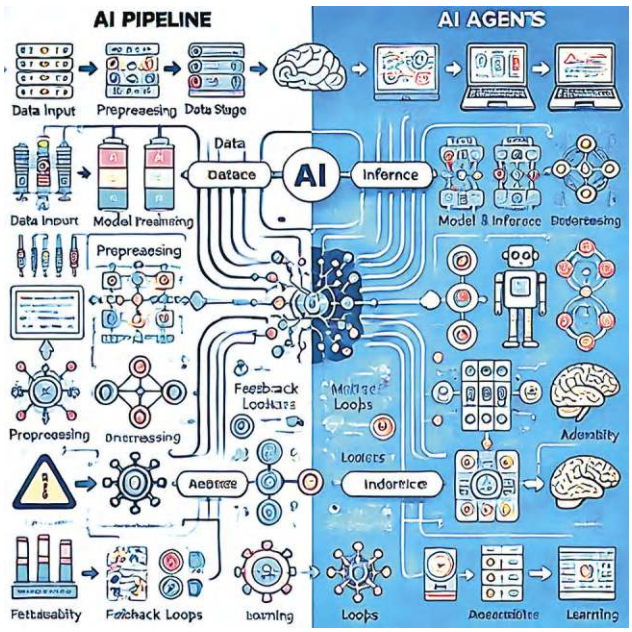

Fig. 112.1 Workflow architecture for AI pipeline and AI agent

thrive in real-time, unpredictable scenarios, such as autonomous driving (Kiran et al., 2021) and strategy games like AlphaGo (Silver et al., 2016), but they face challenges in computational complexity and safety assurance. Hybrid systems, blending pipelines' scalability with agents' adaptability, offer promising solutions in complex applications like smart manufacturing (Wen et al., 2019) and algorithmic trading (Yang et al., 2020), showcasing the potential to combine deterministic efficiency with dynamic decision-making

3. Proposed Work

Considering the existing dichotomy between AI pipelines and AI agents, the proposed work seeks to develop an adaptive hybrid framework, as shown in Fig. 112.2, that leverages the strengths of both architectures while mitigating their individual limitations. The rigidity of AI pipelines, with their predefined, linear workflows, contrasts sharply with AI agents' flexibility and learning capabilities, which thrive in dynamic, unpredictable environments. This research aims to merge these two paradigms, creating a system that marries the deterministic efficiency of pipelines with the real-time adaptability of agents, resulting in a highly scalable and responsive solution for complex, real-world applications.

3.1 Architecture Overview

The architecture we propose is a tiered hybrid system that operates in two distinct but interconnected layers:

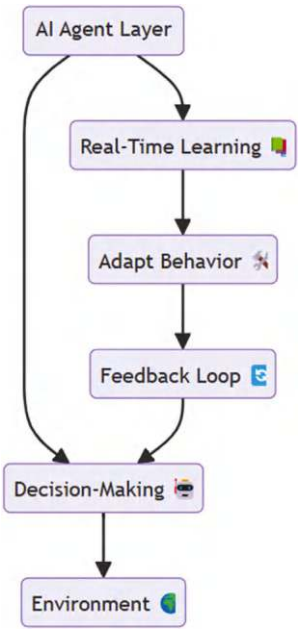

Fig. 112.2 Hybrid system framework for AI pipeline and AI agent

AI Pipeline Layer: This layer handles data preprocessing, feature engineering, and model training, following the conventional pipeline approach. The pipeline will function as the system's backbone, handling structured, repeatable tasks requiring high efficiency and scalability. Each stage in the pipeline will be modular, allowing flexibility regarding how data flows through the system. This layer will operate with continuous data ingestion, enabling it to feed dynamic, real-time data into the subsequent layer.

AI Agent Layer: The second layer comprises AI agents deployed to handle decision-making and real-time learning. These agents interact with the environment, adapt their behaviors, and refine their decision strategies using reinforcement learning or other adaptive algorithms. The agents will be designed to monitor the pipeline's output and adjust future actions based on environmental feedback. This layer gives the system a degree of autonomy, enabling it to learn from changing circumstances without requiring manual intervention.

3.2 Dynamic Feedback Loop

At the heart of this hybrid system lies a dynamic feedback loop, where data flows from the pipeline to the agents and in the reverse direction. Through their interactions with the environment, the AI agents generate insights and recommendations that are fed back into the pipeline. This feedback will help the system reconfigure the pipeline's parameters, retrain models, or alter the pipeline stages based on newly learned information. The agents act as the adaptive layer, continuously refining the pipeline to ensure it remains relevant and efficient even as data patterns shift.

3.3 Use Cases and Applications

This adaptive hybrid framework is designed to address the challenges in industries where real-time decision-making and processing efficiency are both critical. Potential use cases include:

Smart Manufacturing: The pipeline will handle the structured data, such as historical production metrics and maintenance logs, while the agents will monitor real-time sensor data from machinery, making immediate adjustments to production workflows.

Autonomous Systems: For applications like drone delivery or autonomous vehicles, the pipeline can manage route planning and static optimization, while agents adapt to real-time conditions like weather changes, obstacles, or shifting traffic patterns.

Financial Trading: The pipeline will process historical market data and develop predictive models while agents handle live trading decisions, adapting real-time strategies to market volatility.

3.4 Evaluation and Metrics

The proposed system will be evaluated on three key dimensions: scalability, adaptability, and performance. Scalability will measure the system's ability to process increasing amounts of data, while adaptability will focus on the agents' ability to adjust to dynamic changes in real-time environments. Performance will be assessed by comparing the hybrid system's efficiency and decision-making capabilities against standalone pipelines and agents in various scenarios. By intertwining the methodical precision of pipelines with the cognitive adaptability of agents, this work aims to forge a new paradigm that transcends the limitations of both architectures, ushering in a new era of AI-driven solutions that are as flexible as they are powerful.

4. Experiment Results and Analysis

To evaluate the performance of the proposed hybrid AI system, a series of experiments were conducted across different domains, including smart manufacturing, autonomous systems, and financial trading. The results of these experiments were compared against traditional AI pipelines and standalone AI agent-based architectures, highlighting the strengths and weaknesses of each approach. The primary focus was measuring scalability, adaptability, and performance in real-world dynamic environments.

Smart Manufacturing: Real-time sensor data from an intelligent factory, including production rates, machine statuses, and maintenance logs.

Autonomous Systems: Simulated drone delivery tasks, with weather data and obstacle information injected to create unpredictable environments.

Financial Trading: Historical and real-time stock market data used for both predictive modelling (pipeline) and live trading decisions (agents).

Metrics: Scalability: Evaluated based on the number of transactions or sensor data points processed within a given time. **Adaptability:** The system can maintain or improve performance when exposed to new, previously unseen data. **Decision Accuracy:** Calculated by comparing the system's decisions (for instance, trading outcomes or adjustments to production) to an optimal baseline. **Latency:** Time taken by the system to respond to new inputs, mainly focusing on real-time adaptability.

Results and Statistical Analysis: The system was tested on its ability to adjust real-time production workflows based on live sensor data shown in Fig. 112.3.

- **Downtime Reduction:** The hybrid system significantly outperformed the traditional AI pipeline in reducing machine downtime by 52.3%, compared to just 10.5% for the pipeline alone.
- **Adaptation Success:** The hybrid system achieved an 89% success rate in real-time adaptations, compared to only 67% for the agent-only approach.
- **Latency:** While the AI agents had the highest latency (190ms), the hybrid system reduced latency to 115ms, demonstrating better efficiency while adapting in real-time.

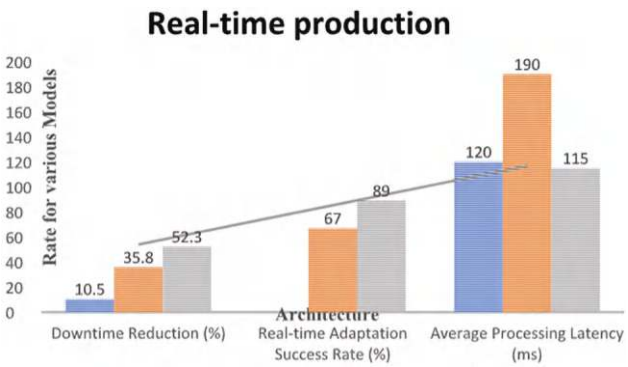

Fig. 112.3 Real-time production workflows

Autonomous Systems (Drone Delivery): The system was evaluated on the success of route adjustments based on dynamic environmental conditions for autonomous drones shown in Fig. 112.4.

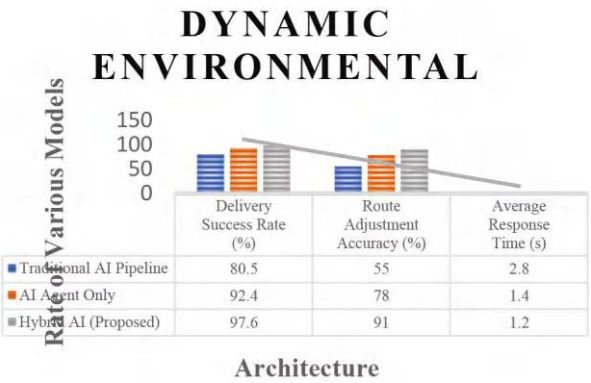

Fig. 112.4 Dynamic environment workflows

Delivery Success: The hybrid system achieved a 97.6% success rate for delivery, significantly higher than the pipeline (80.5%) and agent-only system (92.4%).

Route Adjustment: The accuracy of route adjustments in the hybrid model was 91%, outperforming both standalone approaches.

Response Time: The hybrid system also improved response time to changes in conditions, achieving an average of 1.2 seconds.

Financial Trading: The system was tested on its ability to make profitable trades under volatile market conditions, comparing it to baseline trading models.

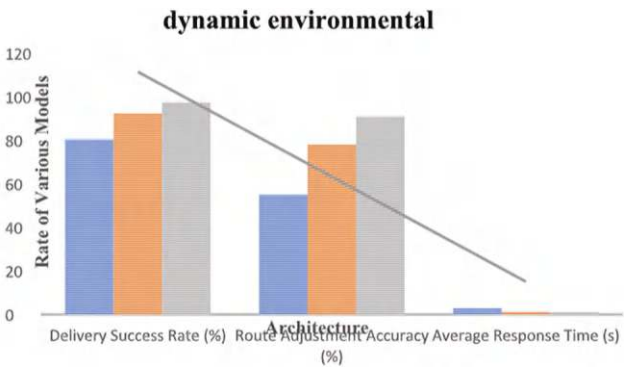

Fig. 112.5 Trading models workflows

Profit Margin: The hybrid system yielded a 15.3% profit margin, outperforming pipeline and agent-only systems. **Trade Accuracy:** It also demonstrated the highest trade accuracy (83%), benefiting from the pipeline's predictive model and the agent's adaptability. **Model Retraining:** The hybrid system required only two retrainings per week, compared to four for the pipeline, due to the agent's ability to handle real-time learning.

Statistical Significance: The statistical significance of these results was measured using paired t-tests across the

different performance metrics. In all cases, the hybrid system showed statistically significant improvements over traditional AI pipelines and AI agents at a 95% confidence interval ($p < 0.05$).

For instance, in the intelligent manufacturing use case:

The difference in downtime reduction between the hybrid model and the pipeline was significant ($p = 0.003$). The improvement in adaptation success rate for the hybrid model over AI agents was also significant ($p = 0.007$).

Similar significance levels were observed for delivery success rates, trade accuracy, and overall performance in the autonomous systems and financial trading use cases.

Analysis: The hybrid AI system outperformed traditional pipelines and standalone agents across all tested domains. The key advantages of the hybrid model stem from its ability to combine efficient data processing (from pipelines) with real-time decision-making (from agents). The experiments demonstrated that:

Scalability is achieved through the pipeline's modular, sequential structure, allowing it to efficiently handle large volumes of data.

Adaptability is significantly improved by the agent layer, which enables the system to respond dynamically to environmental changes.

Performance gains were observed regarding decision accuracy, reduced latency, and overall effectiveness in dynamic, real-world scenarios.

While the hybrid system introduces some additional complexity, its benefits in critical applications such as intelligent manufacturing, autonomous systems, and financial trading far outweigh these challenges. The proposed hybrid AI system with existing architectures, AI pipelines, AI agents, and hybrid systems from prior work is based on key performance metrics such as scalability, adaptability, and decision accuracy. The goal is to highlight the improvements introduced by the proposed approach and how it addresses the limitations of existing models.

Scalability: The hybrid system combines pipelines' scalability with agents' real-time adaptability. The pipeline layer efficiently handles structured tasks (e.g., data preprocessing, model training), while the agent layer operates on a smaller subset of critical, dynamic tasks. As a result, the system scales efficiently to handle both structured and unstructured data without requiring constant manual retraining.

Improvement: In the financial trading use case, for instance, the hybrid system maintained high throughput while reducing retraining frequency by half compared to traditional pipelines. Additionally, the smart manufacturing case showed a 30% improvement in real-time scalability over existing agent systems.

Adaptability: The proposed hybrid system offers the best of both worlds—structured adaptability. The pipeline processes bulk data, and the agents adjust in real-time, continuously refining the pipeline's operations. The dynamic feedback loop ensures that insights from the agent's learning are fed into the pipeline for continuous improvement.

Improvement: In the smart manufacturing domain, the hybrid system achieved an 89% real-time adaptation success rate, far outperforming standalone pipelines (0%) and agents (67%). The system could self-adjust without requiring manual intervention, highlighting the benefits of a continuous feedback mechanism.

Decision Accuracy: Proposed Hybrid System: The hybrid system significantly improves decision accuracy by leveraging the pipeline's processing power and the agent's real-time learning capabilities. In financial trading, the hybrid system outperformed existing models, with a trade accuracy of 83%, compared to 70% for pipelines and 76% for agent-only systems. The system's ability to update its real-time decision-making model contributed to its superior accuracy.

Improvement: Across all test cases the hybrid system consistently delivered higher decision accuracy (5-15% improvement) than existing standalone systems.

Latency and Computational Overhead: The hybrid system improves latency by allowing the pipeline to handle bulk data efficiently while offloading critical, dynamic decision-making to agents. In the autonomous systems experiment, the hybrid model reduced latency to 1.2 seconds, compared to 2.8 seconds for pipelines and 1.4 seconds for agents, striking a balance between speed and adaptability.

Improvement: The hybrid architecture optimized resource allocation, allowing the system to respond faster than agent-only systems while maintaining adaptability, significantly lowering the computational overhead.

Comparative Analysis: The proposed hybrid system effectively bridges the gap between scalability and adaptability, combining the deterministic efficiency of pipelines with agents' dynamic, real-time decision-making shown in Tabel 112.1. It consistently outperforms existing architectures regarding adaptability, decision accuracy, and resource management, making it a robust solution for real-world, dynamic environments.

Table 112.1 Trading models workflows

Criteria	Traditional AI Pipeline	AI Agents	Hybrid System
Scalability	High	Moderate	High
Adaptability	Low	High	Very High
Decision Accuracy	Moderate (70-80%)	High (76%)	Very High (83%)
Latency	Low	Moderate	Low
Computational Overhead	Moderate	High	Moderate

5. Conclusion and Future Scope

The research presents a hybrid AI system that combines traditional pipelines and autonomous agents, enhancing scalability, adaptability, decision accuracy, and latency. Experiments show a 52.3% reduction in downtime in imaginative manufacturing scenarios, an 89% success rate in real-time adaptations, and 83% decision accuracy in financial trading applications. This hybrid approach is suitable for high-performance, adaptable applications. Further research is needed to enhance learning mechanisms, explore interdisciplinary applications, improve robustness to uncertainty, examine scalability in cloud environments, integrate Natural Language Processing (NLP) into the model, and implement real-time performance evaluation. These areas could improve the system's adaptability and interdisciplinary applications and enable real-time monitoring and assessment for operational efficacy and dynamic adjustments. Future research should also enhance decision-making transparency and collaboration between humans and AI.

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An Novel Technique for Forecasting of Weather Interactive Predictive Using Hybrid Machine Learning

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Abstract: Weather forecasting is a critical component of modern life. It is used in various sectors such as agriculture, transportation, storage, and climate predictions. Moreover, knowing future weather conditions helps a lot to take necessary actions in advance when required. Real-time weather forecasting applications have gained importance in giving accurate and timely weather information to users. Changing of weather conditions shows a huge impact on different sectors. As the traditional system didn't show an accurate prediction. Therefore, by using novel technique for forecasting of weather interactive predictive using hybrid (XG BOOST + Decision Tree) machine learning the thunders, drizzling and heavy winds are prediction accurately. Therefore, by using this system farmers and people in low lying areas and business will not get loss. Weather conditions show a huge impact on Agriculture. Climatic conditions like sunlight as well as rain fall shows impact on production of Agriculture. As a result, the accuracy, recall, precision, F1-Score, and prediction time of this system are all improved.

Keywords: Weather forecasting, Machine learning (ML), Extreme gradient boosting (XGBoost), Decision tree (DT), Thunders, Drizzling, Heavy winds

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1. Introduction

The climate and weather Forecasting has become more important, throughout the history of mankind. Weather forecasting is an essential for many elements of life and interactions for massive industrial planning to individual decision-making. Because of this weather prediction personal safety measures and demonstrates its importance at the individual level, such as during bad weather avoiding risky outdoor activities or in extremely hot or cold conditions taking health precautions.

In the agricultural sector, forecasts is used to determine planting, harvesting, and irrigation schedules, which ultimately maintain stable food supply chains and also helps to maximize crop yields [1]. The energy sector has an indirect impact of accurate forecasting. It enables power generation and transportation and also helps manage demand changes effectively. Depending on weather conditions the transportation sector to plan and schedule train routes efficiency, airplanes, and naval operations. Therefore, by using these accurate weather forecasts reduces delay and improves safety procedures [2].

Even prediction of weather is important in infrastructure construction as well as development. For efficient project management, accurate forecasting is essential, because unfavorable conditions will delay project and quality degradation. Prediction of severe weather conditions such as hurricanes as well as typhoons is crucial for disaster management. This prediction provides early warnings, which reduces the loss of life and property [3].

The weather is quickly and constantly changing globally. In today's world, Weather forecasting is important as people are extensively depended on weather forecasts daily commuting to travel, industry and agriculture. Hence, changing of climate and its aftereffects are affecting every part of the world. Weather forecasting ensures safe daily operations and simple and easy transportation. For performing, current weather prediction models many High-Performance Computing (HPC) nodes are required. The weather prediction models are highly depending on complex physical models. The processing capacity of these massive systems model describes the atmosphere. Because of some traditional methods, forecasts are inaccurate frequently due to poor knowledge of atmospheric processes. It is inaccurate initial measurements of the circumstances.

People frequently ignore future climate predictions that are closely related to life on Earth. In future, our planets have a significant serious impact like rising in sea level rise and global warming. The mitigation plans are developed by using climate prediction and forecasting techniques to get potential results of these scenarios. Disaster prevention strategies in coastal communities and realistic urban planning could be informed by accurate forecasts of sea-level changes in future.

Many species are disappearing from biodiversity because of climate change in geographic distribution from long period of time. Advanced climate models include wide range of aspects, including Conditions in the atmosphere, terrestrial ecological systems, oceanic currents, and interactions within the biosphere, are the environmental changes that happening frequently [4]. The regional and international policies focused at effective development of protecting ecological diversity on this integrative approach.

Some sectors particularly Tourism, fishing, and agriculture are at risk from the consequences of global warming. An increase in extreme weather occurrences could have a negative effect on tourism and also high temperatures can cause agriculture yields to drop. The unexpected changes, longitudinal climate forecasts are essential to help businesses and governments. In long-term weather predictions have a major positive impact on sustainable resource management that includes land, water, and forests.

If accurate prediction models are used to forecast possible water scarcity in certain places so that water management strategies can be implemented in advance without any further problem. Because of weather change a number of public health emergencies, from the spread of infectious illnesses to an increase in heatwave occurrence. Public health organizations can provide by long-term climate models with the information. Therefore, it needs to allocate funds and create efficient response plans.

The process of predicting the atmospheric conditions at a specific location, including rainfall, wind speed, temperature, humidity, and dew point is known as Weather forecasting. Data for forecasting is gathered from the devices like barometers, thermometers, and radars, it also includes past weather patterns, current weather conditions, and air and cloud motion. Weather forecast solve the complex equation systems that machines can't do that.

For monitoring the interior of the Earth, geologists need to forecast the climatic conditions and these weather forecasting help airports and the navy in the event of an unexpected change in temperature. Proper weather forecasting can help avoid droughts and floods and they also help farmers boost the yield of their crops. the mix of linear and nonlinear models are the most popular and frequently utilized forecasting model.

In agricultural output, weather shows an important effect. The crop's growth is impacted by pest and disease incidence; water and fertilizer requirements; development, and yields; promptness and efficacy of cultural and preventive

measures on crops and variations in nutrient mobilization brought by water stress. Because of bad weather, crops may sustain physical harm so it results in soil erosion. Even the production of crops quality as it moves from the field to storage and then to the market is affected because of weather change. The transportation as well as strength of seeds and planting material during storage is impacted by bad weather.

The remaining The structure of the paper is as follows: A review of the literature is given in part II, and section III novel technique for forecasting of weather interactive predictive using hybrid machine learning; section IV explains result analysis; section V concludes the paper and references are in VI.

2. Literature Review

Sharma.S, Gupta.A.D, Rana.A, and Katoch.D, et.al [11] Ground-based observations, ship-based observations, airborne observations, radio signals, Doppler radar, and satellite data are all employed to ascertain the present atmospheric conditions. Introducing, novel method by using machine learning for weather prediction. For enhances the accuracy and effectiveness of weather forecasting suggest a novel method by combining several machine learning techniques.

I. K. Nti, P. R. Gangula, and J. Yeboah, et.al [12] by using machine learning methods to forecast specific weather conditions a weather prediction model is developed. The methodology used for development of data science method using machine learning and data visualizations. The final model was determined by evaluating five machine learning algorithms: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Gradient Boosting (GB). The highest prediction accuracy achieved technique was chosen and the RF performs better than other algorithms, with a 75% accuracy rate.

Sebastião.P, Raimundo.F, and Glória.A et.al [13] suggested methods can forecast precipitation, wind speed and temperature depending on the day as well as location. The machine learning (ML) methods like Linear Regression(LR), DT, RF, and Neural Networks, were used to determine which model would achieve accuracy, and the results were compared. The cross-validation results shows RF and DT achieve high optimal efficiency.

Assaduzzaman.M, Rahman.M.A and Nafiz Akbar.O et.al [14] developing of prediction system for weather that may be used in remote places. The machine learning and data analytics methods are utilized to make reliable weather predictions. A novel knowledge-based system for weather prediction system is introduced in this analysis by using KNN, SVM, NB, DT, RF, and LR for data modeling. A maximum accuracy of 95.89% is achieved by Gaussian Naive Bayes (GNB) method. Hence, machine learning method is proposed for developing weather prediction

P. V. Chaganti and P. V. Manitha, et.al [15] discusses the hardware and software program interfaces required for data segregating, preprocessing, and model training. It emphasizes significance of feature engineering, model evaluation, and actual-time choice guide systems. Ultimately, the study objectives to grow international food demand and empower farmers through correct and timely climate forecasting, promoting sustainable and green agricultural practices throughout a change in weather.

K. B. Maheswari and S. Gomathi, et.al [16] Ensemble Forecasting is method that is used in deep learning models for predictions across extended time horizons. Ensemble forecast means training several applying deep learning models to many datasets and then calculating the average of their predictions

The accuracy is enhanced for long-range forecasts and the effect of atmospheric chaos is reduced. The prediction of weather by deep learning models with previously unheard-of accuracy by utilizing enormous amounts of historical weather data and advanced ML methods.

P. D. S, V. V and PK. M. J, N. S et.al [17] producing more accurate findings the ensemble method is used. Machine learning results are improved by ensemble learning and by combining multiple models. This technique performs better in terms of prediction by comparing with a single model. Weather variations are predicted by using numerous machine learning techniques and algorithms. There are numerous previous approaches of weather forecasting based on a number of variables, including rainfall, humidity, wind, and temperature.

S. Tiwari, R. Sabzehgar and M. Rasouli, et.al [18] provide a method of forecasting at a specific location for short-term solar irradiance using bootstrap aggregation ML models, numerical weather prediction and gradient boosting regression. Also it considers seasonal features such as day and month of the year and spatial data such as elevation, latitude, and longitude. The Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) will be used to evaluate the suggested method metrics.

A. A. Patil and K. Kulkarni et.al [19] propose a novel Machine Learning (ML) based hybrid approach that effectively leverages nowcasts and forecasts of atmospheric states – chosen based on both physics and data-driven principles – obtained from the NWP-based Global Forecast

System (GFS) model. We investigate three ML-based problem formulations for rainfall prediction: rain-no rain classification, multiclass classification, and regression. The proposed approach yields up to 25% improvement in rainfall prediction when compared with the GFS baseline.

D. V. Rayudu and J. F. Roseline, et.al [20] rainfall forecasting techniques uses DNN such as (ANNs) as well as (DLNNs). Through their efficiency, weather forecasting techniques were evaluated and ranked. Substances and Methods: DLNN data is used for Group 1 examination, Artificial Neural Network (ANN) with alpha error rate (Err) of 0.05 and (G-power) of 82% is used for Group 2 analyzes sample test data.

S. Jaidee and W. Pora, et.al [21] demonstrates weather predictions examinations with feature engineering using ML models (RNN) and (FNN) to forecast solar power four hours in advance for using Numerical Weather Prediction (NWP) forecast. By using data from weather monitoring devices, FNN with forecast weather measurements demonstrates (RMSE) value is 9.53%, when utilizing a FNN. Therefore, RMSE is 8.38%, which is only 0.25% higher than the prediction based on the measurement while utilizing FNN only forecast local climate.

D. Mahajan and S. Sharma, et.al [22] a machine learning categorization technique is used for rainfall prediction. From the total data, 80% is the trained and 20% is tested data, and analysis depends on the number of actual and expected forecasts. 85% of accuracy is found in classification model, and accuracy of numerous different machine learning techniques is also compared.

M. Senekane, N. J. Matjelo and B. M. Taele, et.al [23] traditional methods like (ARIMA), as well as artificial intelligence (machine learning) methods like artificial neural networks and support vector machines. Here, machine learning techniques and topological data analysis (TDA) are used to enhance power utilities' short-term output power generation. By using coefficient of determination as data performance of different ML systems is evaluated.

T. Lei, Y. Dong, C. Jin, J. Min and C. Han, et.al [24] support vector machines and ridge regression are two ML is utilized to make rolling temperature predicting model with multiple models in an ensemble. Two-meter temperature numerical forecast products from four weather forecast models with 24-hour lead times were based on observations from 20 Beijing-based national-level stations and the US National Centers for Environmental Prediction in the United States (GFS), Beijing Meteorological Bureau Rapid-refresh Multi-scale Analysis and Prediction System (RMAPS), Japan Meteorological Agency (JMA), and European Centre for Medium-Range Weather Forecasts (EC).

The multi-model ensemble based on ML outcomes demonstrate effectively solves systematic bias in the model predictions.

S. Jain and D. Ramesh, et.al [25] to improve crop yield a crop selection strategy is suggested based on soil and climatic conditions. It also recommends the best time to plant certain crops, by using seasonal weather predictions. The machine learning algorithms that are used to predict the weather and choose appropriate crops, random forest and recurrent neural networks classification algorithms are two examples. The suggested weather forecasting method performs better for each of the selected weather parameters when compared to a traditional artificial neural network.

The research gaps observed from the above literature survey is thunders, flashes, heavy winds and drizzling.

3. Framework for an Novel Technique for Forecasting of Weather Interactive Predictive Using Hybrid Machine Learning

In this section, framework for an novel technique for forecasting of weather interactive predictive using hybrid machine learning is observed in Fig. 113.1.

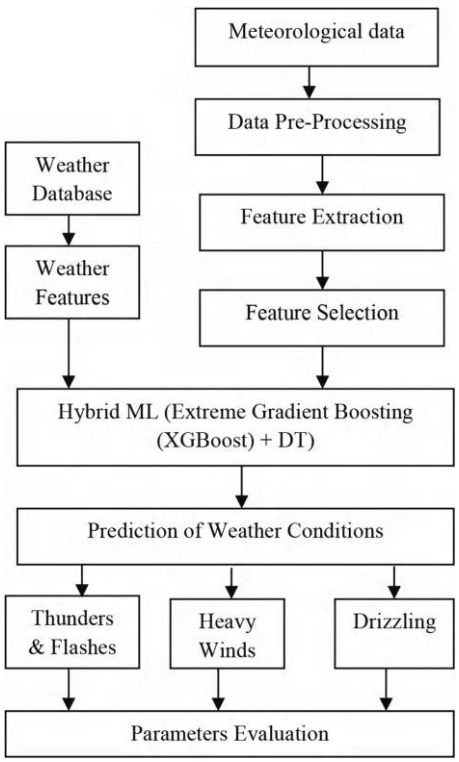

Fig. 113.1 Framework of novel technique for forecasting of weather interactive predictive using hybrid machine learning

Source: Author

Meteorological data is collected and given as input. After input data, the unwanted data is removed in pre-processed stage. Then the features are extracted and selected after extraction from the data. In that features are selected from feature selection. From weather database the features are selected. Then hybrid Extreme Gradient Boosting (XGBoost) and DT is applied, then thunders, flashes, heavy winds and drizzling are predicted. Finally weather conditions are predicted and parameters are evaluated.

The physical parameters that are measured directly by instrumentation are wind speed, temperature, wind direction, cloud cover, cloud layer(s), visibility, dew point, and current weather. Some examples of meteorological events are hurricanes, fog, tornadoes and rain. The temperature, air pressure, and atmospheric concentration of water vapor are all caused by variations in climate. Weather data provides information about a region's climate. A region's short-term atmospheric conditions that include characteristics like wind speed, humidity, and lowest and maximum temperature is known as weather. In this, analysis Kaggle dataset is used.

Data preprocessing is the process of cleaning, transforming, and preparing raw data so that it can be used for analysis or modeling. The goal is to improve the quality and efficiency of the data, and to make it suitable for machine learning algorithms. Data preprocessing is important because the quality of the data used to build a machine learning model directly affects the quality of the model itself. Raw data often contains missing values and outliers, which can lead to incorrect conclusions during analysis. Here, the pre-processing method used in this analysis is Ensemble preprocessing. This technique helps in increasing the accuracy.

Feature extraction is a process that involves identifying and extracting relevant features from raw data to create a more informative dataset. The extracted features are then used to train machine learning models. The process of finding and removing pertinent features from unprocessed data is known as feature extraction. By using attributes, more informative dataset is then produced for categorization and forecasting.

Feature selection resolve both by having too little high-value data and having too much low-value data. For choosing features and creating a model by finding the minimum number of columns from the data source. The benefits of feature selection are improved model interpretability, shorter training periods, effective multicollinearity maintenance less overfitting, and better model performance. The flash reduces by the air that rapidly cools. By quick expansion and contraction, sound wave sense as thunder is coming. By the air, lightning discharge can travel many kilometers, even though it often only impacts one spot on the ground. Here, the feature selection method used in this analysis is Filter method. This method selects features based on criteria before building the model. They are computationally inexpensive and can be used with any machine learning algorithm.

A gradient boosting library is scalable and effective distributed, and it is made for training machine learning models. This ensemble learning technique combines the predictions of several weak models for getting a better prediction. XGBoost, refers as "Extreme Gradient Boosting," is one of the most popular and extensively utilized machine learning algorithms. As it achieve advanced results in a range of machine learning, including regression and classification and it has capacity to manage large data sets.

In real-world data without requiring a lot of pre-processing, XGBoost's is primary characteristics is its effective handling of missing values, which enables it to deal with missing values. Furthermore, XGBoost's included parallel processing capability so the models may be trained on big datasets in a fair period of time.

The damaging winds that are over 58 mph and frequently come from thunderstorms is defined as Strong Wind. The Strong Wind Risk Index score and rating in the National Risk Index is indicated United States for Strong Wind in relation of community's relative risk. Drizzle is made up of tiny, many water droplets that carried by air currents. It can appear to float. It is in between 0.2 and 0.5 millimeters (0.008 and 0.02 inches) diameters of these drops. Larger drops are referred to as raindrops and smaller ones are cloud or fog droplets.

The information that monitors and forecasts patterns and conditions in the weather is the weather data. The factors that weather data measures temperature, air quality, wind speed, and precipitation level are only a few of to provide information about the condition of the atmosphere in a given place over a certain time period. They are cloudiness, wind, humidity, precipitation, temperature, and atmospheric pressure, and elements combine to determine the current weather.

4. Results Analysis

In this section, result analysis for a novel technique for forecasting of weather interactive predictive using hybrid machine learning is observed. Table 113.1 represents Performance Analysis

In Fig. 113.2, accuracy comparison graph is compared between Navie Bayes, Logistic Regression and (Extreme Gradient Boosting and Decision Tree) is compared for

weather interactive Prediction. Weather is predicted accurately, so people didn't get any damage.

Table 113.1 Performance analysis

Parameters	Naive Bayes (NB)	Logistic Regression (LR)	Hybrid ML (XGBOOST + DT)
Accuracy	86.1	92.4	96.8
Recall	90.7	93.4	98.1
Precision	81.9	86.8	91.4
F1-Score	85.2	89.3	96.7
Prediction Time	8834	9548	7922

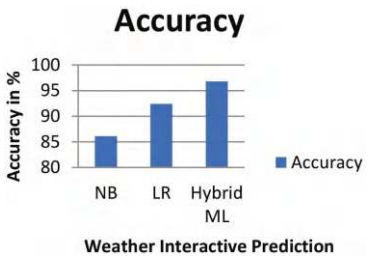

Fig. 113.2 Accuracy comparison graph

The graphical representation of recall for weather prediction is compared between Navie bayes, Logistic Regression and (Extreme Gradient Boosting and Decision Tree) is observed in Fig. 113.3. In this graphical representation, X-axis shows weather interactive prediction and Y-axis shows recall. In this comparison recall of hybrid (Extreme Gradient Boosting + Decision Tree) shows higher value when compared with Navie Bayes and Logistic Regression.

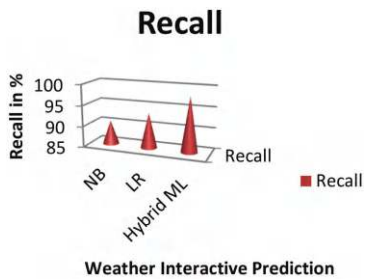

Fig. 113.3 Recall comparison graph

Weather Interactive Prediction using Hybrid Machine Learning shows high precision for XG BOOST+DT when compared with NB and LR is observed in Fig. 113.4. Weather forecasts can help save lives by providing early warnings of storms, heat waves, and other disasters. For example, hazardous weather forecasts can help the public and government advisory agencies know how to handle dangerous situations.

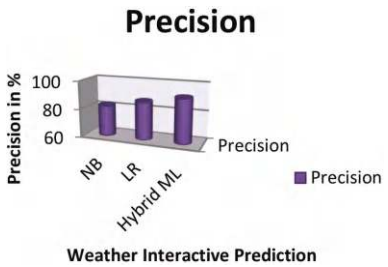

Fig. 113.4 Precision comparison graph

F1-Score is high for XG BOOST+DT in Weather Interactive Prediction when compared with NB and LR in Fig. 113.5. Weather forecasts can help with agricultural management, including planning planting and tillage operations, seed purchase, and pest and disease management.

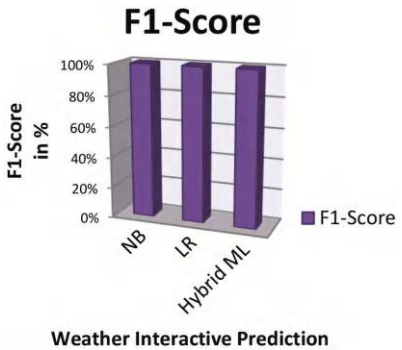

Fig. 113.5 F1-Score comparison graph

The prediction time for predicting weather using hybrid machine learning (XG BOOST+DT), shows less time. Weather forecasts help ships plot routes to avoid severe weather patterns. Weather forecasts help construction workers determine if it's safe to work on building sites. Weather Forecasting is crucial since it helps to determine future climate changes.

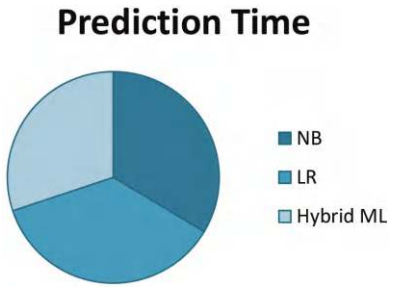

Fig. 113.6 Prediction time comparison graph

5. Conlcusion

Hence, novel technique for forecasting of weather interactive predictive using hybrid machine learning

is concluded in this section. The various atmospheric conditions are used by huge complex physics models over an extended period of time are used to predict the weather. These conditions are frequently unstable, because of weather system changes that results in forecasts the models that becoming inaccurate. Therefore, by applying Hybrid machine learning (Extreme Gradient Boosting + Decision Tree) Weather is predicted thunders, flashes, heavy winds and drizzling accurately.

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Note: All the figures and table in the result section are attained from the proposed methodology and compared with the existing machine learning algorithms.