Sustainable Artificial Intelligence-Powered Applications
IEREK Interdisciplinary Series for Sustainable Development

Chander Prabha · Md. Mehedi Hassan ·
Farhana Yasmin · Asif Karim *Editors*

Emerging AI Applications in Earth Sciences

Challenges, Impact and Analysis

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Sustainable Artificial Intelligence-Powered Applications

IEREK Interdisciplinary Series for Sustainable Development

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Contents

Introduction to AI and IoT in the Field of Earth Sciences

Shalini Kumari, Nabanita Roy, and Vinod Kumar

Abstract

Integrating Artificial Intelligence (AI) with the Internet of Things (IoT) signifies a radical shift in Earth Sciences, enhancing our capacity to identify, evaluate, and understand intricate planetary phenomena. This investigation examines the significant influence of AI and IoT technologies on environmental monitoring, data processing, and scientific comprehension. Contemporary machine learning methodologies, intricate sensor networks, and cutting-edge data acquisition technology empower researchers to amass, analyse, and interpret environmental data with unparalleled accuracy and magnitude. IoT devices produce continuous, detailed data streams from oceanic, terrestrial, and atmospheric settings, which AI algorithms transform into actionable insights, predictive models, and extensive scientific comprehension. Data preparation, model customisation, community distribution, and operational maintenance are needed to apply AI to Earth sciences. Machine Learning Operations (MLOps) frameworks enable AI model generation, deployment, and improvement. This study shows how AI in Earth Sciences requires computer scientists, mathematicians, and geologists to collaborate. The future of environmental research depends on powerful, flexible AI tools that can uncover new patterns, accelerate scientific advances, and provide deeper insights into planetary dynamics.

Keywords

Artificial intelligence · Internet of things · Earth science · Machine learning · Deep learning · Wireless sensor networks · Edge computing

1 Introduction

Artificial Intelligence (AI) and the Internet of Things (IoT) represent a paradigm leap in Earth Sciences, enhancing our ability to detect, assess, and understand complex planetary phenomena. Modern machine-learning techniques, sensor networks, and data-gathering technology allow researchers to collect, process, and interpret environmental data with unprecedented precision and scale. These tools monitor real-time climate change, natural catastrophe prediction, biodiversity mapping, and ecosystem dynamics. IoT devices create continuous, fine-grained data from ocean, terrestrial, and atmospheric environments that AI algorithms convert into actionable insights, predictive models, and scientific understanding. In this way, scientists can construct more sophisticated, flexible, and responsive environmental management, conservation, and sustainable development solutions by connecting technical innovation with environmental stewardship. Deep learning (DL) processes have also benefited the multidisciplinary field of Earth science, which studies diverse aspects of the Earth. This essay describes how DL has been used to support Earth technology and special study topics (Lin et al., 2022). For instance, Earth's technology utilized DL models for remote sensing, climate modelling, and geoscience data analysis. The fact that DL has achieved significant. The weather models simulate Earth's ecology, oceans, and land bottom to study future climates. DL algorithms improve the accuracy of weather forecasting by analyzing outputs and observations (Sun et al., 2022b). Highly significant implications exist for understanding climate exchange processes

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and reducing their effects. DL algorithms have changed the face of geoscience data analysis by enabling the identification of complex patterns and correlations in large datasets. Due to their volume and complexity, seismic data, geophysical pictures, and geological maps are hard to understand. Deep mastery algorithms effectively extract statistics from data sets, improving geological understanding, exploration, and risk assessment. One of the advantages of deep Earth technology research is its ability to address massive data sets (Zhu et al., 2022). With advancing technologies, Earth-watching buildings and climate models, among other scientific units, churn out large volumes of data. Deep mastering algorithms can process large datasets faster than traditional methods.

Scientists can observe Earth's tactics in more detail, improving their knowledge of its movements. The introduction of DL processes in Earth's technology has several challenges. One of the biggest challenges is the need for many computational sources and information. DL models with millions of parameters require effective hardware and neural network designs (Zaini et al., 2022). Also, such models require skilled researchers who can create, train, and thrive in these models. Finally, DL uses categorized information for education, which may be missing in some Earth scientific domains.

AI is a computer science field that develops smart computers that can perceive, analyze, and respond to inputs (Spector, 2006; Sun et al., 2022b). Humans are known to be the smartest species on Earth. They can also plan, innovate, and solve issues more effectively. From discovering fire to reaching Mars, one invents many things for his benefit. However, new inventions are boundless, according to researchers. The target was to build a "man-made homosapien" species just like AI. A system with primary capabilities like learning, reasoning, self-improvement, understanding of the language, and problem-solving is regarded as AI. AI implementation in different industries, especially technology, will generate 2.3 million jobs by 2024.

This advanced technology impacts business, defence, aerospace, and healthcare industries. It is also known as human-programmed human intelligence simulation. Humans can have a well-equipped life with the help of AI by saving time and energy due to automated equipment. Two types of assistants are proposed for humans: manual (robots) and digital (Chatbots) for risky, repetitive, and challenging work. The development of machines involves understanding human behaviour and incorporating logic through algorithms that make software, devices, and robots smarter. Figure 1 presents the Earth Science AI application roadmap.

Popular AI applications include ChatGPT for writing and Midjourney for image creation. These represent important learning opportunities for the scientific community. AI applications have already shown the capacity to drastically change geoscience practice by revealing hitherto unknown patterns and linkages in diverse datasets. AI in Earth sciences is an exciting and expanding field. AI can analyze vast databases, speed up procedures, and uncover hidden links, revolutionizing geoscience approaches and enabling previously impossible discoveries. This paper explores best practices and future directions to make AI more practical and useful for Earth scientists. Developing AI tools for Earth sciences is an interdisciplinary activity involving computer science, mathematics, and geology. Training geoscientists in AI tool usage fosters innovation and teamwork. Improving these variables is critical for practical and usable AI, which may lead to discoveries. Table 1 presents the types of AI in terms of capabilities and functionality. Table 2 presents the IoT Technologies.

2 The Significance of AI in the Earth Sciences

Before using AI, it is essential to comprehend its potential contributions to Earth sciences. This section delineates research trajectories and endeavours to illustrate the potential characteristics of future practical AI products or services.

2.1 Data Collection and Processing

An increasingly large part of data gathering and processing has been automated, as shown in Fig. 2. Coordinated data collecting, standardization, and open data sharing can improve scientific study on crucial topics, such as global environmental change, which AI methods can further accelerate. Our future civilization will rely heavily on existing or developing data infrastructure, such as satellites, drones, stations, in-situ sensors, and mobile devices. AI will improve the collection and processing of daily or on-site data. For example, interruptions such as unpredictable variables like solar magnetic storms, sensor malfunction, cloud cover, extreme weather, and low batteries often lead to missing and poor-quality data. Artificial Intelligence has surfaced as a potential means to offer continuous time series via automatic gap-filling. A common use of machine learning is rectifying Landsat 7 imagery affected by stripes due to the malfunction of the Scan Line Corrector since 2003. In the future, we can anticipate AI services that can intelligently fill and modify the first gathered raw data to produce more comprehensive and continuous observations, which is always preferable. AI-enhanced data enrichment can enrich substantial and practical insights for scientists from vast data and help create a stronger link between science and society.

Optimally, methodologies like Diffusion Models (Yang et al., 2024) and Generative Adversarial Networks (GAN)

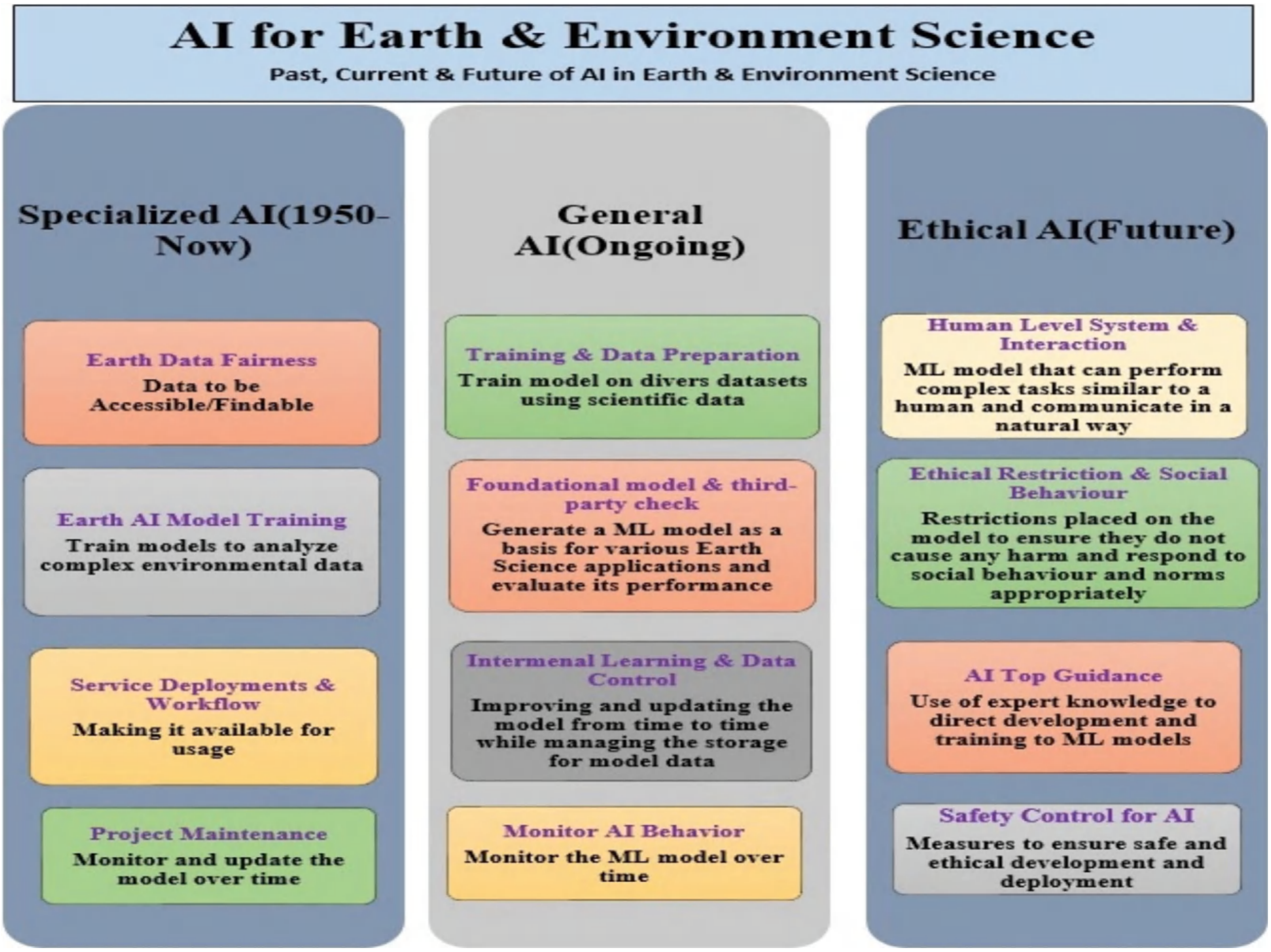

Fig. 1 Earth Science AI application roadmap

Table 1 Types of AI

Feature	Types of AI	Description
Capabilities	Weak AI	It is a type of AI that can execute certain commands without thinking. This sort of AI is the most prevalent worldwide. Popular instances of weak AI include Siri, Alexa, Alpha Go, Watson, and Sophia (the humanoid)
	General AI	This sort of AI can execute activities similar to humans. There are currently no machines that can think or work like humans, although this may change shortly
	Strong AI	In this sort of AI, the computer is predicted to surpass human capabilities. It will outperform humans, though it is challenging but not impossible. Machines may eventually become the master and surpass humans. It is viewed as a significant threat to society by scientists like Stephen Hawking
Functionality	Reactive machines	These machines operate on specified datasets. They lack data storage for previous and future data. Dependent on current data. The chess algorithm that defeated Garry Kasparov and the deep blue system, as well as AlphaGo, are instances of reactive machines (Singh, 2017)
	Theory of mind	These computers are designed to understand and respond to human emotions and psychology. Although only a dream, scientists are attempting to construct such devices in the near future
	Self-awareness	These machines are supposed to be super-intelligent, capable of thinking, acting, and being self-aware with human-like cognition and emotions. Research aims to produce robots that are deemed future AI

Table 2 IoT technologies

IoT technologies	Description
Wireless Sensor Networks (WSN)	Wireless Sensor Networks (WSN) offer environmental monitoring through networked, intelligent sensor nodes that can gather, interpret, and transfer data across complex landscapes. In these networks, many small, autonomous devices with temperature, humidity, pressure, audio, and chemical sensors can wirelessly and collectively collect real-time environmental data. Each sensor node contains data acquisition, local processing, and energy-efficient communication protocols like ZigBee, 6LoWPAN, or LoRaWAN to operate in harsh and remote environments without human intervention. WSNs can produce complex, real-time data meshes with unparalleled spatial and temporal resolution to monitor climate change, agricultural fields, natural disasters, and ecosystem dynamics because to their distributed nature. Advanced WSN architectures integrate edge computing and machine learning algorithms directly into sensor nodes, improving local data filtering, anomaly detection, and intelligent decision-making, reducing bandwidth and making environmental monitoring systems more responsive and adaptive
Edge computing	Edge computing in IoT technology transforms environmental data processing by putting computational intelligence to the sensor network's periphery instead of the cloud. Sensor devices can perform real-time data analysis, filtering, and preliminary processing at data gathering in remote maritime habitats, dense woods, or difficult geological terrains in Earth Sciences. Edge computing improves environmental monitoring system responsiveness, latency, and bandwidth by enabling local processing. Edge sensors with advanced machine learning algorithms can detect abnormalities like seismic activity, temperature shifts, and ecological changes promptly, speeding up decision-making and data transfer. Monitoring glacial melt, following wildlife in remote areas, or investigating deep-sea environmental conditions require this approach because typical cloud-based systems would struggle with limited connectivity
Satellite communication systems	Satellite communication systems enable global, inaccessible environmental monitoring powered by IoT. These advanced communication networks transfer data worldwide using LEO, MEO, and GEO satellites for Earth scientific applications. Combining IoT sensor networks with satellite communication technology allows researchers to collect real-time data from polar regions, deep oceans, dense rainforests, and high-altitude mountain ranges. Advanced onboard processing filters, compresses, and analyses initial data, and contemporary satellite communication systems provide several data transfer protocols for smooth interaction with ground-based sensors, drones, and autonomous monitoring stations. These systems can provide near-instantaneous insights into planetary-scale environmental processes by tracking sea-level rise, deforestation, arctic ice melting, global weather patterns, and biodiversity changes

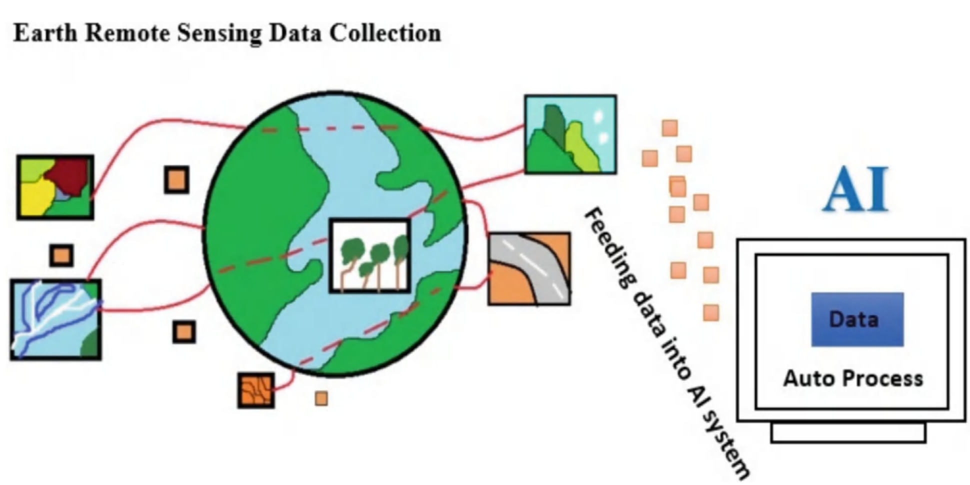

Fig. 2 Illustration of data collection and processing

(Goodfellow et al., 2020) could generate reliable data drawn from the data stream of other variables even in the absence of a device that is monitoring that variable. This would save considerable resources and ensure that functionally redundant physical sensors are not deployed. For example, the future Earth Science Community could create a single stationary network that would collect all the necessary datasets, allowing experts in the different Earth Science disciplines to create their own domain-specific datasets using AI. To use the existing satellites or develop a new set of satellites to provide a global constellation with minimal revisit time and a large radio spectrum. Proceed by automatically generating all datasets from the raw satellite observations using AI services. Though the original constellation may fail to meet the coverage or frequency criteria of the domain or is missing coverage in the first suggestions, AI can be highly useful in modelling the relationships and transforming the information into the new datasets directly needed by scientists in the new domain.

2.2 Anomaly Detection

Anomalies indicate events that differ from what was expected to occur or are part of the known physics governing a model and represent essential information for scientists and stakeholders. Determining anomalies in large data sets is an important application of AI/Machine Learning (ML) for big data. Future Earth scientific communities will begin to understand the interacting or tele-connecting processes within Earth systems to reach a fully integrated understanding of the controlling mechanisms. The problem now facing scientists is the identification of anomalies. Separating meaningful anomalies from noise in data or minor events has been challenging (Bergen et al., 2019; Nassif et al., 2021). An example of Anomaly Detection (AD) applying ML is the architecture that combines deep belief networks and a one-class support vector machine, OCSVM (Xiong & Zuo, 2020). The DBN model extracts abstract features and then feeds them to the input of the OCSVM to detect the anomalies. Training for this DBN model happens sequentially over layers, allowing extraction from the input data pertinent to the task.

In the future, AI will automate the process and find valuable abnormalities with great precision and without human intervention using pre-configured production-grade AI systems. The detection of anomalies is often associated with alarm systems (e.g., flooding alerts, windstorm alerts, etc.). AI services might significantly reduce or even eliminate warning spam or false alarms, as shown in Fig. 3. AI will free scientists from the tedium of routine data-sifting tasks, freeing them to focus on discovering strong evidence to answer fundamental scientific questions. Another area in which AI could make a difference is in the threshold settings. Currently, most anomaly threshold settings are manually set by experts and require much knowledge to establish the appropriate threshold values, which are mostly static and, therefore, not optimal in some time-sensitive scenarios such as landslides or wildfire early warning signals (Guzzetti et al., 2020). AI can dynamically change thresholds according to complex settings and knowledge acquired from decades of historical data, thus being more accurate and fast than thresholds set by professionals. The expected outcomes will give prompt and precise alerts for different natural catastrophes, thus enabling the emergency response teams to be better positioned to act effectively and reduce damage.

2.3 Surveillance and Assessment

One of the most important advantages of AI in monitoring the Earth and environmental system is automation. Most teams hope to integrate AI to limit the amount of time a human needs to be present in their monitoring process. Unmanned monitoring covers larger areas more often because it is much more scalable. The ability to merge workflows directly through data translation and enforcement of rules by AI will likely reduce the latency from observation to monitoring times of scientists to near-real-time. Several researchers expect that AI can further improve data quality both in terms of time and spatial dimensions (Bortnik & Camporeale, 2021). AI is a protective tool so that bad-quality data does not flood the system and that good-quality data is delivered to scientists or decision-makers in the dashboards. The measuring strategy has to be tailored according to the problem at hand. The scientists encounter problems locating the most appropriate locations in field measurement, determining the battery life required for any instrument and the frequency of the observation intervals in the case of field measurement. According to the parameters and objectives set up by scientists, such as the range of permissible locations for sensor deployment, the desired observation coverage, and the maximum number of accessible devices, the models can learn. Using techniques like genetic algorithms, AI can translate the problem into an optimisation problem

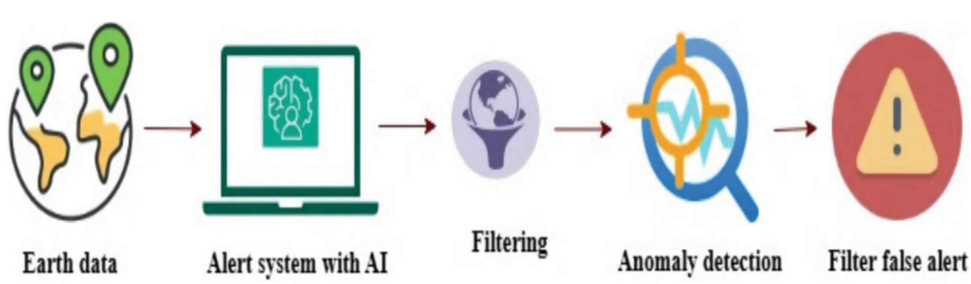

Fig. 3 Anomaly detection illustration

and find a reliable model to help scientists cost-effectively perform their measurement strategy.

Moreover, AI will help integrate unconventional monitoring approaches with standard monitoring techniques like crowdsourcing and citizen science. Crowdsourcing is the cheapest method to monitor and collect data for several research teams. However, it is recognized that the quality of crowdsourced data is a significant issue (Nguyen et al., 2020). Despite the best efforts to increase data quality, including awarding a "reliability score" to each crowdsourcer and prioritizing data from those with higher scores, overall quality concerns remain for data users. AI will be incorporated into collection devices used by citizen scientists to improve the quality of their observations. Simultaneously, AI services will be developed to improve the quality of crowdsourced data and make it more accessible and reliable to the scientific community.

2.4 The Short-Term Prediction

Short-term forecasts usually refer to predictions of a few hours or days in advance, which is the most commonly encountered prediction and is an essential aspect of running specific sectors such as agriculture and aviation. Most meteorological services have their focus on short-term forecasting, which includes hindcasting within 6 h and forecasting that spans for several days. DeepMind, a Google subsidiary, has improved short-term weather forecasting through AI algorithms. Many workshops have been held to discuss using the latest AI techniques in operational weather forecasting (NOAA & PSL, 2023; SMD AI, 2024; Silverstone, 2024). These seminars bring together experts from academia, industry, and governmental organizations to share their views, cooperate on research projects, and address problems in using AI for meteorological forecasting.

The integration of AI signifies a paradigm shift for Earth's scientific research communities from traditionally physics-informed numerical models to primarily data-driven AI models. Scientists will find that AI prediction is less interpretable than numerical models because AI has learned all the patterns directly from the data instead of relying on predefined physical equations. However, AI techniques are more likely to improve standard process-based models by effectively making relationships between variables or processes previously unknown, as found in the case of ecological systems (Lewis et al., 2023). Rationale in models and simulated processes will be less transparent and malleable than it is in traditional models. The main focus of research will gradually shift from model parameter optimization to data engineering. In the future, AI may totally replace the current numerical model-based prediction. Scientists will remain in a hybrid environment in which numerical models and AI models survive for an extended period, and their interactions will be interdependent.

2.5 The Long-Term Prediction

Long-term is a relative term in Earth sciences and can span different durations depending on the specific field. For example, in geology, the long term refers to tens of thousands to millions of years of global and regional tectonism. In contrast, for meteorology, it can be several months to years. "Long Term" is usually used in strategic planning and requires large-scale patterns as background data. A typical example is predicting global climate changes for the next century (O'Leary, 2022). However, the experimental results so far suggest that both AI and numerical models face long-term prediction challenges. This difference between AI and physics-based models tends to fade as the forecast horizon becomes longer. This makes sense since AI performance heavily depends on the quality of training data. The training data would have covered comparatively less for long-range predictions, hence being of lower quality. This would make it challenging for AI to understand long-range trends comparable to the difficulties faced by the numerical modelling groups during the past several decades.

3 Implementing Practical AI in Earth System Sciences: Best Practices

Creating feasible AI models requires surmounting many challenges. This chapter deals with two practical challenges for novice AI scientists: cloud data usage and community-centric AI deployment and operation, in addition to common challenges such as training sample scarcity, poor generalization, and explainability.

3.1 AI Project-Specific Product Development and Collaboration

Although general AI is being thoroughly researched, most models require major customizations for specific projects and tasks. AI prototyping entails problem definition and model creation.

Defining the tasks intended for AI and finding proper scientific questions are as hard as building AI models. Experts in AI project experience must determine which problems AI can solve and which it cannot. AI generally requires a dataset with patterns rather than random or near randomness. The patterns do not need to be obvious to humans but should exist. Current AI efforts have a regular protocol for the experiment stage. People gather datasets that usually contain ground truth or training labels, as most of the AI tasks fall under supervised learning. Data preparation is a very time-consuming and careful process. No pipeline of an industrial sort in a sequential manner. A lot of iterations for preparing data and tuning a model are used. For example, precipitation prediction models might find combinations of pressure, temperature, terrain, and land valuable cover in certain models but not helpful at all in others.

To enhance prediction accuracy, creating different training sets for diverse models is critical.

Researchers often have to duplicate data preparation and model trials in several projects manually. Good management of projects, including experiment transcriptions and result sharing, can prevent AI projects from developing into resource-draining black holes (Sun et al., 2022a).

3.2 AI Deployment and Production in the Community

AI-based data-driven automatic analysis of this kind has replaced empirical hand-holding to analyze geographic data sciences in the wake of revolutionizing Earth science scenarios through model development. The major problem still facing production-level stability and reliability to client satisfaction through AI technology is that most AI-based projects fail in real-world needs. Most AI projects are still not ready to be implemented in the field. AI models are highly important for accurate, rapid, explainable, dependable, and trustworthy findings in many scenarios. These include seismic signal explanation, hurricane forecasting, weather prediction, air quality simulation, and water discharge forecasting. Interactions between the community users and AI models are necessary. Research users can directly deploy AI models to lab servers or cloud platforms. For public users, data product teams must transform AI results into meaningful formats, such as maps or text statements. Examples include "Fash fooding in Fairfax County between 5:00 PM and 6:00 PM; seek shelter and remain indoors." Coordination must be made with science communicators and public health specialists. The community must update the present information pipeline to integrate the AI models into the workflow. The user interface should be enhanced with probability scores and then linked with provenance for verification and explanation by geoscientists/meteorologists, thereby enhancing the understanding of the predictions made.

3.3 Operation and Maintenance Team Guidance

MLOps (Machine Learning Operations) is an operationalization method of AI, which applies the DevOps principle to deploy and monitor machine learning systems for real-world functionalities (Microsoft: Machine Learning Operations, 2024). MLOps considers the complete model lifetime, from data collection until final use. Exploratory data analysis is done first in starting MLOps to examine data quality and specific concerns. Model training happens in the middle part of MLOps after performing data cleaning and removing poor data. Model performance must be tested between training and deployment to avoid systemic errors. Optimize the model to maximize utility if misclassification risks have different real-world effects. In 2022, Toronto used an AI model to estimate bacterial levels at its beaches: over or below the safety threshold (Martineau, 2022). If the consequences of users visiting dangerous beaches are tougher than those of underused safe beaches, the model should predict "unsafe." Observe the model in deployment and operation to avoid degradation from "data drift" or other issues. The model can be modified with user feedback and testing to improve utility or avoid deterioration. The NASA Interagency Implementation and Advanced Concepts Team (IMPACT) incorporated MLOps for Earth observation in its open-source SpaceML Initiative (Koehl, 2021). With Technology Readiness Level 9, the MLOps tools are ready for deployment and can be utilized for both Earth-directed satellites like Worldview and sky-oriented spacecraft like Hubble. Given the rarity of events of interest relative to the gigabytes to terabytes of non-interest data, MLOps is crucial. SpaceML collaborated with students worldwide at the high school level to provide low-cost data labelling (Lewis et al., 2023).

4 Obstacles in the Application of AI Within Earth-Science

This section discusses the overall need for AI from the perspective of data scientists and data users in the Earth's scientific community. The research community is now exploring AI models to generate better socioeconomic products relevant to societal decision-making. The community is looking into AI to overcome issues that are currently almost impossible to overcome with traditional research approaches. There is a strong demand for data-driven sciences today.

- **Addressing missing data, biases, and uncertainties**: AI requires constant access to high-quality data for training and validation. The Earth science community has an enormous collection of data. However, high-quality data on the critical factors, accuracy, and spatial–temporal coverage is lacking.
- **Preparing data suitable for AI**: It is an implicit reality that geographic data scientists spend most of their effort on data preparation rather than analysis (Jain et al., 2022). This procedure delays the ML cycle for experts and creates a high barrier for less experienced people to pass over. Less effort is dedicated to creating a holistic appreciation of the challenges associated with the data before it is allowed into model development. More so, geospatial data have features that mandate specific attention.
- **Minimising experimental and operational expenses**: Earth scientists spend a lot of time modelling to understand Earth systems and the possible changes resulting from climate change and human–environment interaction. Current practice is to prepare thousands of models and run them concurrently to decide which one provides the best consensus estimate. It is very computationally intensive; therefore, models demand clusters or supercomputers for processing large amounts of data. Numerical methods are slow and need a better technique. Growing concerns exist over the carbon footprint of resource-intensive models (Loft, 2020). The modelling community exploits AI, which consumes few resources and is a straightforward technique to discern patterns in how input factors impact the target phenomenon. Incorporation of AI models into numerical models can bridge gaps and replace computationally intensive operations.

5 Conclusion

Integrating Artificial Intelligence (AI) and the Internet of Things (IoT) represents a transformative paradigm for Earth sciences, offering unprecedented capabilities to monitor, analyze, and understand complex planetary systems. Researchers can now collect, interpret, and predict environmental phenomena with remarkable precision and scale by leveraging advanced machine-learning techniques, sophisticated sensor networks, and innovative data processing technologies. The future of Earth sciences hinges on interdisciplinary collaboration, particularly among computer scientists, mathematicians, and geologists, who must work together to develop flexible AI tools capable of uncovering hidden patterns and generating actionable insights. While challenges remain—such as data quality, computational requirements, and model interpretability—the potential of AI to revolutionize environmental monitoring, climate change prediction, and ecosystem dynamics is immense. As technology evolves, AI will likely transition from being a supplementary tool to becoming a core methodology in scientific research, enabling more responsive, adaptive, and comprehensive approaches to understanding our planet's intricate systems. The journey towards fully integrating AI in Earth sciences is about technological advancement, expanding human knowledge, and developing more effective environmental stewardship and sustainable development strategies.

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Growing Beyond the Earth: The Potential of Extra-Terrestrial Agriculture from Earth to Space

Parveen Badoni, Mehak Chauhan, Aanya Agrahari, and Maadhav Hira

Abstract

Growing plants on extraterrestrial bodies is crucial for sustaining human life in space habitats. This study examines the feasibility of plant growth on Mars and the Moon. This study also examines the efficacy of hydrogels, space soil that has been treated, and controlled environments in promoting plant growth under conditions similar to those in space. The discoveries we made provide valuable insights into the feasibility of space farming and enhance our understanding of human habitation on extraterrestrial planets. The feasibility of plant growth on Mars and the Moon is investigated in this study, which looks at the soil's composition, the atmosphere, and controlled environments. These studies lay the groundwork for understanding the obstacles and opportunities associated with maintaining human existence on Mars and the Moon as space exploration advances. International Space Station and the studies on the impact of light, temperature, and water on plant growth help solve agricultural problems related to farming on other planets. The study also stressed the need to consider the soil characteristics, the type of plants, and their cultivation methods necessary for efficient space farming. In this work different ML based models are implemented on the data collected through various sources which can be helpful in agricultural research beyond the earth and select the best crops that are suitable to grow in space with the key findings. These findings can be helpful in the coming years for the colonization in other planetary bodies.

Keywords

Astrobotany · Extra-terrestrial agriculture · Machine learning · Microgravity plant growth · Space farming · Regolith

1 Introduction

Exploration of space has led human civilization to develop new techniques for cultivating and sustaining life on other planets. In order to establish human colonies on celestial bodies like Mars, a crucial consideration is the potential for cultivating crops and fungi to sustain a long-term human presence. The study utilizes various approaches to develop comprehensive solutions for space farming, taking into account economic, environmental, and biological factors that are unique to these environments (Lopez et al., 2019). This paper examines the impact of soil composition, atmospheric conditions, and controlled environments on the growth of plants. Experiments conducted using simulated Mars and Moon soil indicate that plants have the potential to grow despite significant challenges such as insufficient nutrition and unconventional soil composition. The unique atmospheric conditions on these celestial bodies need the development of novel methods to sustain life. This domain of "plants in space" refers to the growth of plants in the hostile conditions of outer space, exactly within the microgravity environment of platforms like the ISS. This frontier area, situated beyond the Kármán line at approximately 200–450 km above sea level, is ridden with numerous dangers and difficulties in the exploration of humankind. Heavily invested in this field are many countries' space agencies, which have a vested interest in further exploring outer space (Betz, 2024). An important outcome of the know-how and

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the techniques acquired in developing the growth system for plants in space is the development of hybrid varieties of crops, also known as transgenic crops or genetically modified organisms (Raman, 2017). Outer space is extreme with extreme temperatures, high vacuum, electromagnetic and particle radiation, and varying magnetic fields. These pose a great threat not only to the safety of humans but are also significantly challenged from a biological perspective in the life forms at hand, including plants (Hellweg et al., 2023). A good understanding of the nature of these effects on plant biology has to be developed to formulate effective countermeasures in order to control negative impacts on human and plant life (Furukawa et al., 2020). Explorations of the Moon and Mars have revealed that their soil contains minerals and regolith similar to that found on Earth which are mostly composed of the most important nutrients for plant growth except for reactive nitrogen (NO_3, NH_4), which is vital for plants. Both bodies contain carbon, but organic material which is the main source of reactive nitrogen on Earth is absent. Mars is very intriguing because, during one period, it was covered with liquid water and, in some places, had Earth-like conditions (Eichler et al., 2020). However, at the moment, it's quite a barrier to life: extreme coldness, a thin atmosphere rich in carbon dioxide, low gravity, high radiation, and a lack of organic nutrients (Serria et al., 2023). Future human habitation of Mars is feasible, especially through greenhouse environments that can reproduce Earth's atmosphere to allow plants to grow. For manned missions and potential colonization, oxygen, water, and food-delivering systems will be needed, all of which plants accomplish on Earth, including: CO_2 absorption O_2 release purification of water and nutrient recycling (Neukart, 2024). Artificial ecosystems, in the guise of BLSS, are the only means of solving problems related to the resource supply required for long-duration interplanetary missions. The systems are interlinked compartments that use diverse groups of organisms to recycle resources and then make them available elsewhere in the system. A very critical component—the photoautotrophic compartment—that relies on external light sources-will convert CO_2, wastewater, and other wastes into edible biomass, oxygen, and water-notable requirements for the survival of the astronauts. MELiSSA is actually one of the most advanced BLSS (Keller et al., 2023). It has been developed by the European Space Agency. This MELiSSA loop will be used to produce food, oxygen, and recycle water and carbon dioxide to preserve life in interplanetary travel, stay away from Earth with smaller payloads. Although some crops have been successfully grown in space, the problem in practice is transition from scientific experiment to practical cultivation. Different methodologies have been proposed in the selection of appropriate plants for BLSS. Space farming places additional demands on plants compared to terrestrial agriculture because the stresses of the space environment demand that plants be able to handle stressors such as cosmic radiation and microgravity in ways that are also supportive of astronaut life. The ideal crop for space must make biomass that is of high quality and easily edible quickly and cheaply with the minimum amount of non-edible material and optimal resource use. The Artemis program conducted by NASA focuses on re-establishing human presence on the lunar surface to develop a permanent presence on the Moon, which will serve as a stepping-stone for further human exploration to Mars and other celestial objects (Kessler et al., 2022). This is programming directed to test and develop technologies that are going to be very comprehensive in supporting long-term space missions, including supporting the setup of extraterrestrial settlements. One of its objectives is also focused on the development of advanced life-support systems and habitats that could serve as models for growing plants and fungi in space. With a Moon base, Artemis provides a proving ground where agricultural systems can be developed and tested to apply not only to Mars, but far beyond as well. The advancement in space exploration and the potential habitation of other planets such as Mars or the Moon has led to the development of methods for growing food and NASA's Artemis program, which aims to establish a permanent base on the Moon, aids in developing space agriculture techniques applicable to other planets can be applied for other planets. Artemis' focus and drive toward a sustainable lunar presence directly complement the development of agricultural techniques transferable to other planets. Research carried out by Artemis can be very useful in making systems for growing plants under controlled environments, such as greenhouses or bioreactors, which are important for life support on Mars. The discoveries on the Moon will pave the way for the development of habitats in which plant life will be sustainable for the provision of food, oxygen, and psychological well-being of long-term space travellers and settlers.

A significant area of study since the 1950s, bioregenerative life support systems (BLSS) were devised from an initial research concept based on photosynthetic organisms, such as algae or higher plants, being used to produce food and oxygen and to scrub CO_2 and process water. Discussions regarding suitable crop plants for a space mission date to 1962. BLSSs remain limited in testing because their application is dependent on a scale relevant to space that is precluded by the volume and mass of conventional spacecraft. Other than NASA's Space Shuttle, the Russian Mir station, and the International Space Station (ISS), which have operated modest space crop production programs since the 1990s, these experiments have largely been time-limited investigations under similar constraints. Most current life support systems on spacecraft operate mostly by physicochemical methods, of which some are regenerative and others reliant upon resupply: For example, on the ISS, crew urine is processed for the recovery of potable water. It reviews plant-based testing for food production in the context of BLSS applications (Barone

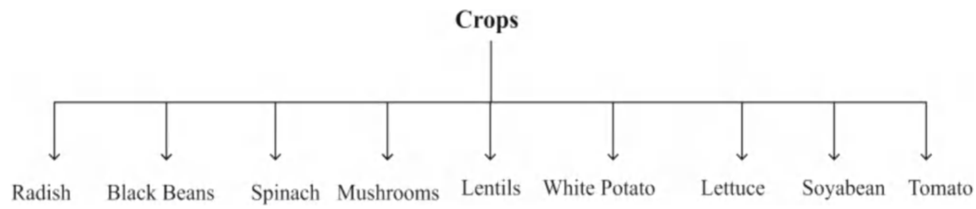

Fig. 1 Different crops discussed

et al., 2023). Controlling the growth of plants in space requires an encompassing understanding of how plants grow and, of course, experience in controlled-environment agriculture. While a long history of growing healthy plants in space exists through extensive review of experiments on plant growth carried out between 1960 and 2000, how long-term effects from this environment affect plant growth and reproduction are still quite unknown. All these effects may critically affect the ability of plants to be considered as a source of food in the bioregenerative life support systems that will sustain human life in the long-duration missions in the Solar System.

Recent discoveries of microbial life in extreme environments on Earth, such as permafrost, hydrothermal vents, and hypersaline lakes, are thus incrementally expanding our knowledge of what it means to live at the limits of life and the resilience of extremophiles. This new knowledge will redound on searches for life on other celestial bodies—especially on Mars, where questions of habitability have been found contentious. Ongoing research on Mars geology, chemistry, and astrobiology is thus important in illuminating the planet's potential to support life.

Astrobiologists explain "habitability" as an environment able to support metabolic activity required for survival, growth, and reproduction. Cockell et al. describe habitability in terms of water, the presence of suitable temperature and physiochemical conditions, an energy source, and necessary elements. These are factors that can be interrelated with the limits of life as we know it. The review will discuss the environmental features of Mars that speak to current or past life on the planet. The experiment "Seedling Growth-1 (SpaceX-2)" is related to one significant space agriculture project. It studies the growth of plants in microgravity on the ISS (Cockell et al., 2023). The experiment is designed to examine how microgravity would be a major factor in the main plant processes: gravitropism and phototropism and root growth in the absence of Earth-like gravity. Seedling Growth-1 is very important to provide essential insights into the adaptation of plants. It looks at gene expressions and plant hormone functions under the view of space conditions. These results are crucial for developing agricultural systems that support long-duration space missions and future human settlement activities in the apparently upcoming lunar and Mars base. The 2016 group project for the Space Life Science Training Program (SLSTP) intended to develop a habitat concept that could germinate the first seeds on Mars. The project focused on two preparatory measures: analysis of seed surface sterilization protocols and the development of an autonomous seed germination habitat (Micco et al., 2013). The design of this habitat will require a small, low power system for gas ventilation, artificial light and water provisions. A visualization scheme will be developed to enable monitoring of seed germination at a distance. Ground study will evaluate how various durations of seed storage influence plant viability and compare different methods employed in their sterilization. The different crops discussed in this paper are as shown in Fig. 1.

The study also focuses on the both extrinsic harsh environmental conditions in Venus, Mars and Moon. Compared to Mars and Moon, Venus raises difficulties due to its rather high temperature 462 °C and unstable behaviour of the atmosphere (Basilevsky & Head, 2003). But the recent studies are being conducted in regard to the future use of fungi like mushrooms in future off-land farming. These fungi can improve the state of the terrestrial environment and provide indispensable nurture needs of the plant growths on Mars, solving critical problems in space farming (Case et al., 2022). Hence, this research builds on knowledge derived from the Seedling Growth-1 experiment, the Artemis programme, investigations into extreme environments, growth of fungi, and plant cultivation at the International Space Station to tackle the virtually generic nature of agronomic issues in extra-planetary agriculture. The fast developing field of space agriculture is essential to humankind's future in space. Researchers want to overcome the difficulties of producing food in the hostile environs of the Moon, Mars, and beyond by creating novel agricultural methods and utilizing the potential of fungus, genetic engineering, and autonomous systems. This effort is made possible by programs like NASA's Artemis and the ISS experiments, which provide information on how plants might be grown in space for long-duration flights and potential space colonies. The creation of strong space agriculture systems will be crucial to the establishment of long-lasting human colonies as solar system exploration continues, guaranteeing that humanity not only survive but flourish in space (Shaw & Soma, 2022). Maintaining Human Existence on the Moon, Mars, and Other Worlds Human exploration will not be confined to our planet in the future. Establishing human colonies on other celestial worlds, including the Moon and Mars, is becoming a feasible goal as countries and business organisations explore beyond Earth. Providing sustainable food supplies is one of the biggest obstacles to developing long-term interplanetary colonies. Future space missions and colonisation initiatives will need the use of space agriculture, the science of cultivating plants and fungi in non-Earthly conditions (Mane, 2024). The critical requirements of astronauts and future residents for food, air, and mental health will be met in part by this developing discipline. Space Agriculture's Contribution to Human Space Travel: The goal of space agriculture is to create systems that let fungus and crops thrive in regulated settings that are similar to or modified from those found on other planets. In order to support long-term space exploration projects like NASA's Artemis program, which intends to send people back to the Moon and ultimately explore Mars, the overall objective is to reduce dependency on Earth-based resources. In addition to providing food, agriculture in space helps meet life support requirements by generating oxygen and recycling trash using bioregenerative life support systems. By fostering a feeling of connection to Earth, plants cultivated in space may also lessen the psychological difficulties astronauts experience during prolonged journeys. This study emphasizes the complex network of elements necessary for promoting plant development on extra-terrestrial bodies. The practicality of interplanetary agriculture is determined by factors like soil composition, atmospheric conditions, environmental controls, and life support systems.

2 Literature Review

2.1 Obstacles to Agriculture in Space

This section discusses various challenges and difficulties encountered in doing agriculture in space. These are:

- **Microgravity**: Plant growth is greatly impacted by Earth's gravity, which affects things like root orientation (gravitropism) and how the plants react to light (phototropism). These processes are modified in microgravity conditions, such as those aboard the ISS or future homes on the Moon and Mars. Research on how plants adjust to the lack of Earth-like gravity, including the Seedling development-1 experiment, looks at hormone modulation, gene expression, and root development (Vandenbrink et al., 2014). Developing systems that enable crops to flourish in space requires an understanding of these adaptations.
- **Radiation**: Plants in space are subject to greater radiation levels since Earth's atmosphere protects them. Plant cells may be harmed by this radiation, which may also stop growth. Protective measures like radiation shielding in greenhouses or bioreactors or the use of genetically engineered crops that can tolerate high radiation levels will be necessary in future space farming systems (Tack et al., 2021).
- **Extreme Conditions**: Terrestrial life finds the environments of planets like Mars and Venus to be exceedingly inhospitable. For instance, Venus has an atmosphere dominated by sulphuric acid clouds with a surface temperature of around 462 °C, but Mars has a relatively thin atmosphere and extreme temperature swings. Innovative methods, such as genetic engineering or growing crops in completely artificial settings, such as controlled-environment agriculture (CEA) systems or subterranean biomes, would be needed to adapt crops to such harsh circumstances (Westall et al., 2023).

By the late 2020s, NASA's Artemis program hopes to have a permanent human presence on the moon. Creating cutting-edge life-support systems, like as plant growing systems that can be transported to Mars and beyond, is one of Artemis' main goals. For evaluating these technologies in a space setting, the Moon offers a useful testing ground. For instance, the Lunar Greenhouse idea suggests growing plants in lunar habitats using hydroponic or aeroponic systems. Bypassing the requirement for soil, which is lacking on the Moon, these methods provide vital nutrients straight to plant roots using nutrient-rich aqueous solutions or mist. Growing plants on Mars, where the soil (regolith) is contaminated with harmful perchlorates and could not be appropriate for conventional farming, would need this study more than on the Moon. To sustain human life in space, a bioregenerative life support system, a closed-loop system, is used to make biological creatures like fungus, algae, and plants (NASA, 2024). These devices provide astronauts access to fresh food, recycle trash, and transform carbon dioxide into oxygen. The integration of plants into such systems is the main focus of BLSS research conducted on the ISS and in controlled Earth conditions. For instance, the ISS's Advanced Plant Habitat (APH) is an advanced growth chamber that enables researchers to examine the effects of several environmental elements on plant development in space, including light, temperature, and humidity. The design of space farms will be guided by the APH's insights, which will maximise plant production and nutrient content in the limited area. Fungi's Function in Space Farming According to recent research, fungi—like mushrooms—may be essential to space agricultural systems in the future. Particularly in nutrient-poor settings like Mars or the Moon, fungi, such as mycorrhizal fungi, may develop symbiotic connections with plant roots to help them absorb nutrients more effectively. Furthermore, certain fungi have the ability to decompose organic materials, which helps BLSS recycle waste. Additionally, fungi are more resistant than plants to harsh space conditions including radiation and high temperatures. They are crucial to the creation of regenerative agriculture systems for space habitats because of their capacity to break down organic waste and promote plant growth. The Greatest Space Agriculture Test Site For space farming, Mars offers both special potential and obstacles. It is a harsh habitat for terrestrial plants because of its thin atmosphere, low temperatures, and high radiation levels. However, it has certain benefits for growing crops in controlled circumstances because of its long day (24.6 h) and the abundance of water ice. According to the Mars Greenhouse idea, crops might be grown on Mars in climate-controlled, pressurised environments with artificial illumination. Hydroponic or aeroponic systems, like those used on the ISS and in lunar habitats, might be used in these greenhouses. According to recent research, Martian regolith may be altered to promote plant development by including organic matter and minerals and eliminating harmful perchlorates. Knowing how to set up a viable agricultural system on Mars depends on research carried out through initiatives like NASA's Mars Exploration Program. By establishing self-sufficient settlements on Mars, these initiatives will lessen the need for resupply trips to Earth. The creation of an autonomous seed germination habitat that might produce the first seeds on Mars was investigated at the 2016 Space Life Science Training Program (SLSTP) (Neukart, 2024). This idea entails creating a habitat that is remotely monitored and has artificial lighting, water supplies, and a low-power gas ventilation system. Making sure that seeds could be sterilised and kept for extended periods of time without losing their viability was a crucial component of this study, since it is a crucial prerequisite for missions that last months or years. Future space missions will need these preliminary steps because they tackle the real-world difficulties of initiating and sustaining crop growth in remote, resource-constrained settings. Managing space farms will need the integration of robots and autonomous technologies, especially in the early phases of colonisation when human presence may be restricted. Synthetic Biology and Genetic Engineering Genetic engineering is probably going to be essential to the viability of space agriculture under harsh conditions. Researchers are looking at methods to alter crops to make them more resistant to severe temperatures, drought, and radiation. For example, plant genomes may be altered using CRISPR technology to make them more tolerant to space conditions. Furthermore, there are intriguing opportunities for creating whole new species specifically suited to space farming via the use of synthetic biology. Bioengineered crops that are more prolific and sustainable for space habitats might be produced by scientists by designing microbes and plants that can flourish in low-gravity, low-nutrient settings (Sami et al., 2021).

The idea of exposing plants on other celestial bodies is itself part of broader scientific themes of space science, astrobiology, as well as exoplanet sciences. Nonetheless, by the last few decades, what people knew about life in space, the potential usage of plants by space, or the extra-terrestrial organisms, and other features have shifted more from just speculative to actually strict scientific research. This history embraces all space exploration and experimental missions, starting from futuristic imaginary science fiction and up to modern practices that include growing plants on the space station and discussing colonization of planets.

2.2 Science Fiction and Early Concepts

While theories of existence and variety of life including plant life outside the planet has always been contemplated in the minds of man the scientific basis for such hypothesis came in the late ninteenth and early twentieth century. So, stimulating the public's curiosity based on erroneous observation with the help of the telescope, people like Percival Lowell have come up with such theories as the existence of the vegetation on Mars. However, the conception of plant life on distant planets was persistent after Lowell's theories in the domains of popular science fiction novels such as by Edgar Rice Burroughs in A Princess of Mars published in 1917, and H. G. Well in War of the World published in 1898 (Britannica, 2024).

Over the course of a century science fiction aroused interest among the public and scientists in biology and space studies. The potential of extra-terrestrial ecosystems was examined in works such as Isaac Asimov's novels and Arthur C. Clarke's 1968 novel 2001: A Space Odyssey. I must say that these stories mentioned some rather scientific concerns about the needs of other worlds for life (Dougherty, 2019).

Exobiology and astrobiology have had cultural and social shifts, that had had an effect on the development of the two disciplines. Astrobiology, which specializes in the existence of life, has been well-known in the middle of the twenty century. Advances in space related platforms and research and developments in the field of biology played a pivotal role in creating subfield of Astrobiology, also known as Exobiology. Some researchers began to seriously consider how life, of which some forms may be plant-like, might adapt the other planets harsh environment with major concerns for radiation and temperature, water and air.

Life-support experimental and biosphere systems for space flight were initiated by both the Soviet and American programs by the 1950s. Beginning with microbes this expanded quite early on to plants. From its roots in terrestrial ecology and botany plant biology has become progressively more closely connected with space travel. The main reason for this was the fact that plants have a side involved in photosynthesis that may be used in long-term life sustaining systems in space. Plants could offer food, alter carbon dioxide to oxygen, and regulate stable environment by synthesizing food from the sunlight and water in more controlled settings (Launius et al., 2012).

2.3 Constellations of Plant Experiments in Space

Conducting direct research on plant life in the orbit was first done by the Soviet Union's space program. Although their development was basically an observational one, in 1960, the Vostok spacecraft put several biological objects, including seedlings, into space. To study the impact of space environment on growth and development, the Biosatellite program was launched by United States in the 1960s (Kiss, 2015).

A few of the biomedical experiments performed during NASA's Apollo programme in the late 1960s and the early 1970s created a foundation for later biological research despite a primary objective of the programme as being human exploration of the moon. As these early testing were limited, but researchers wanted to know how seeds and tiny plans could perform in the lunar environment that offered almost negligible gravity (Lee et al., 2019).

2.4 The Evolution of Research on Space Agriculture

Space agricultural studies started getting more progressive when long-term manned space flights were becoming realistic in the 1970 and 1980s. Cos-microbiology experience was performed on the Soviet space stations Salyut and later on the Mir. A milestone in research on plants in other-world conditions was accomplished in 1982, when Soviet cosmonauts had grown the first crops in space such as wheat, peas and mung beans aboard the Salyut 7. The new direction for the plant biology study in space came in the Eighties with the start of the NASA Space Shuttle program (Mortimer & Gilliham, 2022). Even more complex microgravity investigations of plant growth from the seed formation to the full generation of the cycle was made possible by the Spacelab module that was carried into space on board the Shuttle. These investigations considered how gravity, or its lack, influenced the synthesis of hormones, the production of energy through photosynthesis, the division of cells.

Enhancements to the plant growth systems, including those involving self-adjusting settings developed to mimic recommended climate conditions of the planet, were developed after realizing that not only could plants be grown but they could also be made to thrive in space. As these systems were necessary to prove that plants could sustain life on long missions perhaps in an extra-terrestrial environment.

2.5 Modern Research and ISS

Although space plant research only began after the launch of the International Space Station (ISS) in 1998, research conducted in space today is based on the ISS. For flights warranted under its biological experiments regulation plan, the ISS, an international project, provided long-term space with minimal gravity exposure. Some plants that have grown on the ISS include; mustard, wheat, radishes, and lettuce amongst others. The Veggie program from NASA that has been initiated from the year 2014 was one of the most significance innovations during this period. To improve the quality of life on the ISS and create the foundation for oncoming space colonies, Veggie is a plant growth platform where astronauts can actually grow their own vegetables while floating in weightlessness. Although the production of red romaine lettuce was successful in 2015, more crops are also viable for space production including mustard greens, zinnias (Bijlani et al., 2021).

At the same time, the development of plants in microgravity conditions has been experimented by other space agencies including Roscosmos, ESA, and CNSA. These investigations, or scientific missions, are aimed at getting insights on how to optmise the growth of plant species in space environments where radiation levels are high, atmospheric pressure low and no gravity is available.

2.6 Terraforming and Agriculture Concerning Other Worlds

Using other planets, especially Mars as the growth medium of plants is the next plant science frontier. While this has been a popular concept with science-fiction writers for decades, the actual theory where a planet can be altered to make it more suitable for life like that on Earth, is only currently being looked at scientifically. Mars is considered to be the closest planet that can support agriculture and man's settlement in the future due to water ice deposit, moderate temperature fluctuation and the day length that is, similar to that of earth. Some of the recent research has focused on the possibility of growing the plants in Mars like soil. Almost four years ago, scientists at Wageningen University in Netherlands experimented with NASA-supplied Martian-like soil in an effort to grow crops. They demonstrated that Mars could sustain the growth of different crops including tomatoes, peas and radish, though with some modification on the type of soil (Wamelink et al., 2014). Test runs for outreach for humanity's travel to Mars are incorporated in the current American Perseverance rover that landed on Mars in 2021. Endurance is a part of a broader thrust to understand the surroundings of Mars and the ability of this planet to support people, farming, whether or not plant biology is the principal target of this mission. Furthermore, researchers are researching on closed-loop ecological systems that are realistic on Martian environment, where plants play vital roles in recycling nutrients, water and air (https://www.jpl.nasa.gov/news/nasas-perseverance-mars-rover-makes-surprising-discoveries/).

Science and exploration of other planets and the possible colonization of space with other planets such as Mars and even the Moon has also drawn much attention in the recent past (Levchenko et al., 2018). This interest has been promoted by advancement in space technology and consideration of the notion of colonization of space outside the earth. An important line of investigation is the possibility of vegetative activity in these conditions, which is crucial for providing communities with food, oxygen, and other essentials for a sustainable human stay. Experiments with Mars and Moon Soil Simulants to Help Plant Growth In the recent past, on the viewpoint of plant germination and growth, carried out a very significant investigation to determine the possibility of plant growth on Mars and Moon soil analogs. This study demonstrated that it is possible to germinate some plants in these exotic soil mimics, but issues of nutrient accessibility and soil porosity remain to be addressed. Particularly it establishes the necessity for enhancing the quality of ground on the Martian and lunar surface as well as adding proper nutrients for plant growth. Artemis, announced by NASA's Creech et al. (2022), is a program for humans to set up long term living on the lunar surface. It goes without saying that this concept of investing in infrastructure/technologies for the new moon is perfect for future Mars and subsequent planetary missions (Creech et al., 2022). The article aims to determine and explain the environmental factors that affect plant growth.

Further expanded this study by using basaltic regolith soil and briny water simulants to support plant growth on Mars. Some of it involves conditioning Mars' soil and water in order to support agriculture on the planet, proving that with the right treatments, plants can grow on the red planet. Looking at the application of hydrogels under Mars analog conditions (Kasiviswanathan et al., 2022). Hydrogels, known for their ability to retain and provide water, proved beneficial in fostering plant growth, thereby resolving a significant water scarcity issue on Mars (Atri et al., 2022). Atmospheric Considerations Knowing the conditions of potential extra-terrestrial biomes is critical to assessing the possibility of plant life. The thin atmosphere on the lunar surface presented numerous challenges for plant growth, including significant temperature fluctuations and the absence of a shield against solar and cosmic radiation (Peyrusson, 2021). The InSight mission on Mars gave information about the Martian environment and atmosphere. Although the pressure and composition of Mars's atmosphere are unfavourable for plant growth, there is still some potential for growth. Despite CO's crucial role in photosynthesis, the low atmospheric pressure and fluctuating temperatures necessitate its cultivation in greenhouses. Human beings provide life support and food production. Human life support systems for the Martian environment have identified several novel approaches, including the management of mushrooms for sustainable food production (Neukart, 2024). Their studies reveal that fungal organisms, being renewable, can serve as a sustainable resource for the closed-loop life support system when grown within a controlled Martian environment. In the M. B. Dastsgiri's (2017) work, the author expounds on the factors that would enable continuity of human life on Mars and Moon especially under an economic view and theoretical views on colonization. The paper calls for the improvement of the current policies and other measures that would help in the sustainable development of humans in Mars (Dastsgiri, 2017). Oregon State University (2024) discussed the well-researched effects of light, temperature, and water on plant growth in the terrestrial environment. Extra-terrestrial agriculture requires the control of these issues to closely resemble a perfect growing environment (Patel et al., 2023). Furthermore, NASA (2023) explains that the investigation of these environmental practices extends beyond outside environments to special facilities like the Advanced Plant Habitat (APH) stationed in the International Space Station. These habitats provide critical information for assessing plant performance under microgravity conditions and designing the life support system for future space missions. Basilevsky and Head (2003) discussed the surface of Venus in detail and set it up as a comparative planetary unit (Basilevsky & Head, 2003). Even though Venus is more hostile to life than Mars or the Moon, studying its geological processes and atmosphere chemistry may help explain the evolution of terrestrial planets and the possibility of life in harsh conditions. The cultivation of mushrooms may also be feasible in environments where conventional agricultural practices face significant challenges, such as arid deserts, regions characterized by persistent snowfall, and extra-terrestrial locations (Badoni et al., 2023).

Studies shown in Table 1 emphasizes the complex network of elements necessary for promoting plant development on extra-terrestrial bodies. The practicality of interplanetary agriculture is determined by factors like soil composition, atmospheric conditions, environmental controls, and life support systems. These studies lay the groundwork for understanding the obstacles and opportunities associated with maintaining human existence on Mars and the Moon as space exploration advances. Plant growth in space is a complex process that involves not only specific problems with growing plants extra terrestrially, such as soil composition and air properties but also innovations related to agriculture techniques. The research is just the beginning, providing knowledge upon which to build our understanding of what will be required in order for humans to live on Mars and even elsewhere like the Moon. Investigating into extra-terrestrial

Table 1 Literature review

Sr No	Authors	Title	Summary	Key findings
1	Creech et al. (2022)	Artemis: an overview of NASA's activities to return humans to the Moon	This report outlines the general details and objectives of NASA's Artemis plan the plan to send humans back to the moon, reassert commitment to exploration, establish a sustainable human presence on the lunar surface, and expand human understanding of the lunar surface	The Artemis program will set the foundation for building infrastructure that can also support future Mars missions
2	NASA	Seedling growth	This resource explains NASA's experiments on plant growth in space and specifically focuses on the environmental effects influencing germination and growth	Shows the potential of plant growth under controlled conditions in space
3	Wamelink et al. (2014)	Can plants grow on Mars and the Moon: a growth experiment on Mars and Moon soil simulants	Examines whether several plant species were able to germinate in simulants of the soils of Mars and the Moon, addressing also questions of the availability of nutrients as well as porosity of the soil	Shows that while some plants can sprout, there is a need for soil enhancement to support sustainable growth
4	Mendillo (1999)	The atmosphere of the Moon	Discusses the lunar atmosphere and conditions for plant growth, including extreme temperatures and lack of protection from harmful radiations	Determine key challenges for plant growth in the provided atmospheric conditions
5	Banfield et al. (2020)	The atmosphere of Mars as observed by InSight	Provides insights into the Martian atmosphere based on data from the InSight mission, including pressure, composition, and temperature fluctuations	This study reveals that controlled environments are required for cultivating plants on Mars
6	Kasiviswanathan et al. (2022)	Farming on Mars: treatment of basaltic regolith soil and briny water simulants sustains plant growth	Researches if treatment of Martian soil and briny water has potential for plant agriculture, concluding that cultivation does indeed take place under certain conditions	Shows that with proper conditioning, plants can thrive on Martian soil, suggesting viable pathways for future agriculture
7	Peyrusson (2021)	Hydrogels improve plant growth in Mars analog conditions	Explores the application of hydrogels in Mars conditions, focusing on their water retention capabilities	Shows Hydrogels can be effective for achieving water security, with improved plant growth
8	Gellenbeck et al. (2019)	Mushrooms on Mars: a subsystem for human life support	Discusses the possibility of using mushrooms as sustainable resources of life support systems in space	Fungi can play a vital role in recycling waste and providing food in closed-loop life support systems

(continued)

Table 1 (continued)

Sr No	Authors	Title	Summary	Key findings
9	Dastagiri (2017)	The theory of economics of Mars and Moon civilization	An examination of the economic and theoretical considerations regarding human life sustainability on Mars and the Moon in relation to improved policies and frameworks	Stresses the need for sustainable practices and effective resource utilization for extraterrestrial colonization
10	Oregon State University (2024)	Environmental factors affecting plant growth	Discusses the impacts of light, temperature and water on plant development in Earth and its implications for agriculture from space	Focus on necessity of control over environmental factors to have optimal conditions for growth in space
11	NASA (2024)	Growing plants on space	Gives insight into the results of studies at the International Space Station's Advanced Plant Habitat, adding emphasis to plant performance in microgravity conditions	Highlights the significance of microgravity studies for developing life support systems for future space missions
12	Basilevsky and Head (2003)	The surface of Venus	Discusses the geological processes and atmospheric chemistry of Venus as a comparative planetary unit	Although Venus is hostile, studying its conditions may provide insights into the evolution of terrestrial planets and life
13	Verseux et al. (2022)	Editorial: bioregenerative life-support systems for crewed missions to the Moon and Mars	Explores bioregenerative life-support systems, focusing on the integration of biological and ecological principles in sustaining human life during long-duration space missions	More emphasis is laid by them on sustainable life-support systems and recycling resources for further missions
14	Johnson et al. (2021)	Supplemental food production with plants: a review of NASA research	A review of the NASA research on supplemental food production with plants in space was summarized to emphasize the possibility of an integrated food system	Strategies relevant to food production in space identified to sustain human life on long missions were identified
15	Ellery (2021)	Supplementing closed ecological life support systems with in-situ resources on the Moon	The paper addresses in situ resource utilization towards enhancing closed ecological life support systems for lunar exploration missions and argues that the availability of local resources is a precondition towards sustained human presence on the Moon	Argues that leveraging local resources is crucial for sustainable human habitation on the Moon
16	Mane (2024)	Greening the Red planet: strategies for cultivating plants on Mars	Strategies for growing plants on mars exploration of various techniques and methods of cultivation of plants on Mars with emphasis on overcoming environmental challenges	Offers insights in the practically developing sustainable agricultural practices on Mars

agriculture will be an increasingly crucial element of the sustainability of human colonization beyond Earth as space exploration progresses.

3 Methodology

Research on plant growth on other planets, especially Mars and the Moon, is important because it will help provide food production during longer space exploration. This research reveals several important problems, including determining soil conditions, choosing plant species, and developing growing techniques to sustain life on such a planet (https://www.nasa.gov/podcasts/houston-we-have-a-podcast/moon-farming/). Successful implementation of these approaches could potentially reduce the need for resupply from Earth in future manned missions, thereby enabling long-duration missions. In the beginning of the Palaeozoic era, at about 500 million years, the surface of Earth was almost fully covered in water and naked rock, inhospitable to modern life. The atmosphere contained much more carbon dioxide and much less oxygen than today, and there was not enough oxygen available to provide the energy requirements in larger animals. As a result, animals in early Palaeozoic times were small and largely aquatic, as water provided protection from damaging UV radiation. The formation of the ozone layer, that shields life from UV radiation, is oxygen-dependent and begins with the process of photolysis that splits oxygen molecules into single atoms which then go on to form ozone (O_3). At this time, there wasn't enough oxygen for the ozone layer to form. Human life on Earth depends upon a delicate biosphere that supports material recycling through environmental processes, such as the lithosphere, hydrosphere, cryosphere, atmosphere, and biosphere. Biomaterial turnover and energy flows characterize natural ecosystems, which are closed to matter but open to solar energy. According to Buckminster Fuller, the Earth should be viewed as "spaceship Earth," with the need for accuracy in artificial systems of support for human life, since those ecosystems cannot buffer like the natural biosphere. Biosphere 2 is a 12,700 m^2 encased glass environment in Arizona, where a crew of eight was confined for nearly two years (1991–1993) in nearly total material closure. Its energy supply was through solar and generator supply, with average power levels between 700 and 1500 kW. The facility had a variety of biomes tropical rainforest, savanna, desert, marshes, ocean, agricultural systems, and human habitat and air temperature control and water management systems. It supported 3,800 species including livestock, which produced much food through recycling. Although the concept was revolutionary, problems started to arise, not so much in terms of the closed atmosphere, but mainly oscillations in O_2 and CO_2 which needed to be controlled and the crew placed on a calorie-restricted diet. Although the Biosphere 2 scale is unrealistic for application in space, it demonstrated that nearly 100% closure is possible for up to six months, although techniques to reliably achieve this have yet to be developed.

3.1 Role of ML

Due to the growth of challenges in the design of sustainable habitats for space exploration, ML has been crucial in algorithmic development for enhancing system functions. In the sphere of terrestrial space farming, it can identify patterns of plant development and growth, climatic factors, and resource utilization to establish the most effective approaches to plant production in unfriendly environments such as in Mars or on the moon. In hydroponics, ML algorithms can identify which specific plant types are likely to grow best in specific conditions, control nutrient supply to plants, and diagnose the health of plants in real-time manner based on changes in light, temperature and moisture. Moreover, machine learning model may be embedded into autonomous control of artificial environments so that they can adapt the conditions like light, water, and air in real time. This adaptability is important for space where things change in unpredictable manner and humans might not be able to intervene immediately. The future uses of space missions could enhance the probability of sustaining agricultural systems thus eliminating the frequent supply shipment from earth by using of ML Technologies.

Therefore, the studies on the plant cultivation in other planets such as Mars and the Moon make future space exploration possible and can change the way food is grown in space. This implies that solving the hurdles of space agriculture comes with the application of bio and agricultural related sciences and technologies such as machine learning. Since the successful implementation of such approaches shall help in leading a life in space, the outcomes of corresponding research might be the change of agriculture on the earth, and, in particular, food production in extreme conditions, such as deserts.

3.2 Soil Conditions

Soil as understood in Earth science is a diverse and active substrate that supports germination and growth of plant life. It is described by the fact that is associated with acidic, nutrient density that is compounded by soluble minerals, microorganisms, and organic substances that are of importance in supporting plant life. Still, the question of soil on Mars and on the Moon is quite different from that on Earth and poses serious challenges to plant growth. The soil on Mars has

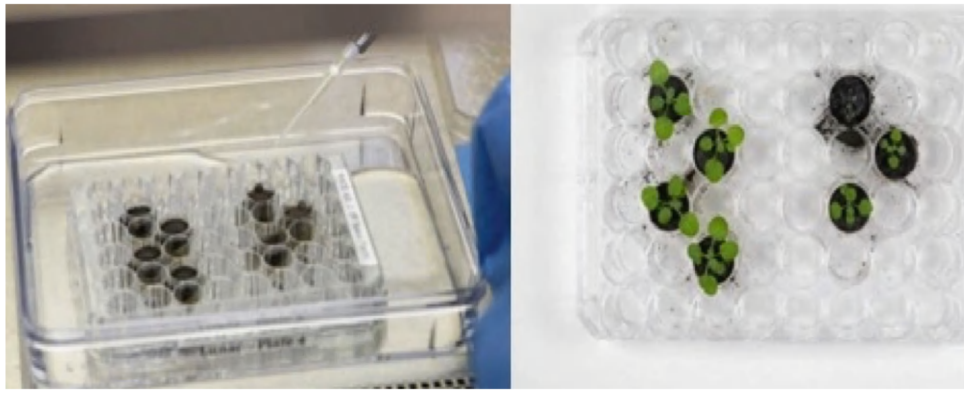

Fig. 2 Different soil conditions and UF/IFAS

several nutrients that are friendly to plants including nitrogen, potash and phosphoric acid. These nutrients are present in relatively high concentrations as might be expected should this planet have the ability to sustain life. However, these nutrients are chelated in forms that are not very soluble; thus making it difficult for plants to absorb them. Also, Martian soil contains iron, sulphur and other metals found helpful in moderation, but which may prove fatal in large doses. This is a metallic composition that can be a limiting factor to plant growth, if controlled. As shown in Fig. 2, Martian soil has another attribute in terms of its chemical properties, it is highly oxidizing. Oxidizing condition is however very destructive to plant growth because it produces reactive products that affect the normal metabolic activities of the plant cells. These oxidative conditions need to be addressed and new ways of reducing them or altering the environment that is present so as to best support plant growth need to be found.

On the other hand, lunar soil also known as lunar regolith has its own properties. The lunar regolith is principally made up of the silicate minerals that makes it have a rough surface. This composition offers certain problems to plant roots, and hinders the growth of a root system that would enable the plant to obtain the right amount of water and nutrients. While Martian soil is already known to be lacking in organic matter, lunar regolith is almost completely barren of it, and water is another scarce resource in both cases. This implies that there are no supplies of organic matter to provide nutrient base or induce microorganisms to support plant germination and growth; the environment is therefore almost completely unfavourable to plant germination and growth. In addition, the fine elements of lunar regolith are abrasive that they may cause mechanical injury to plant root hair. It may even make it challenging to learn ways for plants to take in water and nutrients to make it easy to cultivate plants in such conditions. The environmental challenges that have relation to the moon include; fluctuating temperatures and radiation which makes it even harder to prepare the environment for plant growth.

Even though the Martian ground contains specific nutrients necessary for plant development, Martian soil is oxidizing, and Martian soil has toxic metals. On the other hand, another component of the Moon called lunar regolith is far worse than the deserts, as it is highly abrasive and does not contain any nutrients, not to mention the complete absence of organic substances needed for plants to grow. Knowledge on these different types of soil is important in growing crops in Mars and the Moon to address future terrestrial horticulture on other planets as shown in Fig. 3.

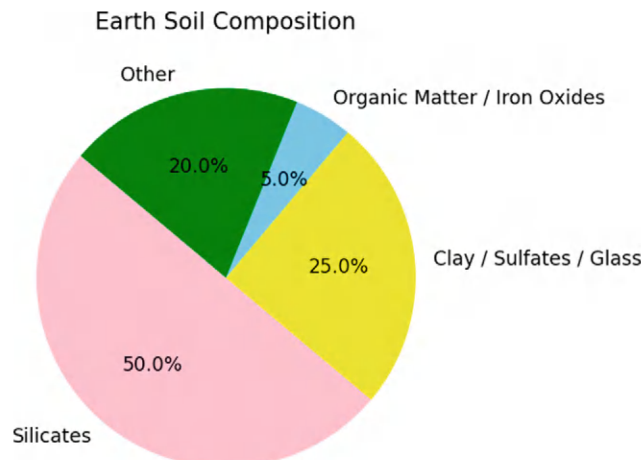

Fig. 3 Earth soil composition

These challenges have to be met if future human expeditions to these celestial bodies are to be sustained and if permanent colonies are to be developed there.

(i) **Silicates (50.0%)**: Soil is primarily made up of silicate minerals that are the primary ingredients in most rocks and soil.
(ii) **Organic Matter/Iron Oxides (5.0%)**: Soil of Earth contains decomposed plant and animal remains as well as iron oxides which causes the soil to be red in some areas.
(iii) **Clay/Sulfates/Glass (25.0%)**: This is true for clay, which improves the continuum of the soil and retains water; sulfates and glass are present in lesser amounts.

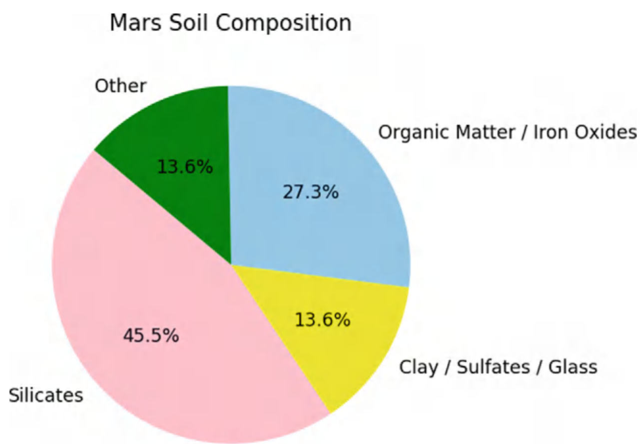

Fig. 4 Mars soil composition

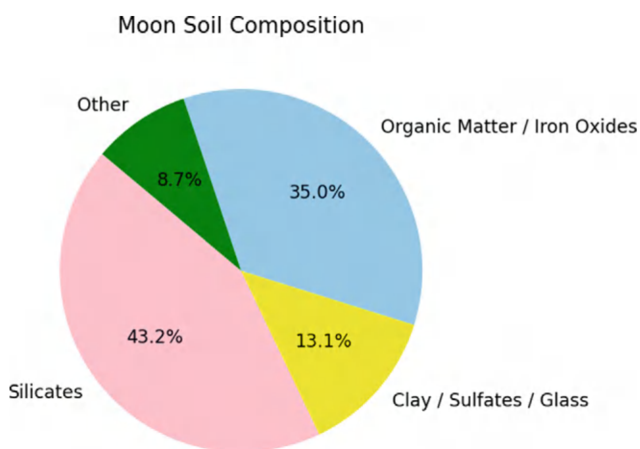

Fig. 5 Moon soil composition

(iv) **Other (20.0%)**: This likely includes various trace elements and minerals that contribute to soil fertility and structure.

In the last few years, researchers have initiated the synthesis of Martian and lunar soil simulants that replicate all the physical and some of the chemical characteristics of the real samples as discussed in Figs. 4 and 5.

(i) **Silicates (45.5%)**: Like Earth, Mars has a significant amount of silicate minerals in its soil.
(ii) **Organic Matter/Iron Oxides (27.3%)**: While Martian soil lacks the organic matter found on Earth, iron oxides are abundant, which is why Mars appears red.
(iii) **Clay/Sulfates/Glass (13.6%)**: These components are present but in smaller amounts compared to Earth's soil.
(iv) **Other (13.6%)**: Includes other minerals or materials specific to Martian soil.

(i) **Silicates (43.5%)**: Lunar soil, or regolith, is also dominated by silicate minerals.
(ii) **Organic Matter/Iron Oxides (34.8%)**: This likely refers to the regolith's content of iron-rich minerals, though the Moon lacks organic matter entirely.
(iii) **Clay/Sulfates/Glass (13.0%)**: A smaller component of lunar soil, similar to Mars.
(iv) **Other (8.7%)**: Includes trace minerals and other substances present in lunar regolith.

These simulants make it easier for various experiments to be carried out in Earth conditions, which are equivalent to the space environment. Some of the most recognized difficulties associated with these soils arise from the fact that they have a low water-holding capacity for plant growth and may also be toxic to the root systems of plants. Hydrogels are networks of polymer chains that can absorb and retain large amounts of water while maintaining their structure. These substances have a reputation for absorbing a lot of water, possibly up to many times their own weight in water. Due to their high water retention capacity, hydrogels provide crucial support for plants growing in environments with limited water resources, such as those found on Mars (Teng et al., 2022). Because of these hydrogels, plants can receive water more often, which helps them thrive in situations with limited water resources. They provide the extra moisture that plants require to develop in such hostile environments by retaining water in the soil. Anna-Lisa Paul is trying to wet the lunar soils with a pipette. Scientists found that the soils were hydrophobic, and therefore, the water beaded-up on its surface. The material had to be vigorously mixed with water to break up its hydrophobicity to uniformly wet the soil. Wetting of lunar soils by capillary action can then proceed for plant culture. On the sixteenth day, it was clearly evident that the plants produced in the volcanic ash lunar simulant left were different from those grown in the lunar soil right (https://www.nasa.gov/podcasts/houston-we-have-a-podcast/moon-farming/).

3.3 Comparative Soil Treatments

The problem of low quality of Martian and lunar soil has raised much concern and studies to improve soil quality to support plant growth. Since the chance of human survival during long space missions relies greatly on agriculture, this study is critical. Soils of Mars and moon are barren of all those nutrients which are required to support plant life and thus they thought of trying out some terrestrial fertilizers. As this initial method has demonstrated, it is evident that reliance solely on fertilisers on Earth will not be sustainable in the long run. It is impossible and unprofitable to transport these supplies long distances from their sources to industrial centres.

To do it, scientists are focusing more attention to in-situ resources, which means that all needed materials may be found or produced on Mars and the Moon. Besides, this strategy helps to minimize the use of resources originating from Earth and promote environmentally friendly policies that may be vital for further interplanetary expeditions.

In Mars it has been found that briny water is more available than pure water, which is good news for plant production. The researchers are trying to find out how hydroponics can be used to fertilize Martian simulant with seawater. The process entails the following stage. First of all, the Martian soil must be rinsed to remove chemicals that may negatively affect plants' development. It is an important process because aside from water, Martian soil contains toxic compounds which are damaging to plant life. After the soil is contaminated, the nutrients have to be brought in to a more suitable ground to accommodate plant growth. These are essential nutrients for plant growth and development and could greatly improve growth when added. Scientists will also investigate how best to protect these nutrients and put them into a slow release system. This slow-release approach is especially advantageous on the dry Martian environment where sustaining soil moisture is a lot harder.

Furthermore, there are attempts by scientists to enhance the abilities of soil to conserve moisture. Because of the desert like condition at Mars, the soil needs to be adequately moist at all times for plants to grow well. The techniques applied for nutrients encapsulation can also be applied to retain and release water and in a controlled manner so that the plants may be supplied with the required water at any one time. This dual function helps not only to meet the needs of plant growth, but also helps to form stable conditions for the formation of a healthy soil.

This way, washing the soil, adding nutrients, and improving the moisture content will not only ensure a new direction in the further development of an agricultural structure but will also help solve the problem of maintaining the growth of plants on Mars. Such breakthroughs are not merely hypothetical; they could revolutionise the basic concepts of space farming as highlighted in Table 2. By using these new soil enhancements we might find ourselves one step closer to colonization of Mars and feeding the future population that might be living there. The process of learning how to grow life on other planets is fraught with difficulties but the payoff is great, thus this is a valuable and promising study for the future of our space endeavours.

Table 2 Soil composition and characteristics comparison: Earth, Moon, and Mars

Conditions	Earth	Moon	Mars
Composition	Rich in minerals and organic material	Regoilth, high in silicates	Similar to Earth, rich in silicates, iron oxides, and some salts
Ph level	Typically, neutral to slightly acidic	Neutral to slightly alkaline	Slightly acidic to alkaline
Moisture content	High, supports plant life	Very low, almost no moisture	Varies, but generally low
Microbial life	Rich in Microbial Life	No known life	Potential
Texture	Varies (sandy, clay, loamy)	Fine, dust-like particles	Coarse
Nutrients	High in nutrients	Low in nutrients	Contains some nutrients

3.4 Plant Selection

The selection of the right plant species is a very vital factor that really plays an important role in growing plants on other planets. Plants are living organisms that need nutrients to survive and grow and can endure different sorts of climates. Amplyhopetaly is best exemplified by the small, rapidly growing plant with a well-understood genetic background, Arabidopsis thaliana. This is due to its short growing period and genetically placed disposition to offer insight into plant reactions to unfavourable conditions.

In addition to Arabidopsis thaliana, several other crops and organisms have been tested for their suitability in extraterrestrial environments:

- Lettuce: Lettuce in particular can be produced in low-nutrient environments, and it has a short generation time, making it ideal for space farming. This crop has the basic compounds needed in the body and can be grown on waste land and in green houses (Johnson et al., 2021).
- Radishes: Radishes are selected for their vigorous growth and high potential for adaptation to conditions in a short time. They also need less attention as compared to other crops; therefore, they are useful for space missions or when planning to go to the next-door neighbor, Mars.
- Potatoes: Potatoes are appreciated for their starchy carbohydrates and are considered to be versatile for so many uses. They have been compared to other uses because of their ability to offer a massive food supply in space.
- Mushrooms: On Martian substrates, mushrooms are viable. The other important thing is that mushrooms do not need light to grow, so they are ideal for space environments where light may be a luxury (Verseux et al., 2022). They also return nutrients and are not limited to plain cultivation, which other traditional plants may not be able to survive.

Table 3 Nutritional information for all the candidate crops (per gram fresh weight)

Crop	Calories (kcal/g)	Carbs (g/g)	Protein (g/g)	Fats (g/g)
Radish	0.16	0.034	0.0068	0.001
Black beans	3.41	0.6236	0.216	0.0142
Spinach	0.23	0.036	0.0286	0.0039
Mushrooms	0.22	0.033	0.031	0.003
Lentils	1.16	0.201	0.090	0.004
White potato	0.69	0.1571	0.0168	0.001
Lettuce	0.2	0.0289	0.014	0.001
Soyabean	4.46	0.3016	0.3649	0.1994
Tomato	0..18	0.0389	0.0088	0.002

- Soybeans: Soybeans are another interesting crop owing to their high protein content and the possibility of enriching the soil's fertility because they fix nitrogen. However, due to their flexibility in growth conditions, they are fit for cultivation in space.
- Tomatoes: The functions of tomatoes from a nutritional point of view as well as how they may fit into a culinary capacity have been explored. They can be grown in a hydroponic system, and a variety of nutrients are available in them.
- Radish (*Raphanus sativus*) and lettuce (*Lactuca sativa*) seeds were planted in pots with basaltic regolith simulant soil or garden soil, with germination evaluated after a week. The plants were cultivated in a growth chamber (Percival-Scientific) under controlled conditions: 16 h of white soft light (650 μmol photons/m^2/s) at 26 °C, followed by 8 h of darkness at 24 °C, and were watered weekly.

It is therefore important to determine plants and organisms that can survive in outer space conditions, mostly for astronauts who may need to spend long periods of time up there. The purpose of these studies is to identify crops that can provide essential nutrients and also target the conditions associated with space environments as mentioned in Table 4.

3.5 Crop Nutritional Data—Inclusive Information

Table 3 provides basic nutritional information about every crop. We are now discussing crops according to their primary macronutrients: calories, carbohydrates, proteins, and fats.

Calories

Highest: Soybean (4.46 kcal/g)—This crop is very energy-intensive; hence it tops the list to be cultivated in space farming because high-calorie food is one of the basic survival factors for a human to sustain his level of energy in a resource-scarce environment.

Table 4 Mean, maximum, and minimum values for calories, carbs, protein and fats

Nutrient	Mean	Max	Min
Calories (kcal/g)	1.19	4.46 (Soyabean)	0.16 (Radish)
Carbs (g/g)	0.162	0.624 (Black Beans)	0.0289 (Lettuce)
Protein (g/g)	0.086	0.365 (Soyabean)	0.0068 (Radish)
Fats (g/g)	0.026	0.1994 (Soyabean)	0.001 (Multiple crops)

Lowest: Radish 0.16 kcal/g—Low-calorie vegetable, good for supplementation in diets but would be quite huge in quantity to provide much energy.

Carbohydrates

Highest Black Beans 0.6236 g/g High carb; good source for readily available energy, which is needed in space for energy.

3.6 Nutritional Implications for Space Farming

To have a nutritional variety of the crops taken, there should be a balance in dietary intake on board. Soybeans are highlighted to be of great importance since they contain high protein and fat content. Black beans are mainly carbohydrate-filled and radishes and lettuce would act as nutrient fillers of low calorie.

Crop Selection for Balancing Diet

Staples: Soybean, Black Beans (high calorie, protein content, and carb)

Vegetables: Spinach, Mushrooms, Lettuce (low-calorie, nutrient-dense)

Supplement crops: Potato, Radish, Tomato (for crop diversification and some nutrient supplementation).

3.7 Growth Techniques

3.7.1 Hydroponics and Aeroponics: Soil-Less Cultivation

Hydroponics is one of the main methods considered for the development of space agriculture. It provides means of plant growth without using soil as it involves the transference of nutritionally fortified water solutions. Hydroponics offer the best method of reducing the rate at which nutrients and water are administered to the plants at the regional requirement level. This matters a lot concerning space because you will only allocate enough space needed and other resources such as water are efficiently used. In this way astronauts can reuse the water used in hydroponic systems and make the most out of it. The nutrient concentration can also be made real time depending with the requirements of the plants in order to produce high yields. In space where every single drop of water is crucial this technique is highly effective.

Another method on the rise for space agriculture is aeroponic, which is even more efficient in the use of water than hydroponics. Aeroponics therefore involves placing the roots of the plant in the air and then sprinkling a nutrient solution on the roots now and then. This does away with any growing medium or large water reservoirs requirements. Another advantage is that for any plant, when roots are left exposed to oxygen, the growth rates are much higher compared to other plants. Aeroponically, the minimum quantities of water required and the nutrients delivery also make aeroponics a viable technique to adopt for the planting on Mars and the moon, where water is significantly scarce.

3.7.2 Bioregenerative Life Support Systems (BLSS)

In space missions, sustaining human life requires not only food production but also oxygen generation, water recycling, and waste management. Bioregenerative Life Support Systems (BLSS) are being designed to create self-sustaining environments in space that can support human life over long durations. Plants play a critical role in these systems by providing food, oxygen, and clean water through natural biological processes like photosynthesis and transpiration. BLSS creates a closed-loop ecosystem that recycles waste products like carbon dioxide and organic matter, using them to nourish plant life, which in turn supports human life. This reduces the need for external supply shipments, which are costly and difficult to deliver. By integrating plants into the space habitat's life support system, BLSS aims to achieve a self-sustaining environment that can potentially support long-term human habitation on planets like Mars.

3.7.3 Vertical Farming Maximizing Space Efficiency

On space, the growing surface space is commonly confined, and thus optimizing the productive use of the available space is highly valued. Vertical farming provides a remedy by placing the plant beds one on top of the next. This method makes it possible to produce a large quantity of food within a restricted floor space in the space settlement hence suitable for use by astronauts. Hydroponic or aeroponic systems can be combined with vertical farming since the latter also increases the efficiency by effectively using less water and nutrients. Vertical farming also comes in stacked formations, meaning that artificial lighting can be installed, especially for plant growth which is familiar with natural light.

3.8 Artificial Light-Driven Photosynthesis

The biggest factor in the process of cultivating plants in space is the absence of sunlight. On Earth, the source of energy in photosynthesis is sunlight, but in space particularly in Mars, there is inadequate or lacking sunlight. In that connection, artificial lighting systems have become absolutely crucial to space agriculture. At present, LED grow lights are applied to replicate sunlight, which contain the correct spectrum for plants' photosynthesis. These lights can be adjusted to produce the right intensity of light to its plants thus enhance the performance of the agricultural system. Also, because LED lights consume power, the LEDs assist in saving power, which is also a major commodity in space missions. Plants can be grown with success in completely sealed environments like those of spacecrafts or space stations, therefore, does not have to wait for natural light.

3.9 IoT and Automation in Space Agriculture

Automated IoT, which serves as an excellent aid in space agriculture, is also applied in space cultivation. These technologies are utilized for tracking parameters including temperature, humidity and nutrient concentration within the environment in real-time. They argued that the growing systems were fitted with sensors that gathered information about the crops, information that eventually could be used to make the process more efficient. For example, if the sensors are picking up lesser humidity or nutrient deficiency, the system can correct the climate control by adjusting water supply or nutrient solution. Hydroponic and aeroponic farming techniques with automation and sensorial facilities to regulate water and nutrient delivery and monitoring of the produced plants with minimal external interference are being invented. This is critical in astronauts' mission where working power is restricted and preserving crops is as passive as it gets. The objects such as drones and devices based on AI technologies can supervise the conditions of plants and evaluate the production potentialities in order to improve the agro-industrial complex of space environments.

3.10 pH and Nutrient Delivery Automation

A key consideration to space agriculture is also the appropriate pH of solutions used in hydroponics and aeroponics for growth of crops. The pH of the growing environment has an actual influence on the plants' ability to uptake nutrients and therefore it should be closely monitored. More innovations are being used to control the pH of the nutrient solutions which the plants have to absorb their nutrients in constantly. This in turn decreases the degree of human interferences in plant growth process and improve the overall homogeneity in their growth. In the same way, automated nutrient management systems guarantee that appropriate amount of nutrients is supplied to the plants at appropriate times. In particular, such systems are capable of providing nutrient proportions in accordance with the plant growth stage which increases the efficiency of space agriculture.

3.11 Future of Space Agriculture

Stemming from current and progressing research, space agriculture will also continue improve with scientist conducting more research to know how to effectively raise plants in space. Hydroponics, aeroponics, vertical farming, artificial lighting, IoT and automation are chief aspects of the modern farming which seem to be robust enough to pre-establish sustainable agricultural systems in space. If these techniques are further elaborated then techniques could be developed that would ensure long-term manned colonization of planets such as Mars where an indigenous food supply could be grown and delivered without further replenishment. One of the services that will be highly important as mankind continues its expansion off the planet is the ability to produce fresh produce in hostile conditions. The techniques in the current advancement will create a successful ambiance for man to survive beyond the earth, and farming would be crucial for survival in space in the future.

4 Results

Further, the scope of research is extending to the inhouse plants, plants grown in biologically controlled polymorphic areas such as greenhouse or growth chambers. These plants are very important in the establishment of ecosystem in other planet environments. Knowledge of how the plants being grown in house plants can grow, produce and adapt to these regions will help in the formulation of favourable space farming practices. Therefore, the advancement in space exploration and the potential habitation of other planets such as Mars or the Moon has led to the development of methods for growing food and NASA's Artemis program, which aims to establish a permanent base on the Moon, aids in developing space agriculture techniques applicable to other planets can be applied for other planets. Overall, Artemis's research could shed light on how to cultivate plants under controlled conditions, such as greenhouses or bioreactors, which are essential for the survival of terrestrial life on Mars. Furthermore, the Seedling Growth-1 experiment on the International Space Station and the studies on the impact of light, temperature, and water on plant growth help solve agricultural problems related to farming on other planets. The study also stressed the need to consider the soil characteristics, the type of plants, and their cultivation methods necessary for efficient space farming. Some problems which the Martian and lunar soils pose are low levels of water retention and nutrient richness, which can be solved by amending them and using available resources. Examples of plant species that have been tried in space are lettuce, radishes, potatoes, mushrooms, soybeans, and tomatoes, among others.

4.1 ML Based EDA

Space farming also use ML to optimize crop selection based on several environmental and nutritional factors involved. The nutritional values of the crops are scaled into a standard range (for instance, between 0 and 1). All variables were then treated equivalently without any cropping bias towards those who naturally have higher absolute values, such as soybeans, being high in calories. Missing or inconsistent information, including new crops with missing value or unusual conditions, can be filled-in with mean/mode imputation or more advanced imputations like K-nearest neighbours imputation. k-means Clustering is a technique related to unsupervised learning that will group the crops into clusters according to similarities in the profile of nutritional contents.

Cluster 1: High-calorie, high-fat crops (Soybeans, Black Beans)— Very suitable for energy-dense diets.

Cluster 2: Low-calorie, high-fiber crops (Lettuce, Radish, Spinach)—Good for vitamins and minerals, not primary energy sources.

Cluster 3: Moderate-calorie, balanced nutrient crops (Mushrooms, Lentils, Tomatoes)—These crops offer a balanced nutrient profile suitable to round out meals.

The correlation analysis is conducted to determine how various nutrients relate to one another in different crops. Positive Correlations highlight soybeans, high protein crops are

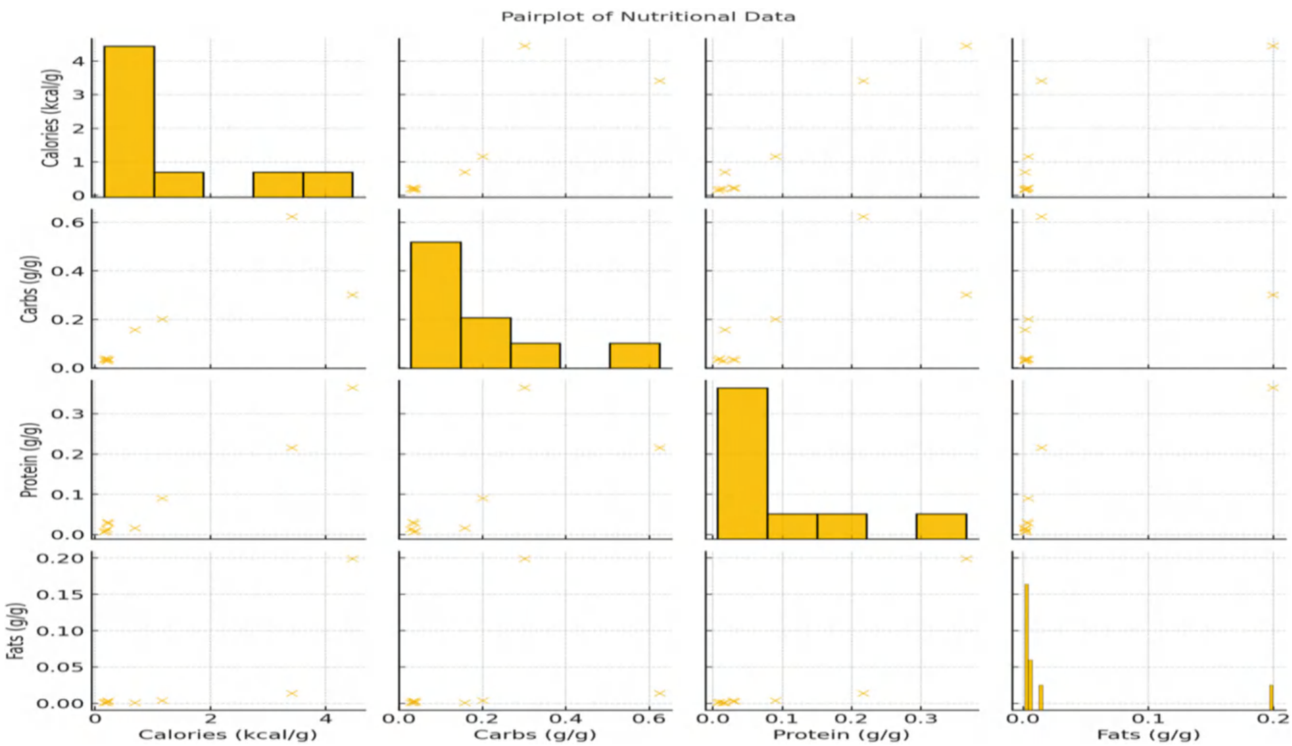

Fig. 6 A pair plot diagram of nutritional data

also often moderately high in fats, thus meaning protein-rich crops would be a natural source of essential fatty acids. Negative Correlations for instance, high-carb crops like potatoes and beans tend to be low in fats, meaning possibly that multiple crops must be used to achieve a proper proportion of fat-to-carb in meals. Recommendation System suggested from the clustering and correlations and the machine learning based recommendation system suggests the following suitable crop combinations for space farming. Energy rich meals include soybean, Black Beans, a high-calorie, high-protein meal with a good balance of fats and carbs. Low-Calorie, High nutrient meals include Lettuce, Radish, Mushrooms, a nutrient-dense meal high in vitamins and minerals, just ideal to complement the energy rich meals. Balanced Diet includes Lentils, Tomatoes, Spinach, a combination of moderate calorie intake, proteins, and necessary vitamins. Environmental Adaptations for Space Farming means environmental dynamics of space demand data-driven crop selection. Hydroponics and Aeroponics includes nutrient-rich water solutions replace soils as the medium for farming crops. Lettuce and spinach can be adapted with these systems by needing less water and space. Artificial Lighting in which LED grow lights ensure crops are exposed to the right amount of light for photosynthesis, especially in plants such as tomatoes and spinach which require massive amounts of light. In ML models, real-time environmental data gathered by sensors predict water/nutrient needs and optimize crop growth with little or no intervention from man.

Figure 6 describes the pairplot graph displays the relationships between the four nutritional variables: calories, carbs, protein, and fats for the different crops. In a pairplot diagonal plots show histograms of each individual variable. From these, we can see the distribution of calories, carbs, protein, and fats across the crops. Calories and fats show a skewed distribution, with a few crops (like Soybean) having much higher values, while most crops have lower values. Protein has a more varied distribution, with some crops showing moderate values, while carbs are clustered around lower values for most crops except Black Beans and Lentils. Off-diagonal scatter plots show pairwise relationships between variables. For instance, there is a noticeable positive relationship between calories and protein, suggesting that crops higher in calories tend to be higher in protein as well (e.g., Soybean, Black Beans). A similar trend is observed between fats and calories, indicating that more calorie-dense crops also tend to be richer in fats.

The correlation matrix offers a quantitative measure of the strength and direction of the linear relationships between the four nutritional variables: calories, carbohydrates, protein, and fats. The values in the matrix range from −1 to 1, where 1 indicates a perfect positive correlation (as one variable increases, the other increases), −1 indicates a perfect negative correlation (as one variable increases, the other decreases), and 0 suggests no linear relationship. Here's a breakdown of the key correlations observed:

4.1.1 Calories Versus Protein (Correlation ~0.98)

The matrix reveals a strong positive correlation between calories and protein. This suggests that crops higher in protein content also tend to provide more calories. For example, Soybeans are rich in both calories and protein, making them an excellent source of energy and a plant-based protein powerhouse. This strong correlation is particularly useful for those designing high-protein diets, as it indicates that protein dense foods also contribute significantly to total caloric intake. It aligns well with the fact that protein is an energy-rich macronutrient, contributing 4 kcal per gram.

4.1.2 Calories Versus Fats (Correlation ~0.93)

There is also a strong positive correlation between calories and fats. Since fats contribute 9 kcal per gram more than twice the energy of protein or carbs it makes sense that crops with higher fat content also have higher calories. Soybeans, for instance, are high in both fats and calories. On the other hand, crops like Radish, White Potato, and Lettuce are low in both fats and calories. This strong correlation indicates that fat-rich crops are ideal for providing dense sources of energy, which is crucial for individuals looking to increase caloric intake without consuming large quantities of food.

4.1.3 Protein Versus Fats (Correlation ~0.88)

The positive correlation between protein and fats, though not as strong as the calorie-fat relationship, is still notable. This suggests that crops with higher protein content often have higher fat content as well, particularly legumes like Soybeans and Black Beans. This relationship is key for understanding the macronutrient composition of legumes, which tend to be nutrient-dense across multiple categories, making them staples in balanced, nutrient-rich diets. However, vegetables like Spinach and Mushrooms, which are low in both protein and fats, reflect the other end of this spectrum.

4.1.4 Carbohydrates and Other Nutrients

Interestingly, carbohydrates show weaker correlations with other nutrients. The correlation between carbohydrates and calories (~0.47) suggests only a moderate positive relationship, indicating that while carbs contribute to the calorie count, they do not dominate the caloric makeup as fats or proteins do in certain crops. This is evident in crops like Black Beans and Lentils, which are relatively high in carbs but have more balanced profiles of protein and fats as well. The correlation between carbohydrates and protein/fats is even weaker (~0.34 and ~0.11, respectively), which implies that carbohydrate content is more independent of the other two macronutrients. This variability in carb content across crops indicates that different crops can offer diverse nutritional benefits without necessarily aligning with protein or fat levels. For example, some crops can be high in carbs but low in proteins and fats, or vice versa.

In Fig. 7, the correlation matrix highlights that calories, protein, and fats are closely related, particularly in calorie-dense crops like soybeans, where all three macronutrients are present in significant amounts. Carbohydrates, on the other hand, show a more independent behaviour, suggesting that different crops can offer a variety of nutritional benefits. This nuanced understanding of nutrient correlations helps

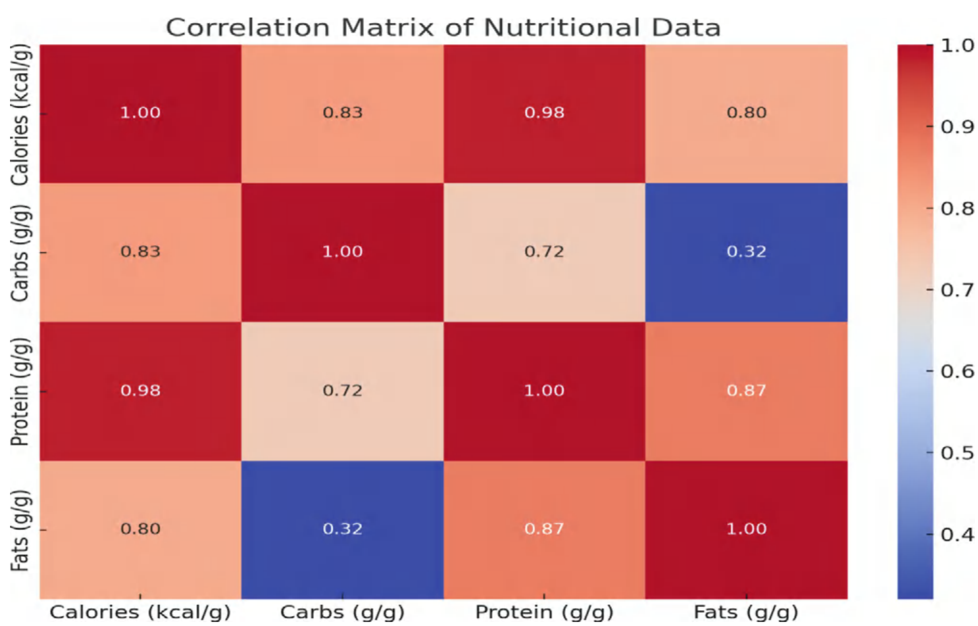

Fig. 7 Corelation data of nutritional vegetables

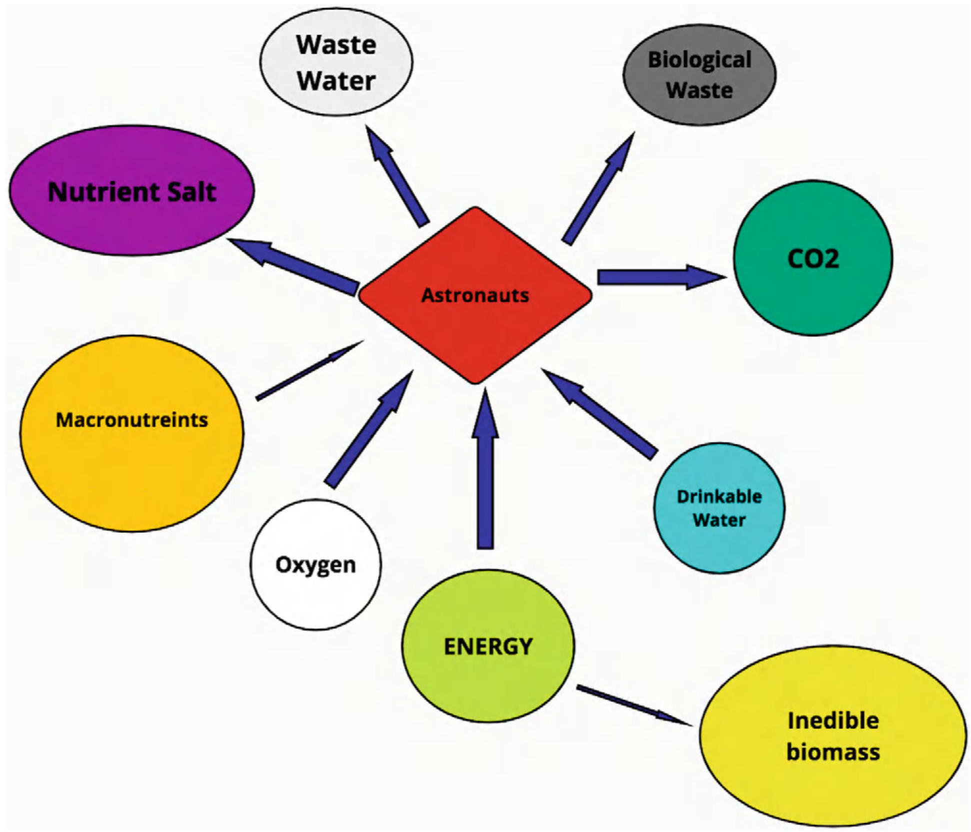

Fig. 8 A diagram of an open-loop system for higher plant cultivation

guide dietary choices, particularly for individuals looking to tailor their macronutrient intake for specific health or fitness goals.

5 Conclusion

Plants will have significant roles in long-duration space missions future due to several reasons first one is biologically based life support systems. Plants are imperative components in a regenerative life support system. They help enhance air revitalization through photosynthesis by capturing carbon dioxide and developing oxygen to make the atmosphere breathable for the astronauts. Second one is food production, since the plants will be able to produce food, then that means the astronauts in the spacecraft will be supplied with a perpetual source of fresh food-which would directly answer their nutritional needs for long-duration missions. Third one is water recycling although plants also have an additional role in recycling water thus turning the life support system closed and self-sufficient. Table 4 provides a detailed summary of the key nutritional components calories, carbohydrates, protein, and fats across a variety of crops. On average, the calorie content per gram is 1.19 kcal, with the highest value observed in soybeans at 4.46 kcal and the lowest in radishes at 0.16 kcal. For carbohydrates, the mean is 0.162 g/g, with black beans leading at 0.624 g/g, while lettuce contains the least at 0.0289 g/g. Protein averages 0.086 g/g, with soybeans again standing out at 0.365 g/g, and radishes have the lowest at 0.0068 g/g. The fats are relatively low across most crops, with an average of 0.026 g/g. Soybeans contain the most fat at 0.1994 g/g, while radish, white potato, and lettuce have the minimum value of 0.001 g/g. This indicates that soybean is a nutritionally dense crop, particularly in terms of calories, protein, and fats, while radish and lettuce are much lighter in nutritional content.

For space travel, a closed loop biosphere is a system in which plants and people are mutually dependent on one another to survive. It is energy, most likely light energy, that powers photosynthesis in plants, which allows them to generate oxygen and other macronutrients. The astronauts use the oxygen produced by the plants to breathe, and the plants absorb the carbon dioxide that the astronauts release, allowing the gases in the atmosphere to cycle more easily. The treated water, enriched with nutrients such as nitrogen, phosphorus, and potassium, is supplied to the plants. Additionally, the plants produce macronutrients that astronauts consume for sustenance. However, inedible biomass generated by the plants must be managed or repurposed. This system demonstrates how resources are recycled to maintain a balance between human survival and plant growth in a sustainable space environment in Fig. 8.

The deficiency of soil-based horticulture is causing the researchers to look for new methods to grow plants, such as hydroponics and aeroponics. These techniques offer the plant a limited, but controlled, environment as well as a controlled nutrient and water supply in outer space. In general, the studies carried out that the line of research look for efficient and independent agricultural solutions for long-term manned space exploration and colonization of planets and other worlds. This study contributes to the advancement of space research and extra-terrestrial farming, which holds significant potential for life beyond Earth.

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A Spatiotemporal Urban Growth Assessment in Bhopal, India from 1992 to 2042 Using Machine Learning Algorithms

Shobhit Chaturvedi, Jay Amin, and Kratika Sharma

Abstract

Rapid urbanization presents significant challenges for infrastructure development and environmental sustainability. This study introduces a robust integrated geospatial framework that utilizes advanced machine learning algorithms to analyze urban growth patterns in Bhopal, India, from 1992 to 2042. By applying the Maximum Likelihood Classification (MLC) algorithm, Land Use Land Cover (LULC) maps were created for the years 1992, 2002, 2012, and 2022, categorizing the entire area into Built-Up, Vegetation, Water Body, and Barelands. The MLC mapping demonstrated high accuracy, with Kappa values of 0.890 (1992), 0.894 (2002), 0.875 (2012), and 0.886 (2022). From 1992 to 2022, Bhopal experienced notable LULC changes: built-up areas expanded from 169.98 sq.km to 224.90 sq.km (32.3% increase), vegetation decreased from 80.58 km^2 to 64.81 km^2 (19.6% reduction), barelands slightly decreased from 543.11 sq.km to 538.91 sq.km, and water bodies declined from 83.33 sq.km to 78.09 sq.km. Further, the Multi-Layer Perceptron-Markov Chain Analysis (MLP-MCA) model projections indicate that built-up areas will rise to 203.74 sq.km by 2032 and 224.90 sq.km by 2042, while vegetation is anticipated to continue declining, and water bodies will experience minimal changes. These results highlight the urgent need for effective urban planning policies that harmonize development with environmental conservation to mitigate the adverse effects of urbanization.

Keywords

Rapid urbanization · Maximum likelihood classification · Sustainable development · Multi-layer perceptron–Markov chain model · Bhopal

1 Introduction

Land Use and Land Cover (LULC) are critical for understanding the transformations of the Earth's surface, reflecting both natural and human-driven processes. Land Cover refers to the physical components of the environment, including forests, wetlands, and urban regions, whereas Land Use relates to the ways humans utilize these areas, such as for agriculture, urbanization, and conservation (Sen Roy et al., 2022; Singh et al., 2023). Accurate LULC data is important for resource management, urban space planning, biodiversity conservation, disaster preparedness, and climate change mitigation. All such details help policymakers implement measures favoring sustainable development and also environmental protection (Mishra et al., 2020; Ullah et al., 2023). LULC alterations arise through several natural forces like climate change variabilities and disaster as well as human-induced, whereby urbanization and agriculture force the change in LULC (Das et al., 2020; Mohamed & Worku, 2020). While natural events like floods or earthquakes can greatly change the environment, human activities usually have a deeper and more enduring effect on landscapes. Issues like deforestation, habitat destruction, and ecosystem degradation often play a key role in defining the environmental impact

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of a particular area or region (Adnan et al., 2020; Ortiz-Oliveros et al., 2022). Socio-economic parameters like population growth and economic development further impacts land use patterns and environmental outcomes.

Although it triggers economic growth, urbanization also poses many problems such as straining infrastructure, pollution, depletion of resources, and environmental problems like the Urban Heat Island (UHI) and rising Land Surface Temperatures (LSTs) (Li et al., 2022; Saleem et al., 2020). Indian megacities such as Mumbai, New Delhi, and Bangalore, are already impacted by the negative impacts of rapid urbanization including housing shortages, pollution, water scarcity, and increased energy demand (Kulkarni & Vijaya, 2021; Sen Roy et al., 2022). Thus, LULC change monitoring has become more important for the sustainable management of urban and environmental systems. Technologies like Remote Sensing (RS) and Geographic Information Systems (GIS), which rely on satellite data, play a crucial role in tracking these changes (Paradis, 2022; Wang et al., 2022). GIS tools facilitate detailed spatial analysis, while Machine Learning (ML) and Artificial Intelligence (AI) improve the predictive modeling of urban growth patterns.

Bhopal, the capital of Madhya Pradesh, is actively involved in India's Smart Cities Mission. The city is undergoing rapid urbanization, leading to considerable socio-economic and environmental challenges (Sharma et al., 2021; Singh et al., 2023). This study introduces a comprehensive RS-GIS framework aimed at analyzing the dynamics of land use and land cover changes over time and predicting future urban growth. The research centers on the following objectives:

RO1. Develop LULC Maps for Bhopal from 1991 to 2021 employing the Maximum Likelihood Classification (MLC) algorithm.

RO2. Investigate the spatiotemporal changes in LULC patterns during this period.

RO3. Predict future urban growth during 2031 to 2041 using the Multi-Layer Perceptron-Markov Chain Analysis (MLP-MCA) algorithm.

This research is aligned with India's commitment to United Nations Sustainable Development Goals (SDG 11: Sustainable Cities and Communities, and SDG 13: Climate Action) and seeks to offer important insights for urban planning and management. The paper is structured as follows: Sect. 2 reviews pertinent literature on land use analysis methods. Section 3 outlines the step-by-step methodology used in this research. Section 4 presents the results, followed by discussions in Sect. 5, and Sect. 6 concludes with a summary, addresses the study's limitations, and provides directions for future research.

2 Literature Review

Accurate LULC mapping is crucial to understand the spatiotemporal urban growth patterns and guide effective urban planning and environmental management. High-resolution remote sensing data from satellite sources like LANDSAT and Sentinel series are critical for developing precise LULC maps (Chopade et al., 2023; Edan et al., 2021). Using these datasets, sophisticated classification algorithms can distinguish across different land cover types, which is crucial for environmental conservation strategies. Unsupervised and Supervised classification algorithms are two primary approaches adopted for LULC mapping. Unsupervised classifiers cluster pixels based on spectral properties without relying on any prior training data, allowing exploratory analysis of land cover types. For instance, unsupervised techniques have been employed to map LULC changes in Salem City (Vimala., 2020) and to compare clustering methods such as K-means and hierarchical clustering in Turkey (Küçük Matcı & Avdan, 2020). While they are good approaches for preliminary explorations of data, they may lack the precision necessary for correct classification of more complex or mixed land cover classes, especially in situations of high spectral variation.

In contrast, supervised classification methods such as Maximum Likelihood Classification (MLC), Support Vector Machines (SVM) and Decision Trees (DT) rely on training samples with known land cover classes to achieve higher accuracy (Gohain et al., 2021). These supervised methods use the marked user training points to derive unique spectral signatures for every class of land cover and map LULC labels for the whole unclassified region of the satellite imagery following specific governing principles, as identified by Ofori Acheampong et al. (Acheampong et al., 2022). Supervised methodologies have been widely used for applications such as Vinayak et al. (Vinayak et al., 2021) for Mumbai, Khalmurzayeva (Khalmurzayeva, 2019) for Austria and Hussain et al. (Hussain et al., 2022) for Pakistan. MLC is particularly useful in tackling spectral variability and generating an accurate LULC product from multispectral and hyperspectral data (Talukdar et al., 2020).

Beyond LULC mapping specialized Machine Learning models like Multi-Layer Perceptron with Markov Chain Analysis (MLP-MCA), Cellular Automata-Markov Chain (CA-MC) are also adopted for developing future LULC maps and projecting future urban growth (Asori & Adu, 2023). For example, MLP-MCA models were applied to predict urban growth across cities like Bogor, Jakarta (Nurwanda & Honjo, 2020) and Addis Ababa, Ethiopia (Mohamed & Worku, 2020). Besides, the CA-MC models have also been applied to predict future urban growth across Saudi Arabia (Alqadhi et al., 2021) and Thiruvananthapuram (Chettry & Surawar, 2021). These sophisticated urban growth prediction models are valuable to predict the future urban growth scenarios and formulate sustainable development policies.

3 Research Methodology

3.1 Study Area

Bhopal is the capital city of the Indian state of Madhya Pradesh. It is located at approximately 23.26° N latitude and 77.41° E longitude. The city covers an area of about 463 square kilometers. The average elevation of the city is about 527 m above sea level. Bhopal has a humid subtropical climate with hot summers, a monsoon season, and mild winters. Temperatures during the summer months from March to June go as high as about 40 °C, and in the winter season from December to February, temperatures vary between 10 and 25 °C. The southwest monsoon is when most of the city receives rainfall, and this period goes from June to September with an annual average precipitation of about 1200 to 1300 mm. The topography of Bhopal itself has both plains and hills within it, and it being situated near the Upper and Lower Lakes, central to the city's ecosystem as well as water supply systems, influences its climate as well as environmental conditions heavily (Singh et al., 2023).

In the past decades, Bhopal has experienced significant urban expansion from economic growth, increased population, and development along Arera Colony, Kolar Road, BHEL Township, and the central business district surrounding New Market and MP Nagar (Sharma et al., 2021). The city's blend of historical significance and modern infrastructure has attracted both residents and businesses, but this rapid growth has also led to challenges, including traffic congestion, rising housing demand, and pressure on water resources and waste management. The preservation of Bhopal's green spaces, lakes, and overall environmental health is crucial as the city continues to expand. Figure 1a shows the location of Bhopal city in India, while Fig. 1b depicts the Bhopal Municipal Boundary in black within the broader 794 square-kilometer study area highlighted in blue. This broader study area is selected for a comprehensive analysis of urban development. Figure 2 outlines the framework for spatiotemporal analysis and urban growth prediction.

For this study focused on Bhopal, India, several mid-resolution (30 × 30 m) LANDSAT datasets were downloaded from the United States Geological Survey (USGS) web-portal for the specified study period, as outlined in Table 1. Specifically, LANDSAT 4–5 (TM) for 1992, LANDSAT 7 (ETM+) for 2002, LANDSAT 8 (TIRS and OLI) for 2012, and LANDSAT 9 (TIRS and OLI) for 2022 were obtained, all corresponding to the timeframe of May 10–15. Furthermore, Bhopal's digital elevation model data for 2022 was acquired. All four LANDSAT images were geo-referenced to the

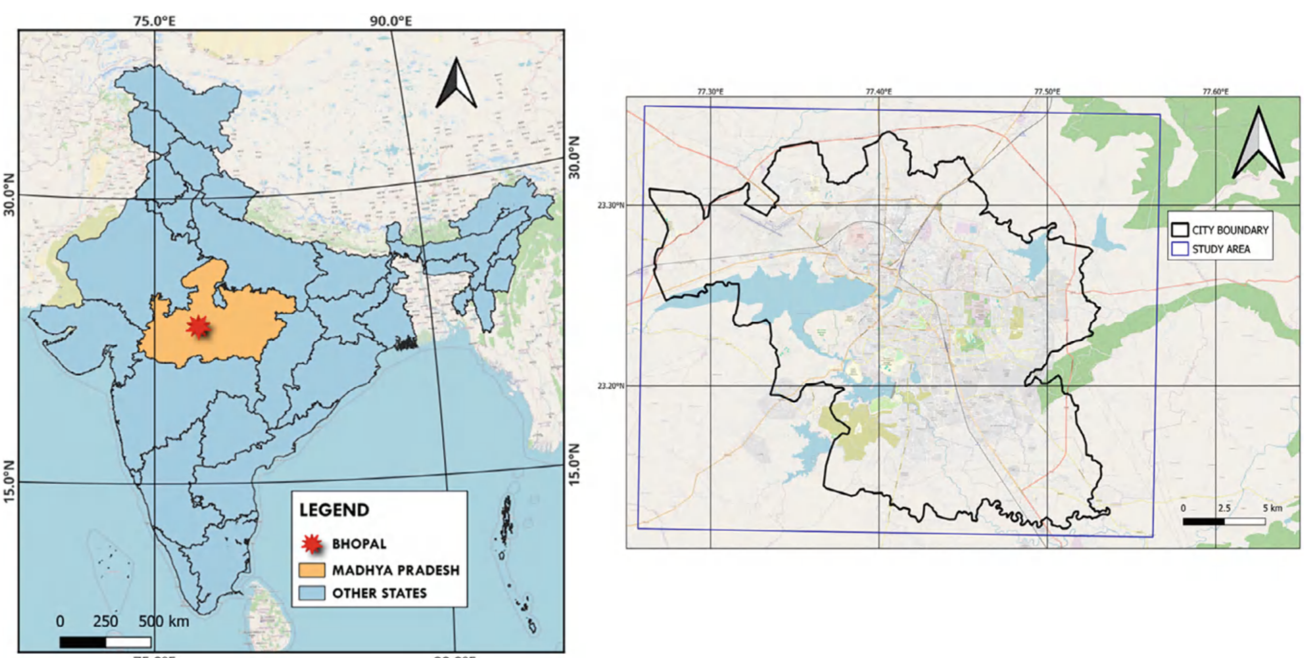


Fig. 1 **a** India's maps showing Bhopal city **b** Bhopal municipal boundary (in black) and study area (in blue) chosen for research

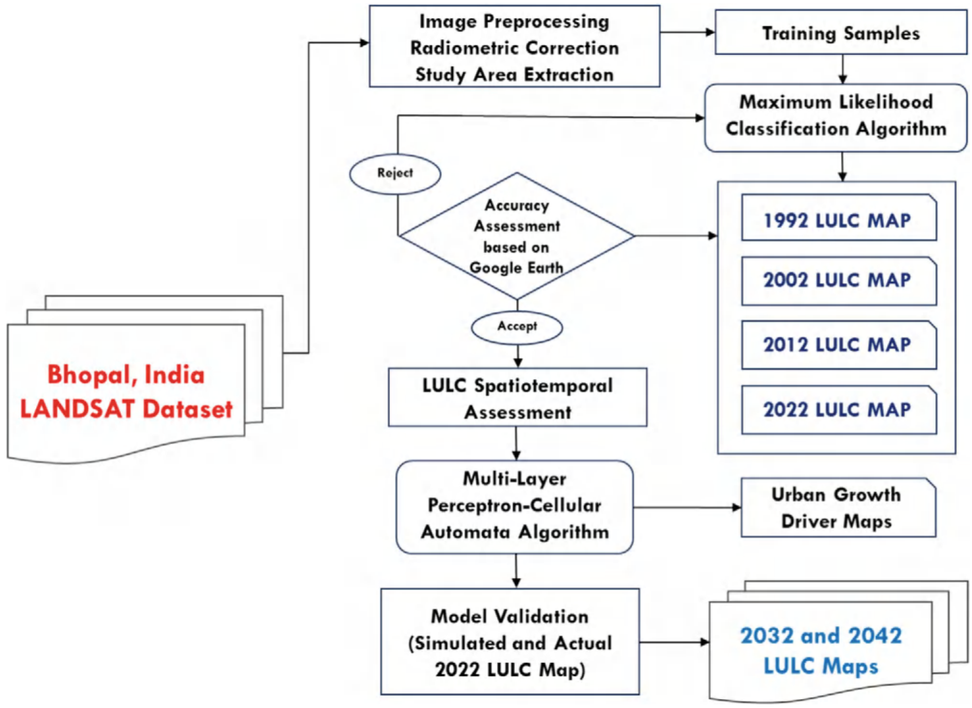


Fig. 2 Research methodology for spatiotemporal LULC assessment and urban growth prediction in Bhopal, India

Table 1 Summary of geospatial datasets utilized in this study

Dataset	Time stamp	Source	Resolution
LANDSAT- 4, 5 thematic mapper (TM)	May 10, 1992	United states geological survey	(30 × 30) m
LANDSAT-7 enhanced thematic mapper plus (ETM+)	May 12, 2002		
LANDSAT-8 thermal infrared sensor (TIRS) and operational land imager (OLI)	May 11, 2012		
LANDSAT-9 (TIRS and OLI)	May 10, 2022		
SRTM digital elevation model	2022	NASA	

Universal Transverse Mercator (UTM) projection system and clipped to a consistent area of interest using the same shapefile in Quantum GIS software. Image sharpening, smoothing, and atmospheric corrections were then applied. These datasets were chosen for their reliability in land cover classification and environmental monitoring, providing a robust foundation for analyzing and predicting urban growth dynamics.

3.2 Supervised Land Cover Classification

In the following stage, the Semi-Classification Plugin under Quantum GIS has been applied with the Algorithms for maximum likelihood classification to produce supervised land-cover maps for Bhopal, India, over four decades 1992, 2002, 2012, and 2022. The MLC Algorithm classified Image regions based on land cover information provided by users and spectral features from training samples. Such a process involved three steps-data preparation, parameter estimation and classification. While preparing the data, the training samples were obtained and spectral signatures for each land cover class were identified. Estimation of parameters involved computing the mean vector μ and covariance matrix Σ of all classes according to the following Eqs. 1 and 2:

Mean vector for the class k:

$$\mathbf{\mu\_k} = \frac{1}{n_k}\sum_{i=1}^{n_k} X_i \tag{1}$$

Covariance matrix for the class k:

$$\mathbf{\Sigma\_k} = \frac{1}{n_k}\sum_{i=1}^{n_k} (X_i - \mu_k).(X_i - \mu_k)^T \tag{2}$$

The classification process employed the likelihood formula, as given in Eq. 3, to evaluate each pixel's association with the respective classes.

$$\text{Likelihood } \mathbf{L}_{\mathbf{k(x)}} = \frac{exp^{(-0.5.(X_i-\mu_k)^T \Sigma_k{}^{-1}.(X_i-\mu_k))}}{\sqrt{(2\pi)^d.(|\Sigma_k|)^d}} \quad (3)$$

where d denotes the dimensionality of the feature vector, $|\Sigma_k|$ denotes the determinant of the covariance matrix, Σ_k, $(X_i - \mu_k)$ represents the deviation of the feature vector from the mean and $\Sigma_k{}^{-1}$ is the inverse of the covariance matrix. This method facilitated the accurate classification of pixels into land cover categories based on spectral data. The land cover was classified into four categories. Built-up areas consisted of roads, buildings, and infrastructures; Water Bodies consisted of rivers and lakes; Vegetation consisted of trees and green spaces; Barelands included vacant plots and uncultivated lands. Validity of these land cover maps is validated using kappa statistics with Eq. 4.

$$KS = (Po - Pe)/(1 - Pe) \quad (4)$$

where Po denotes the observed agreement proportion, and Pe is the expected agreement by chance. Kappa values above 0.80 was considered acceptable. A total of 300 ground control polygons (75 for each class) were created using the Google Earth Layer to validate the classification results. Furthermore, LULC change detection maps for three periods—1992–2002, 2002–2012, and 2012–2022—were developed to quantify the transitions from vegetation, bare lands, and water bodies to built-up areas, aiming to estimate the extent of urban encroachment over these different periods.

3.3 Land Cover Prediction

Using the Terrset Software Package, a Multi-Layer Perceptron Markov Chain Analysis model was employed to estimate long-term spatiotemporal LULC changes and project future urban growth in Bhopal, India. The process involved:

- **Data Collection and Preparation**: Historical land cover maps L_t and explanatory variables X_t , including ground slope, ground elevation, proximity to roads, built-up areas were gathered and prepared for analysis.
- **Training the MLP Model**: A Multi-Layer Perceptron (MLP) neural network was trained to generate statistical relationships between X_t and L_t . The strength of these relationships was evaluated using the Cramer V metric, defined by Eq. 5.

$$V = \sqrt{\frac{\chi^2}{n.\min(k-1, r-1)}} \quad (5)$$

where χ^2 represents the chi-squared statistic, n is the total number of observations, k is the number of categories in one variable, and r is the number of categories in the other variable. Variables with Cramer's V values greater than 0.15 were selected for further analysis.

- **Scenario Generation and Markov Chain Analysis**: Future scenarios were developed by incorporating projected values of the explanatory variables X_{t+1} into the model. The transition probabilities P_{ij} for land cover changes were estimated using Markov Chain Analysis, as outlined in Eq. 6.

$$P_{ij} = P(L_{t+1} = j | L_t = i) \quad (6)$$

where P_{ij} represents the probability of transitioning from land cover state i to state j.

- **Predicting Future Land Cover**: The future land cover maps L_{t+1} were produced by combining MLP model predictions with Markov Chain transition probabilities, given by Eq. 7.

$$L_{t+1} = MLP(X_{t+1}).P_{ij} \quad (7)$$

In this equation, $MLP(X_{t+1})$ generates the predicted probabilities based on explanatory variables, and P_{ij} denotes the transition probabilities.

- **Model Validation and Forecasting**: To validate the model's accuracy, the predicted land cover maps for 2022 were compared with actual data, achieving a high accuracy rate of over 90%. The validated model was then used to forecast land cover for the years 2032 and 2042, taking into account past LULC maps and urban growth drivers.

4 Results

4.1 Land Cover Mapping

Figure 3 illustrates the LULC maps for Bhopal for the years 1992, 2002, 2012, and 2022. These maps are accompanied by the corresponding land cover class areas in Table 3 and Fig. 4, detailing Built-up, Vegetation, Water Body, and Bareland categories. Further, Fig. 5 illustrates the transition of Barelands, Water Bodies, and Vegetation into Built-Up Areas in Bhopal from 1992 to 2022. The classification accuracy of

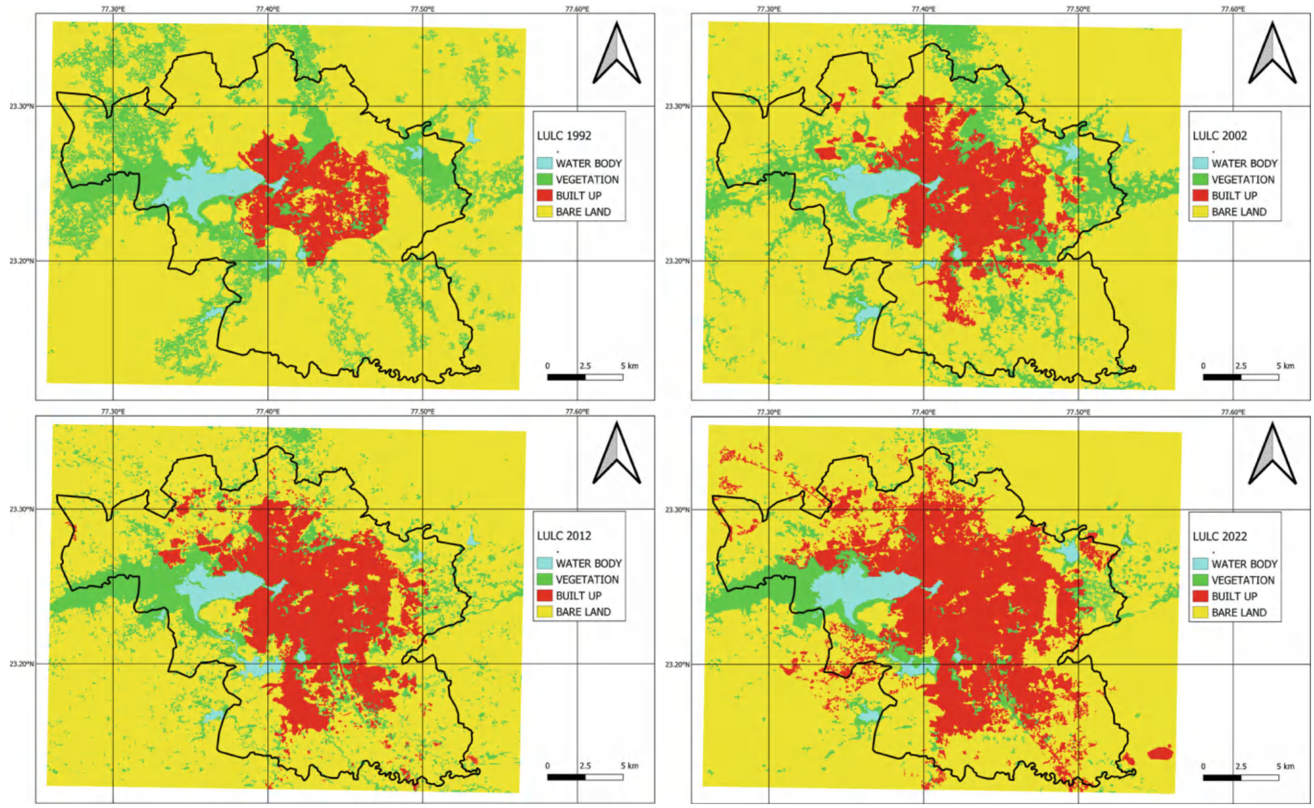
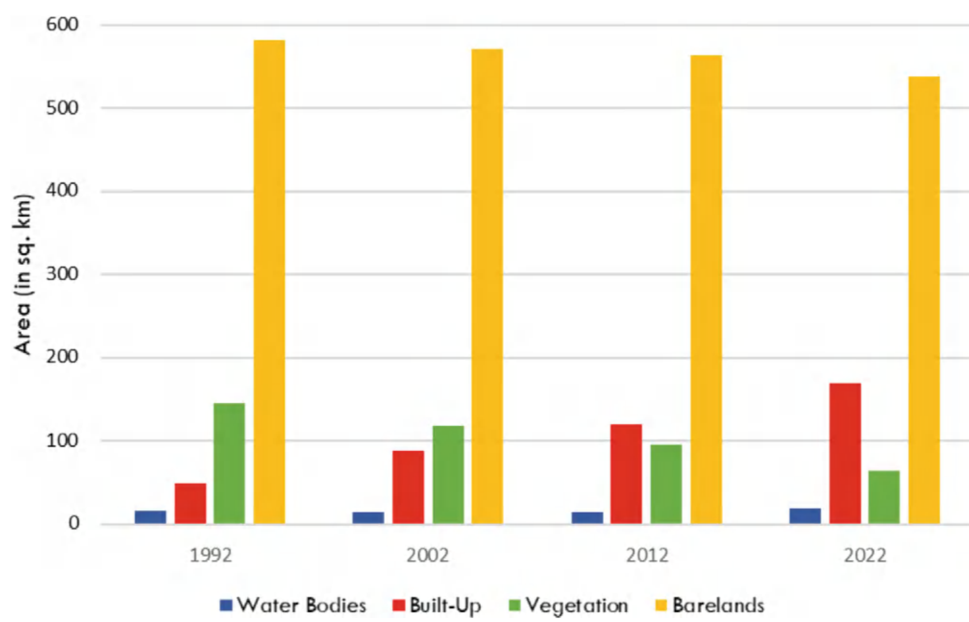


Fig. 3 Land use land cover maps for Bhopal, India region during 1992, 2002, 2012 and 2022

Fig. 4 Coverage of built-up, vegetation, waterbody, and Bareland areas in Bhopal, India from 1992–2022



these maps was validated using the Classification Accuracy tool in the QGIS SCP toolbox, which provided Kappa Statistics to assess the reliability of the land cover classifications. The Kappa coefficients, which are presented in Table 2, indicate a high level of accuracy in classifying various LULC types, particularly for water bodies and built-up areas, which exhibited stable Kappa values over time. Water bodies had Kappa values ranging from 0.917 in 1992 to 0.921 in 2022, while built-up areas showed values between 0.906 and 0.921. Vegetation and barelands displayed more variability, with Kappa values for vegetation ranging from 0.877 to 0.876 and barelands fluctuating from 0.861 in 1992 to 0.826 in 2022.

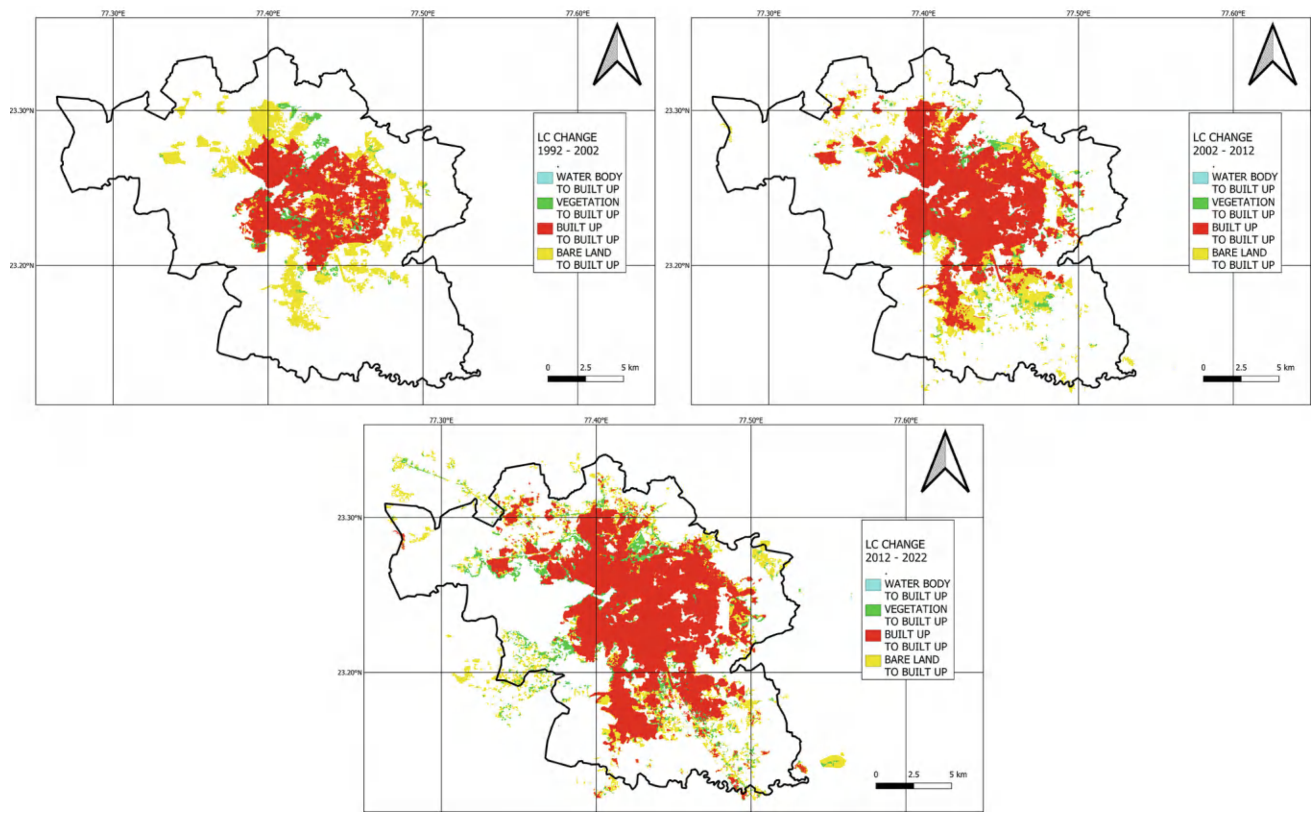


Fig. 5 Transition maps illustrating the conversion of Barelands, water bodies, and vegetation into built-up areas in Bhopal, India from 1992 to 2022

Table 2 Classwise and overall kappa values calculated for Bhopal, India LULC Maps from 1992–2022

LC class	Kappa coefficient				
	1992	2002	2012	2022	Overall
Water body	0.917	0.921	0.908	0.921	0.917
Built-up	0.906	0.897	0.880	0.921	0.901
Vegetation	0.877	0.881	0.864	0.876	0.875
Bareland	0.861	0.877	0.846	0.826	0.853

Table 3 Land use land cover coverages (in sq. km) in Bhopal, India during 1992–2022

Land cover class	Area (in sq. km)			
	Year			
	1992	2002	2014	2022
Water bodies	16.68	14.42	15.13	19.04
Built-up	48.59	88.00	119.39	169.98
Vegetation	146.07	118.93	95.20	64.81
Barelands	581.40	571.39	563.02	538.91
Total	792.74	792.74	792.74	792.74

Despite these fluctuations, all Kappa values exceeded the 0.85 threshold, underscoring the reliability of the land cover mapping process for Bhopal over the 30-year period.

In the last thirty years, Bhopal has experienced notable changes in land cover, mainly due to the growth of urban areas. According to data from Table 3, the area occupied by built-up spaces in Bhopal increased substantially from 48.59 sq. km in 1992 to 88.00 sq. km in 2002, marking an 81.13% rise. This growth continued, with built-up areas expanding to 119.39 sq. km by 2014, representing a 35.67% increase from 2002, and

Table 4 Land cover transition to built-up areas across Bhopal during 1992–2022

LULC conversion	Areas in sq.km		
	1992–02	2002–12	2012–22
Water bodies to built-up	0.01	0.04	0.08
Built-up to built-up	47.92	86.19	116.24
Vegetation to built-up	5.38	6.26	17.18
Barelands to built-up	34.69	26.93	36.54

further reaching 169.98 sq. km by 2022, which is a 42.37% increase from 2014. In contrast, vegetation coverage significantly declined during this period, decreasing from 146.07 sq. km in 1992 to 118.93 sq. km in 2002, a 18.56% reduction. The downward trend persisted, with vegetation areas shrinking to 95.20 sq. km by 2012 (a 19.96% decrease from 2002) and further declining to 64.81 sq. km by 2022, marking a 31.90% reduction from 2012. Similarly, barelands decreased from 581.40 sq. km in 1992 to 571.39 sq. km in 2002 (a 1.73% decline), continuing to 563.02 sq. km by 2012 (a 1.46% decrease from 2002) and further dropping to 538.91 sq. km by 2022 (a 4.28% decrease from 2014). The expansion of built-up areas has primarily encroached upon vegetation and barelands, with vegetation experiencing a particularly steep decline over the three decades.

Table 4 presents the LULC transitions in Bhopal from 1992 to 2022, showing a clear pattern of increasing urbanization. Between 1992 and 2002, bare lands experienced the most significant conversion, with 54.71% (34.69 sq.km) transitioning to built-up areas, followed by vegetated areas at 8.48% (5.38 sq.km). From 2002 to 2012, bare lands continued to dominate the transitions with 24.45% (26.93 sq.km) converting to built-up zones, while vegetated areas accounted for 5.69% (6.26 sq.km). In the final period from 2012 to 2022, bare lands again led the transitions at 24.84% (36.54 sq.km), with vegetated areas seeing a significant increase to 11.68% (17.18 sq.km) converting to built-up areas. These trends highlight the fast-paced urban growth in Bhopal, emphasizing a continuous transition from natural land covers, like vegetation and bare lands, to built-up areas during the past 30 years.

4.2 Predicting Future Urban Expansion

The MLP-MCA model from the TerrSet software package was used to forecast urban growth in Bhopal, India. This model relied on historical land use and land cover (LULC) maps from 2002 and 2012, incorporating important Urban Growth Drivers (UGDs) like ground elevation, ground slope, distance to roads, water bodies, developed areas, and vegetation, as shown in Fig. 6. Through 1000 iterations, the model achieved a Root Mean Square Error (RMSE) accuracy of 91.23%. To forecast LULC for 2022, 2032, and 2042, the analysis focused UGDs with high Cramer V scores, specifically built-up proximity (0.437), vegetation proximity (0.421), and road proximity (0.365), as these factors had a significant influence on urban growth. UGDs with lower Cramer V scores, such as slope, water proximity, and elevation, were deemed less influential and were therefore excluded from the analysis.

The validation of the MLP-MCA model for Bhopal involved comparing the predicted LULC map for 2022 and the actual LULC map derived using the MLC algorithm. Figure 6 illustrates the UGD maps whereas actual and predicted LULC maps for 2022 are shown in Fig. 7. As detailed in Table 5, the model exhibited high accuracy in forecasting LULC classes, with errors of 5.41% for water bodies, 0.46% for built-up areas, -3.83% for vegetation, and 0.12% for barelands. The overall prediction accuracy was 97.54%, underscoring the model's efficacy in predicting LULC changes. The same model parameter settings were utilized to predict Bhopal LULC maps for the 2032 and 2042 periods.

Figure 8 and Table 6 illustrate the predicted LULC changes for Bhopal, India, during 2032 and 2042. Built-up areas are projected to expand significantly, increasing from 169.98 sq. km in 2022 to 203.74 sq. km in 2032 (a rise of approximately 19.86%), and further to 224.90 sq. km by 2042 (an additional increase of 10.37%). Conversely, vegetation is expected to decline from 64.81 sq. km in 2022 to 50.77 sq. km in 2032 (a reduction of about 21.89%), with a further decrease to 43.43 sq. km by 2042 (an additional decline of 14.44%). Barelands are expected to decrease from 538.91 sq. km in 2022 to 520.01 sq. km in 2032 (a reduction of 3.53%), and further to 504.40 sq. km by 2042 (a further decline of 3.00%). These projections highlight the anticipated urban expansion and environmental changes in Bhopal's landscape over the next two decades.

5 Discussion

The projected urban expansion in Bhopal, India, poses significant challenges related to infrastructure, environmental health, and ecological sustainability. The built-up area is projected to rise from 169.98 sq. km in 2022 to 203.74 sq. km by 2032 (a 19.9% increase) and 224.90 sq. km by 2042 (a 32.4% increase). This expansion will exert considerable pressure on existing infrastructure. Areas such as New Market and M.P. Nagar are likely to face severe traffic congestion, increased energy consumption, and heightened strain on water supply and waste management systems, potentially compromising quality of life and economic stability. Environmentally, the reduction in vegetation—from 64.81 sq. km in 2022

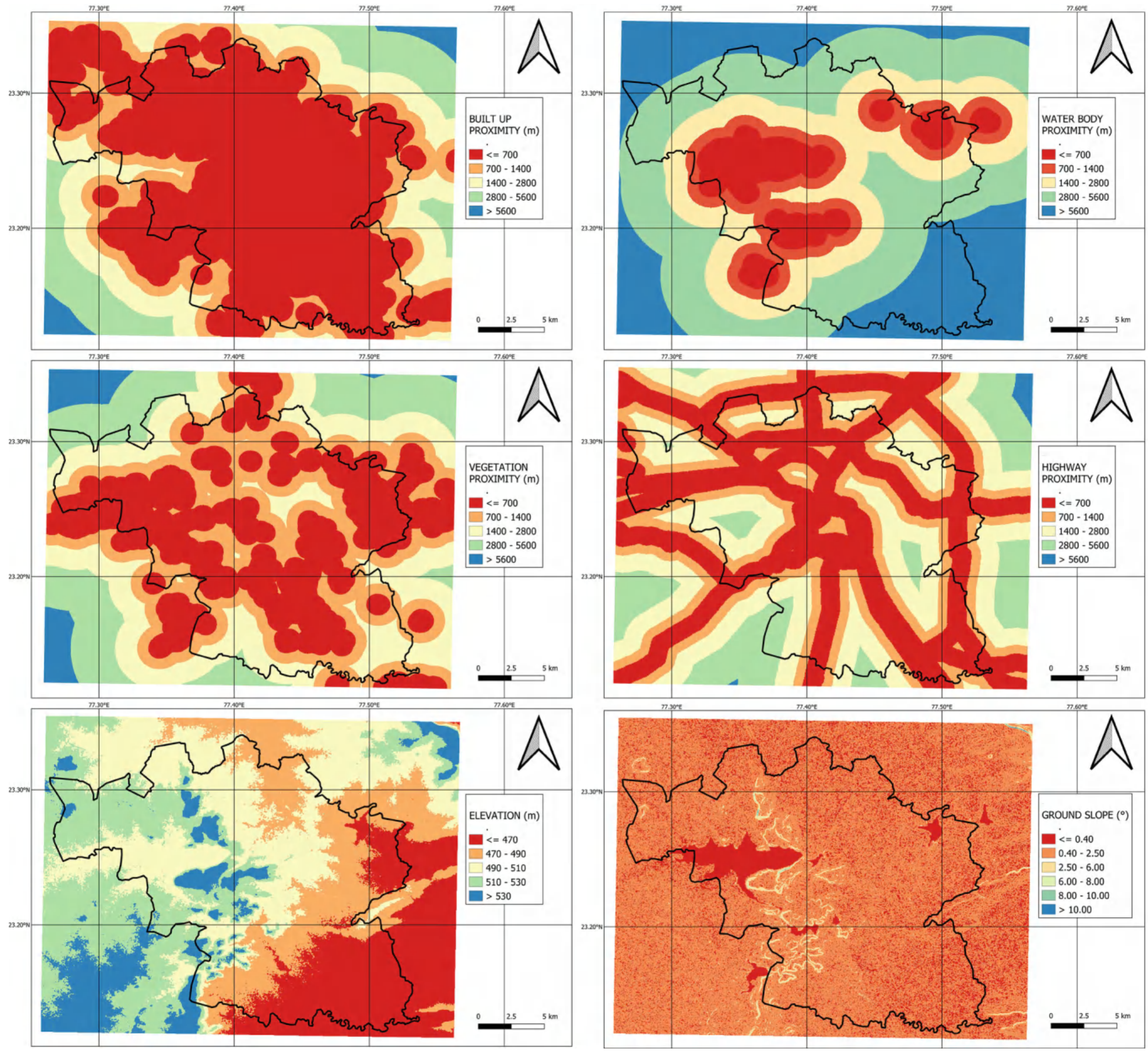
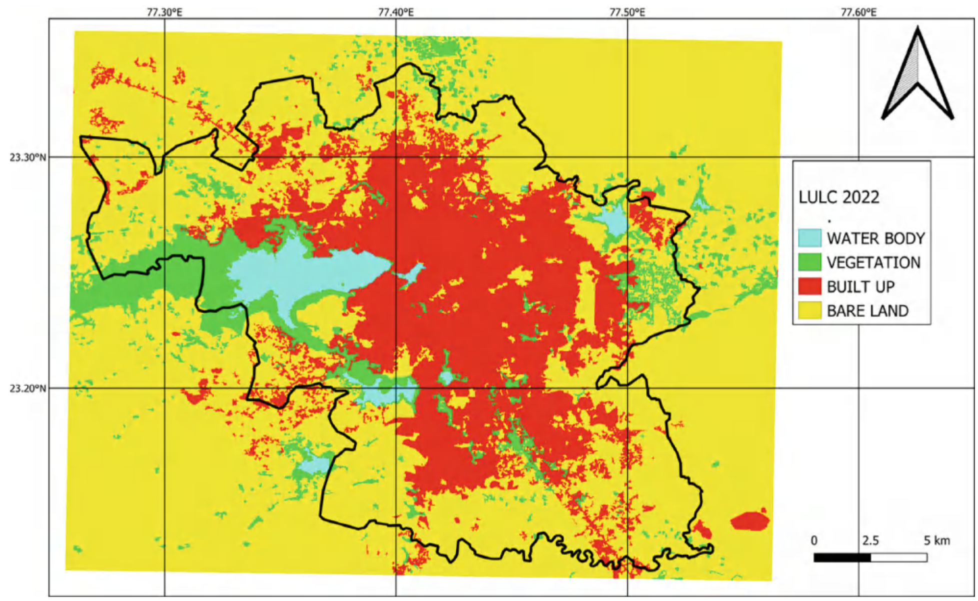


Fig. 6 Urban growth drivers used for predicting urban expansion for Bhopal, India

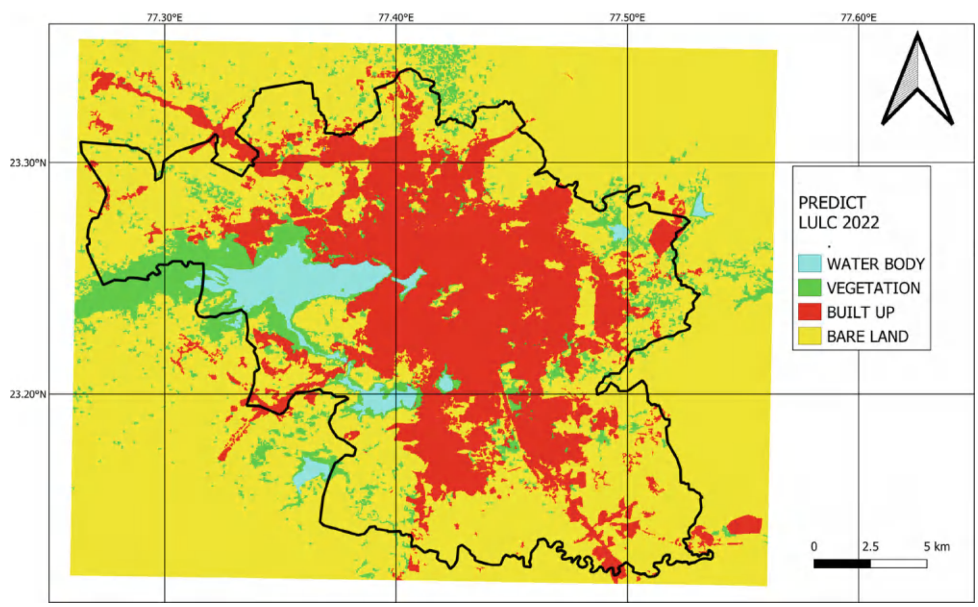
to 50.77 sq. km in 2032 (a 21.6% decrease) and 43.43 sq. km by 2042 (a 33.0% decrease)—presents significant risks. Key green spaces, including Van Vihar National Park and the Lower Lake, are vital for mitigating urban heat island effects and maintaining air quality. The reduction in vegetation, along with a decline in barelands—from 538.91 sq. km in 2022 to 520.01 sq. km in 2032 (a 3.5% decrease) and further to 504.40 sq. km by 2042 (a 6.4% decrease)—could significantly affect local hydrology and heighten flood risks, especially in low-lying regions like Hoshangabad Road and Shahpura Lake. The diminishing green spaces and disruption of habitats may also result in biodiversity loss and fragmentation, negatively impacting local plant and animal life.

To tackle the challenges posed by urban growth in Bhopal, a comprehensive strategy that combines effective urban planning with thorough environmental management is essential. Infrastructure development needs to be carefully designed to support the increasing population while promoting sustainable growth. This includes expanding transportation networks, such as roads and public transit systems, particularly in densely populated areas like New Market and M.P. Nagar, to ease traffic congestion and lower energy use. Upgrading water supply and waste management systems is critical to meet rising demands and avoid service shortfalls. Protecting the environment is equally crucial; enforcing strict zoning regulations is necessary to preserve important natural areas like Van Vihar National

Fig. 7 **a** Actual and **b** Predicted LULC maps for Bhopal, India in 2022



(a) Actual LULC Map



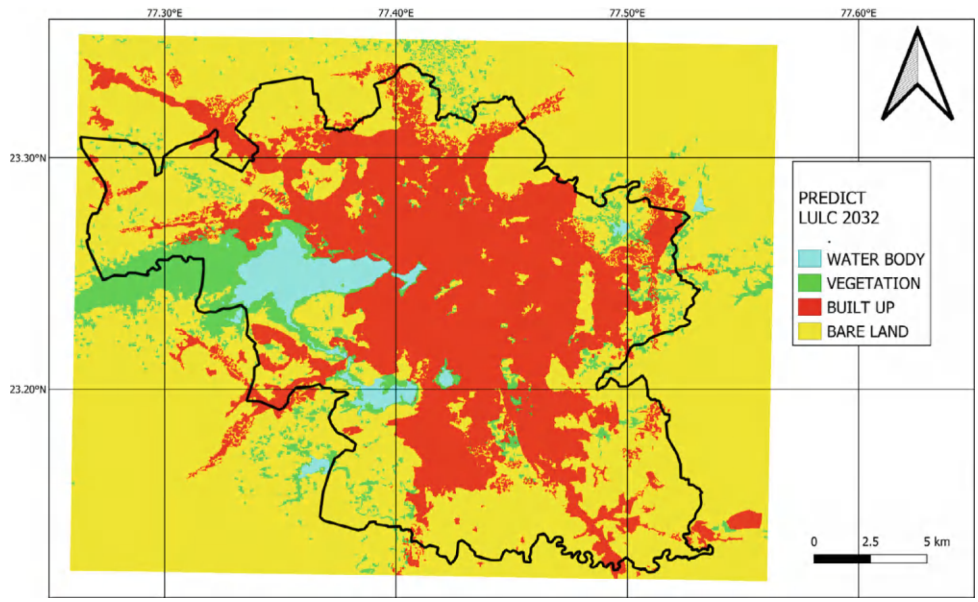
(b) Predicted LULC Map

Park and the Lower Lake from encroachment and degradation. Encouraging urban green initiatives, such as establishing new parks and green belts, will help counterbalance the loss of vegetation and strengthen urban resilience. Additionally, developing robust infrastructure and revising building codes are vital for adapting to climate change. Involving local communities and reinforcing environmental policies is essential for fostering a collaborative approach to sustainability. To support these initiatives, regular monitoring of land use and land cover (LULC) using advanced computational and machine learning techniques is important. This monitoring offers precise insights into LULC changes, enabling informed urban planning and the development of responsive policies to secure a sustainable future for Bhopal.

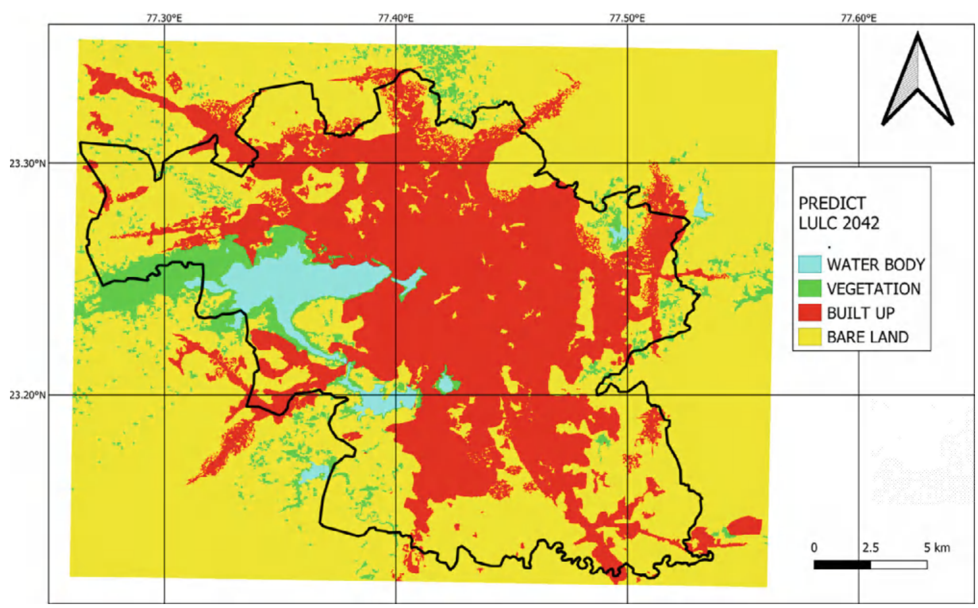
Table 5 Actual and predicted LULC coverages (in sq.km) for Bhopal, India in 2022

Coverage	LULC class			
	Water-Bodies	Built-Up	Vegetation	Barelands
Actual	18.23	203.74	50.77	520.01
Predicted	20.02	224.9	43.43	504.4
Error (%)	5.41%	0.46%	−3.83%	0.12%

Fig. 8 Predicted LULC maps for Bhopal, India during 2032 and 2042



(a) Bhopal LULC Map -- 2032



(b) Bhopal LULC Map -- 2042

Table 6 Predicted LULC coverages (in sq. km) for Bhopal, India during 2032 and 2042

Period	LULC class			
	Water-Bodies	Built-Up	Vegetation	Barelands
2032	18.23	203.74	50.77	520.01
2042	20.02	224.9	43.43	504.4

6 Conclusion

This study introduced a robust integrated geospatial framework that utilized advanced machine learning algorithms to explore the spatiotemporal dynamics of urban growth in Bhopal, India, spanning from 1992 to 2042. The Maximum Likelihood Classification (MLC) algorithm was employed to create Land Use Land Cover (LULC) maps for the years 1992, 2002, 2012, and 2022, categorizing the land into Built-Up, Vegetation, Water Body, and Bareland. Projections for future urban growth in 2032 and 2042 were conducted using a Multi-Layer Perceptron-Markov Chain Analysis (MLP-MCA) model. The overall Kappa values, which indicate the accuracy and reliability of the MLC mapping process, demonstrated strong performance throughout the years: 0.890 for 1992, 0.894 for 2002, 0.875 for 2012, and 0.886 for 2022.

From 1992 to 2022, Bhopal's land cover underwent significant changes. Built-up areas expanded by 32.3%, from 169.98 sq.km to 224.90 sq.km. Vegetation decreased by 19.6%, from 80.58 sq.km to 64.81 sq.km. Barelands saw a minor reduction from 543.11 sq.km to 538.91 sq.km, while water bodies declined from 83.33 sq.km to 78.09 sq.km. Looking ahead, urban growth is projected to continue, with built-up areas increasing to 203.74 sq.km by 2032 and 224.90 sq.km by 2042, marking increases of 19.9% and 10.4%, respectively. Vegetation is expected to decrease to 50.77 sq.km by 2032 and 43.43 sq.km by 2042, with reductions of 21.7% and 14.4%. Barelands will likely reduce to 520.01 sq.km by 2032 and 504.40 sq.km by 2042, showing decreases of 3.5% and 3.0%. Water bodies are anticipated to experience only slight reductions.

The projected rapid urban growth in Bhopal presents challenges for infrastructure, environmental health, and sustainability. Addressing these requires strategic urban planning and environmental management. Key actions include expanding transportation networks, upgrading water and waste systems, and enforcing zoning regulations to protect natural areas. Developing new parks and green belts will help counter vegetation loss and improve resilience. Pollution control and climate adaptation strategies, including resilient infrastructure and updated building codes, are also essential. Engaging local communities and reinforcing environmental policies will foster sustainability.

The presented geospatial framework utilizing MLC and MLP-MCA algorithms offered key insights into LULC changes and future urban growth in developing cities. This approach enabled precise monitoring and forecasting, facilitating informed decisions for sustainable development and environmental management aligned with the global sustainable development goals. The accuracy of these findings can be further improved by using high-resolution satellite datasets, such as Sentinel-2 or WorldView-3, which provide detailed observations and better delineate land cover types. This enhanced resolution can identify additional LULC types, like various vegetation species or smaller water bodies. Incorporating deep-learning models, like Convolutional Neural Networks (CNNs), can further improve predictive accuracy, offering more precise insights into land cover dynamics and supporting more effective urban planning strategies.

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Emerging Areas and Applications in the Field of Earth Sciences

Shweta Agarwal and Neetu Rani

Abstract

This chapter provides an extensive coverage of modern technologies and their applications in Earth Sciences which address global issues. Big data, satellite systems, and geoinformatics for better observation and management of Earth domains are showcased after the introduction to Earth Sciences. Climate change, hydrogeology, and geohazard management all focus on the critical function that this discipline has in risk management and promotion of sustainable development through achievement of the United Nations' Sustainable Development Goals. Others use predictive modelling and data analysis tools, artificial intelligence, and machine learning for advanced analyses of biogeochemical systems shall be emphasized as well. The chapter lastly summarizes some of the upholsterers as brief conversations that the future has with regard to cross-border collaborative efforts in technological advancement and development earth sciences towards tackling global concerns on climate change.

Keywords

Earth sciences · Big data · Innovations · Geohazard · GIS · ML · AI

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1 Overview of Earth Sciences

Earth Sciences involves the composition, properties, dynamics, and the interactions of the outer environments of the earth. The domain refers to aspects of diversified sub disciplines in geology, climatology, oceanography, and environmental science related to knowledge of the Earth on its physical, chemical, or biological dimensions. This discipline forms the basis of understanding natural phenomena, including plate tectonics, climate change, the hydrological cycle, and natural hazards including earthquakes, tsunamis, and volcanic eruptions. The analyses are based on collecting and interpreting geospatial data, numerical modeling, and sophisticated remote sensing technologies; hence, an emerging scientific discipline.

Earth sciences have advanced technological innovations of the GIS, machine learning, and satellite data gathering. New applications are innovative in management of natural resources, prevention of catastrophes, and sustainability of the environment; thanks to instruments provided for researchers to observe and analyze earth systems to unprecedented accuracy (National Research Council, 2001). New-age research and innovation in Earth Sciences has been the result of the growing call fed by such critical global issues as climate change and energy demands.

1.1 Importance of Emerging Areas and Applications

Earth sciences strategic emerging domains that directly address the modern global challenges pertain to the integration of AI, Big Data, and simulation models in advancing predictive precision and resource exploitation. An example of using AI climate models is where simulated effects of greenhouse gas emission into the environment are on a global

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scale, thereby providing an assessment of global warming and changing precipitation patterns. Big Data analytics transform methodology in complex data sets to analyze seismic activity, ocean currents, and atmospheric conditions in real-time (Wackernagel & Rees, 1998; Zhu & Woodcock, 2014).

These developments apply beyond the scope of the academic institutions toward a practical world. Instances are catastrophe preparedness and resilience, sustainable use of resource, and urban plan, among others. Moreover, remote sensing is essential and readily available for monitoring deforestation, glacial melting, and agricultural production trends. Geothermal energy exploration necessitates the application of precise geophysical and geochemical techniques. These breakthroughs enhance scientific comprehension of Earth systems and facilitate policy formulation and decision-making on environmental management and sustainability.

Objectives of the Chapter

This chapter identifies emerging themes and technological applications pertinent to Earth Sciences, advanced topics in geospatial technologies, climate modeling, sustainable resource management, and data science transforming the nature of research in Earth Sciences. Focus areas are:

- **Climate Change and Environmental Monitoring**: An environmental sustainability support would demand a better monitoring and modeling system in place to monitor climate impacts.
- **Geospatial Technologies**: Application of GIS and remote sensing for spatial data analysis in natural resource management and disaster management.
- **Geohazards and Risk Evaluation**: New methodology and modern tools are used today in hazard recognition related to earth quakes, slides, volcanic eruptions etc.
- **Resource Sustainability**: Comment on how Application of Technology contributes towards sustainability of resources for water, minerals and renewable sources of energy.
- **Data Science and Earth Sciences**: Potential to use big dataset, AI, and machine learning for new advancement in predictive models in a broader space of applications within Earth science.

Structure of the Chapter

This chapter will therefore holistically update major topics of Earth Sciences. It begins with Big Data, understanding its contribution to advancing the development in climate modeling, geohazards, and also to the ecosystem monitoring in Sect. 2. Then comes Remote Sensing and Satellite Technology, as discussed in Sect. 3, highlighting its applications in environment and disaster management. Section 4 of the report presents Geospatial Technologies, including rather very important tools in mapping resource management and spatial analysis, such as GIS and GPS.

The chapter also touches on Climate Change and its effects on Earth systems, pointing to the importance of Earth Sciences in predicting and mitigating climate-related challenges explained in Sect. 5. The SDGs are discussed in Sect. 6, which explains how Earth Sciences has struck a balance between keeping the environment and human development. Section 7 shows the integration of Artificial Intelligence and Machine Learning into Earth Sciences, concerning their power to transform data analysis and predictive techniques.

Section 8 is Hydrogeology and Water Resources Management, Geohazards and Risk Management addresses the role of Earth Sciences in assessing and mitigating natural disaster risks. Biogeochemical Cycles and Ecosystem Dynamics are then considered in terms of their relevance to understanding and maintaining ecosystem health.

This is concluded by Future Directions in Earth Sciences with a scope on new emerging technologies, trends, and changing landscapes in Earth Science research. As such, the organization makes an all-round view on Earth Sciences and its applications in other fields of discipline, which marks the progression in the field.

2 Big Data and Earth Sciences

This section provides a structured guide for exploring these emerging areas, with an emphasis on the practical applications that are driving innovation in Earth Sciences today.

2.1 Definition and Importance of Big Data

Big Data are defined as those enormous amounts of data coming at high velocity from multiple sources and structured, semi-structured, or unstructured. In this case, the five V's Volume, Velocity, Variety, Veracity, and Value describe the nature of Big Data (Vance et al., 2024). In Earth Sciences, Big Data is crucial because it means scientists will be able to understand the complex, highly large environmental phenomena for improving models and predictions. The embedding of Big Data into the Earth Sciences as shown in Fig. 1 has transformed its field to become a playground where researchers have discovered numerous patterns and relationships that before were not possible.

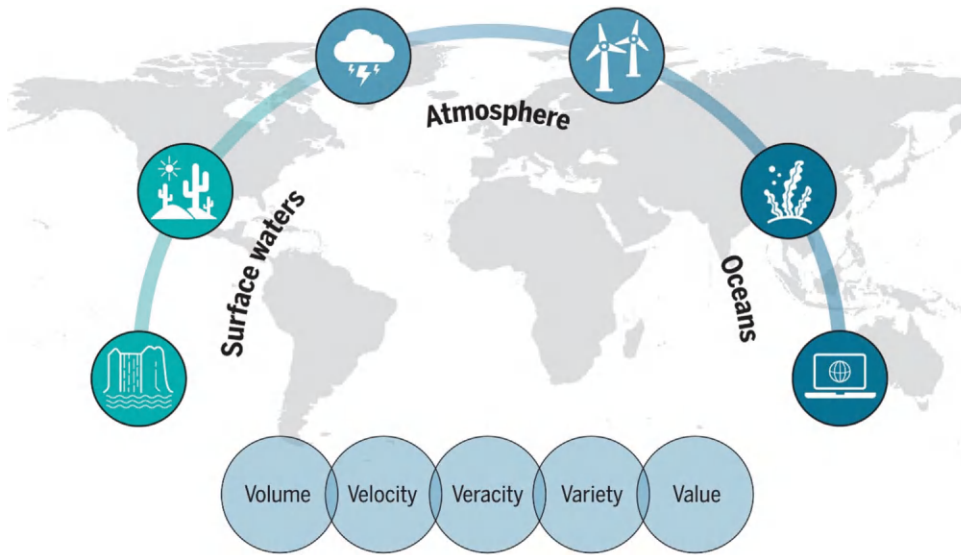

Fig. 1 Big data in earth sciences

2.2 Applications in Hydrology, Oceanography, and Atmospheric Science

Hydrology: Big Data changed the hydrology scenario through improving the accuracy and spatial resolution of hydrological models. The real-time monitoring of water bodies, precipitation, and soil moisture levels with satellite data and remote sensing technology can be used. The data is essential in water resource management, predicting flood, and understanding changes due to climate change that alter the availability of water (Baumann et al., 2016).

Oceanography: Big data are continuously monitored and modeled big data are studied regarding ocean currents, ocean temperature, ocean salinity, and marine ecosystem studies in oceanography. This data is gathered from deep waters to top height as mass between bottom to depth by floats, ocean observatory and Autonomous Underwater Vehicles. Ocean circulations includes those involved in studying, changing of weather conditions, cases concerning the hurricane events. Events on change marine as related to climate (Baumann et al., 2016).

Atmospheric Science: The collection of vast sources from satellite images at high resolution, ground-based sensors and climate models is defined as Big Data for the improvement of atmospheric composition, climate dynamics by atmospheric scientists. Huge datasets resulting from Big Data include determination capability of climate dynamics, improvement in the accuracy of air quality analysis, and enhancement ability in weather forecasting accuracy related to Big Data analytics (Baumann et al., 2016).

The applications in hydrology, oceanography, and atmospheric science are summarized in Table 1.

Table 1 Applications of big data in earth sciences

Field	Applications
Hydrology	Real-time monitoring of water bodies, flood prediction, water resource management
Oceanography	Monitoring ocean currents, temperature, salinity, marine ecosystems
Atmospheric science	Weather forecasting, air quality studies, climate dynamics analysis

2.3 Case Studies and Examples

Hydrology Case Study: This is one of the obvious examples in hydrology in terms of using Big Data in flood prediction and management. The real-time flood monitoring and early warning system combines satellite images, weather forecasts, and hydrological models. For instance, 2013 Colorado floods were predicted with Big Data analytics by predicting the flood's extent and impacts, which, in turn, helped in evacuation and proper resource allocation (Baumann et al., 2016).

Oceanography Case Study: Argo program is an oceanography deployment of a global array of profiling floats that provides continuous data on ocean temperature and salinity. This information has hugely assisted in the determination of the heat content of oceans and its contribution to the global climate systems. Besides, Argo floats improved the accuracy of ocean circulation models, which are of paramount importance in predicting the variability of climate (Baumann et al., 2016).

Fig. 2 Evolution of satellite imaging technologies

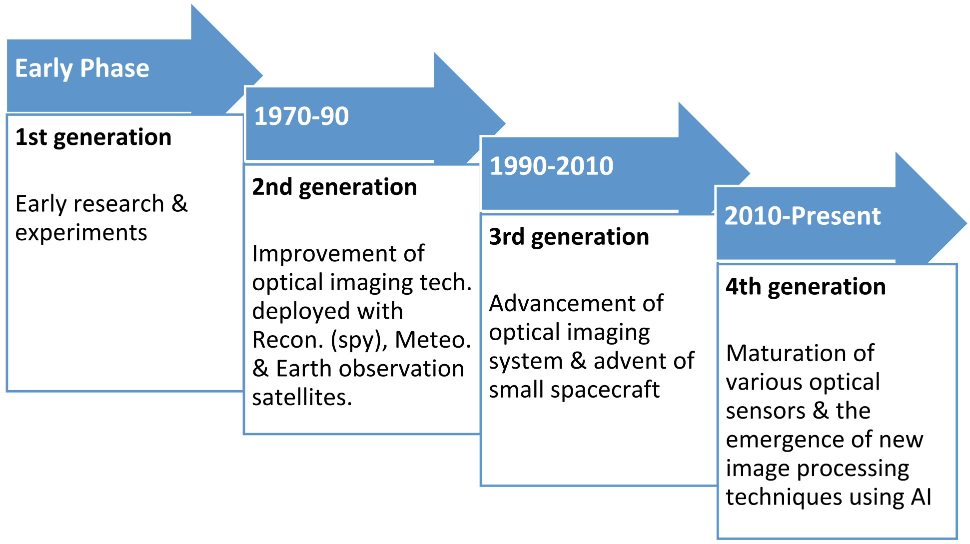

Table 2 Comparison of leading earth observation satellites

Satellite	Resolution	Sensor type	Temporal frequency	Key applications
Sentinel-2	10–60 m	Multispectral	5 days	Land cover mapping, agriculture
Landsat 9	30 m	Multispectral	16 days	Environmental monitoring, urban planning
Sentinel-1	5 m	SAR	6 days	Surface deformation, maritime surveillance
PlanetScope	3–5 m	Multispectral	Daily	Real-time environmental monitoring
RADARSAT-3	1 m	SAR	1 day	Ice monitoring, disaster response

Case Study of Atmospheric Science: Big Data played a vital role in the 2020 Australian bushfire season in atmospheric science. The fires, air quality, and weather data were aggregated using satellite data, ground-based observations, and climate models. Aggregated datasets enabled an estimate of environmental impacts of fires and insight into the design of strategies for mitigation (Baumann et al., 2016).

3 Remote Sensing and Satellite Technology

The technology of satellite and remote sensing has revolutionized Earth Sciences by providing high-resolution data, which is very important for the monitoring, analysis, and management of Earth's dynamic systems. This section covers the recent advancements in satellite-based observations, applications in environmental monitoring and disaster management, and future prospects and challenges in this fast-evolving domain. The evolution of Satellite Imaging Technologies is presented in Fig. 2 and comparison of Leading Earth Observation Satellites is shown in Table 2.

3.1 Advances in Satellite-Based Observations

- **High-Resolution Imaging and Sensors**: Over the past couple of years, space technology has observed the introduction of high-resolution imaging systems and advanced sensors that produce more resolution in spatial, temporal, and spectral data capture. Today, multispectral and hyperspectral imaging capabilities can be found on satellites from the European Space Agency known as Sentinel series and Landsat 9 mission through NASA, and they reach up to a spatial resolution of 30 cm like that seen on the Sentinel-2.

- **SAR Upgrades**: SAR technology has dramatically improved and is now an all-weather, day-and-night imager. High-resolution SAR data missions are those of the NASA Sentinel-1 and the Canadian RADARSAT Constellation, used for surface deformation, vegetation monitoring, and maritime surveillance (Pettorelli et al., 2014).
- **Cubesats and small satellite constellations**: Cubesats and smaller satellite constellations democratize access to satellite data because of their enhanced capability toward more frequent and cheaper observation. Companies like Planet Labs have large fleets of smaller satellites, offering near-daily global imaging in ways that improve on the time resolution, or the ability to monitor and observe environmental changes nearly at real time (Labs, 2024).
- **Advanced Data Processing and AI Integration**: This integration of AI and ML algorithms with the satellite data processing pipelines improved the accuracy and efficiency of interpreting data. Techniques like deep learning are used in auto-feature extraction, classifications, and anomalies for really large geospatial datasets (Zhu et al., 2017).

3.2 Applications in Environmental Monitoring and Disaster Management

- **Environmental Monitoring**: Satellites remote sensing is one of the very important tools for monitoring many environmental parameters, which have been considered critical data in the understanding and management of Earth's ecosystems.
- **LULC Mapping**: Sentinel-2 and Landsat 9 high-resolution satellite imagery can be used for LULC classification that provides an accurate basis for the tracking of urban growth, deforestation, and habitat fragmentation (Zhu & Woodcock, 2014).
- **Climate Indicators**: Satellites keep track of the main indicators of climate, from which the dynamics of an ice sheet and the amount of atmospheric gases can be judged. For example, from NASA's MODIS data, the global pattern of temperature and health status of vegetation can be gained (Turton et al., 2012).
- **Water Resource Management**: Using remote sensing, surface covering of water bodies is assessed as well as alterations in their quality. Groundwater depletion: Various changes occur with the storage and depletion of ground water, the changes in ground water being measured using the GRACE (Gravity Recovery and Climate Experiment) mission that computes earth's gravity field variations (Rodell et al., 2018).
- **Disaster Management**: Satellite technology is very essential in disaster management since it provides them with a timely and accurate information of preparedness, response, and recovery.
- **Early warning systems**: SAR and optical sensors are sensitive to precursors to such natural disasters, like earthquakes, tsunamis, and volcanic eruptions. For example, Sentinel-1 SAR data is used for ground deformation monitoring associated with seismic activity (Pettorelli et al., 2014).
- **Damage Assessment**: The satellite images taken right after the disaster will easily provide an overview of areas damaged and can assist resource distribution. For example, images taken from PlanetScope and Sentinel-2 come with resolutions that can greatly aid in the mapping and documentation of the destruction infrastructure has incurred as well as its effect on the surroundings (Graf et al., 2024).
- **Flood Monitoring and Management**: Using SAR and optical data, real-time flood mapping supports both flood forecasting and the emergency response. The Copernicus Emergency Management Service gives the maps to the authorities in decision-making at the time of floods (Velegrakis et al., 2024).

The case studies highlighting the role of satellite applications in disaster management across various scenarios are detailed in Table 3.

Table 3 Case studies of satellite applications in disaster management

Disaster type	Satellite used	Key application	Outcome
Earthquake	Sentinel-1	Ground deformation monitoring	Enhanced understanding of fault movements
Flood	Sentinel-1, MODIS	Real-time flood extent mapping	Improved emergency response coordination
Wildfire	MODIS, VIIRS	Active fire detection and monitoring	Timely alerts and resource deployment
Hurricane	GOES-R series	Storm tracking and intensity estimation	Better forecasting and evacuation planning

3.3 Future Prospects and Challenges

3.3.1 Future Perspective

- **Enhanced Spatial and Temporal Resolution**: Satellites sensors should improve in the future at a rate permitting greater spatial and, more importantly, temporal resolution: more frequent and better sampling. Real-time capabilities might be seen from missions coming soon (Lee et al., 2010). The satellite data combined with ground-based IoT sensors allow for the creation of immense monitoring networks, which enable the improvement of data quality and easy integration of datasets from different sources for analyzing the Earth system holistically (Gubbi et al., 2013).
- **Improvements in AI/ML**: The more effective exploitation of more sophisticated algorithms in AI and ML to make sense of the data through pattern recognition and as forecasting tools will lead to far more accurate models and the ability to predict in the Earth Sciences (Goodfellow et al., 2016).
- **Commercialization and Availability**: The more commercial satellite operators made data more accessible, thereby cheaper, and this further facilitated further innovation with the creation of many applications in other areas (Schwab, 2017).

3.3.2 Issues

- **Volume and Data Management**: There is such a huge quantity of data from satellites, which creates a gigantic challenge in storage, processing, and handling. Efficient data infrastructure accompanied by cloud computing should be employed to handle big data well (Yang et al., 2017).
- **Quality of Data and Standardization**: This includes ensuring the quality of data as well as the standards required to obtain, process, and exchange data that plays a critical role in doing reliable analysis and interchange of data across various systems and missions (Hamm et al., 2015).
- **Cyber Security and Data Privacy**: The increased usage of satellite data and services raise questions regarding Cyber Security and Data privacy issues. Information protection is crucial, not only in cyber crimes but also through the ethical use of data (NASCIO, 2021).
- **Cost and Access Barriers**: Much of this has been done and launching and maintaining satellites involves a lot of cost for which developing countries cannot keep up. Global cooperation would be increased with public and private partnerships that can even reduce these challenges (UN-SPIDER, 2023).

Table 4 Future satellite missions and their expected contributions

Mission	Launch year	Key features	Expected contributions
NASA-ISRO SAR	2025	High-resolution SAR imaging	Enhanced earthquake and landslide monitoring
ESA biomass	2024	Advanced biomass and carbon mapping	Improved carbon cycle modeling
EarthNet	2026	Multi-spectral and thermal sensors	Comprehensive environmental monitoring
Lunar gateway	2027	Earth observation from lunar orbit	Novel perspectives on Earth systems

The details of future satellite missions and their expected contributions are provided in Table 4.

4 Geospatial Technologies

4.1 Geographic Information Systems (GIS)

A geographic information system is a computer-based tool that enables users to collect, process, analyze, manage, and display spatial or geographic data. Combining data from various sources, it becomes a unified platform that enables spatial analysis and informed decision-making. The basic components of GIS include hardware, software, data, people, and methods (Reddy, 2018). The applications are as follows:

Urban Planning: GIS cannot apply planning in an urban situation. GIS helps in its application provide land use plan, transport infrastructure development plans, environmental management plans as well. The urban planner is aided by GIS on visualization of spatial data, examination of city growth patterns as well as directing decisions into sustainable development support (Singh et al., 2024).

Agriculture: In agriculture, GIS provides precision farming, crop monitoring, soil analysis, and resource management. It helps farmers use the inputs like water, fertilizers, and pesticides more effectively, which maximizes crop yield and reduces environmental damage (Jha et al., 2022).

Resource Management: GIS is an important aid in natural resources like water, forests, and minerals. It is useful for resource mapping and monitoring as well as for the analysis of environmental impacts and planning resource use in a sustainable way (Singh et al., 2024).

4.2 Integration with Other Technologies

Geospatial technologies are integrated with other emerging technologies to enhance capabilities as well as applications. The applications of GIS in various fields are outlined in Table 5. Such important integrations include:

- **Remote Sensing**: Integration of GIS with remote sensing technologies can collect and analyze real-time data from satellites and aerial platforms. This integration is very important for environmental changes, disaster management, and land use planning (Reddy, 2018)
- **Global Positioning System (GPS)**: The integration of GIS with GPS provides accurate location data, which is essential for mapping, navigation, and spatial analysis (Reddy, 2018)
- **Artificial Intelligence and Machine Learning**: AI and ML algorithm helps in understanding large geo spatial datasets for identifying patters and forecasting. The number of users improves the level of accuracy coupled with efficiency concerning the processing of geospatial information (Singh et al., 2024).
- **Urban Planning**: In New York City, GIS has been used in the analysis and visualization of land use, transportation networks, and environmental factors. This analysis will help city planners strategize on sustainable growth in urban areas and disasters (Singh et al., 2024).
- **Agricultural**: In India, crop health monitoring and yield prediction were integrated with water resources management through GIS and remote sensing technologies. This increased agricultural productivity and efficient use of resources (Jha et al., 2022).
- **Resource Management**: In Australia, it is very prominently applied in terms of water resources mapping and monitoring, rating the mining activities, planning towards ensuring sustainable resource management in relation to the economy but, at the same time, conserving the environment (Singh et al., 2024).

Table 5 Applications of GIS in various fields

Field	Applications
Urban planning	Land use planning, transportation planning, infrastructure development
Agriculture	Precision farming, crop monitoring, soil analysis, resource management
Resource management	Mapping and monitoring resource distribution, environmental impact assessment

Geospatial technologies, particularly GIS, continue to play a transformative role in various fields, providing valuable insights and tools for sustainable development and resource management.

5 Climate Change and Earth Sciences

5.1 Impact of Climate Change on Earth Systems

Climate change impacts profoundly on all Earth systems: atmosphere, hydrosphere, cryosphere, biosphere, and lithosphere are summarized in Table 6 and connect the implications each causes in ways of increasing in strength, there by intensifying the obstacles in environmental areas.

Atmosphere: Altogether, in significant quantities of greenhouse gases, it increases the temperatures worldwide, making the heat waves and storms more frequent and hotter as well. It also leads to changing the intensity as well as distribution of fall in rain in some type of weather conditions and ultimately, it makes stronger weather occur more frequently either through hurricanes or typhoons.

Hydrosphere: Alters hydrological cycles associated with changes in precipitation patterns and increased stream flow; likewise, changes in levels and depth of groundwater, incurring the more intense dry or wet periods in affected locations; thereby altering their use and quality (Parmesan et al., 2022).

Cryosphere: Increases sea levels through melt-water release from glaciers and ice sheets, posing further hazards to coastal communities as well as their ecosystems and will eventually disrupt ocean circulatory system and weather-related parameters as well (Masson-Delmotte et al., 2022).

Biosphere: Alteration of temperature and precipitation patterns modifies ecosystems and biodiversity. Examples include changes in species movement, changes in breeding

Table 6 Impacts of climate change on earth systems

Earth system	Impacts
Atmosphere	Increased heatwaves, altered precipitation, extreme weather events
Hydrosphere	Changes in precipitation, river flow, groundwater levels, severe droughts and floods
Cryosphere	Melting glaciers and ice sheets, sea-level rise, altered ocean circulation
Biosphere	Species migration, altered breeding cycles, habitat loss, reduced biodiversity
Lithosphere	Soil erosion, desertification, land degradation

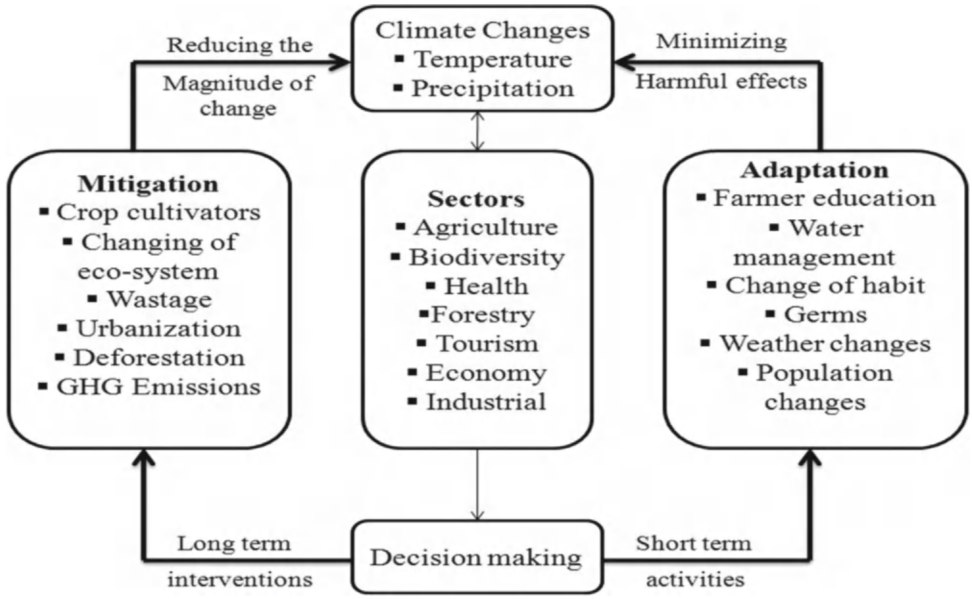

Fig. 3 Role of earth sciences in climate change mitigation and adaptation

time, and loss of habitats which can contribute to reduced biodiversity and services within the ecosystems (Parmesan et al., 2022).

Lithosphere: Changes in the climate will enhance the phenomenon of soil erosion, desertification, and degradation. These modifications change agriculture, food security, and life of human beings (Parmesan et al., 2022).

5.2 Role of Earth Sciences in Climate Change Mitigation and Adaptation

Earth sciences are thus crucial for mitigation and adaptation to climate change. Comprehension of complex Earth systems allows scientists to work out ways of lowering the emission of greenhouse gases as well as resilience to the impacts of climate change. The role of Earth sciences in climate change mitigation and adaptation is illustrated in Fig. 3.

Mitigation: Earth scientists are mitigative in the sense that they study carbon cycles, look for carbon sinks, and technologies for capturing and storing carbon. In addition to this, renewable energy resources such as geothermal, wind, and solar could be encouraged to reduce dependence on fossil fuel sources (Currie-Alder et al., 2021).

Adaptation Strategies: Adaptation strategies refer to changing human and natural systems in ways that minimize or counteract the impacts of climate change. Earth scientists are involved in designing a resilient infrastructure, developing an early warning system for natural calamities, and adopting responsible land and water management approaches (Currie-Alder et al., 2021).

Table 7 Emerging research areas in earth sciences

Research area	Focus
Climate modeling	High-resolution models, integration of big data
Geoengineering	Solar radiation management, carbon dioxide removal
Resilience and sustainability	Adaptive strategies for communities and ecosystems
Interdisciplinary approaches	Integration of ecology, economics, and social sciences

5.3 Emerging Research Areas

Emerging lines of research in Earth Sciences relate to broadening knowledge of climate change and the discovery of creative ways of mitigating the impacts on society are highlighted in Table 7.

Climate modeling: To predict future climate scenarios and to assess the performance of the mitigation and adaptation measures, further development in climate modeling would play a great role. High-resolution models developed and merged with huge amounts of big data have enhanced the accuracy of climate predictions (Vance et al., 2024).

Geoengineering: Geoengineering study refers to the deliberate measures that are undertaken to control the Earth's climate system with the intention of regulating global warming. These include techniques such as solar radiation management and carbon dioxide removal technologies (Vance et al., 2024).

Resilience and Sustainability: The resilience and sustainability studies have been developed to find adaptive strategies that can improve the capacity of communities and ecosystems to withstand climate impacts. These include research on sustainable agriculture, water management, and urban planning (Currie-Alder et al., 2021).

Interdisciplinary Approach: Interdisciplinary collaboration is significant while dealing with climate change. New research focuses more on integrating knowledge from many different fields, including ecological knowledge, economic knowledge, and social sciences, towards more holistic solutions (Currie-Alder et al., 2021).

Climate change remains one of the most pressing challenges of our time. The contributions of Earth Sciences are vital in understanding, mitigating, and adapting to its impacts, ensuring a sustainable future for all.

6 Sustainable Development and Earth Sciences

6.1 United Nations Sustainable Development Goals (SDGs)

The UN Sustainable Development Goals presented in Table 8, are 17 global objectives adopted in 2015 under the 2030 Agenda for Sustainable Development. The targets of SDGs among global challenges include poverty, inequality, climate change, environmental degradation, peace, and justice (Nations, 2015). SDGs are interlinked and balanced between social, economic, and environmental sustainability.

The area of Earth Sciences is significantly important in realizing the attainment of SDGs because it proffers critical insights and appropriate tools for understanding, monitoring, and managing natural resources and environmental processes. Several key contributions include the following contributions:

SDG 2: Zero Hunger

- **Soil Health and Fertility**: Geoscientists study soil properties and process for the enhancement of the efficiency of agricultural productivity and sustained land use (U, 2015)
- **Water Management**: Hydrologists develop efficient irrigation and manage water resources to serve support agriculture (Gill et al., 2021).

SDG 6: Clean Water and Sanitation

- **Water Quality Monitoring**: The geospatial technologies along with remote sensing enable earth scientists to monitor water quality and resources management (Zheng et al., 2023).

Table 8 The 17 sustainable development goals

Goal number	Goal description
1	No poverty
2	Zero hunger
3	Good health and well-being
4	Quality education
5	Gender equality
6	Clean water and sanitation
7	Affordable and clean energy
8	Decent work and economic growth
9	Industry, innovation, and infrastructure
10	Reduced inequality
11	Sustainable cities and communities
12	Responsible consumption and production
13	Climate action
14	Life below water
15	Life on land
16	Peace and justice strong institutions
17	Partnerships to achieve the goal

- **Groundwater Management**: Hydrogeologists determine and monitor the availability of groundwater resources, which then serves as the basis of ensuring a water supply of sustainable quantity.

SDG 13: Climate Action

- **Climate Modeling**: Earth scientists produce and modify climate models, predicting the possible future climatic scenario in order to support strategies to mitigate and adapt (Zheng et al., 2023).
- **Carbon Sequestration**: Earth scientists investigate and design the process of carbon capture and storage in reducing greenhouse gases emission (Zheng et al., 2023)

SDG 14: Life Below Water

- **Marine Ecosystem Monitoring**: Oceanography students investigate marine ecosystems and responses to environmental changes to conserve biodiversity (Zheng et al., 2023)
- **Pollution Control**: Earth scientists design ways to monitor and manage marine pollution (Zheng et al., 2023)

SDG 15: Life on Land

- Biodiversity Conservation: Geoscientists analyze and monitor land ecosystems for the conservation of biodiversity and also preserve natural habitats (Zheng et al., 2023)
- Land Degradation: Earth scientists study the process of soil erosion and land degradation processes to devise sustainable land management practices (Zheng et al., 2023)

7 Artificial Intelligence and Machine Learning in Earth Sciences

AI and ML are some of the disruptive technologies enabling computers to learn from data to make predictions or make decisions. AI encompasses an incredibly wide range of techniques; one of the aspects covered by ML is building algorithms that can learn data patterns. These technologies in Earth Sciences have become even more widespread and already used for data analysis, improvement of predictive models, and even enhancement capabilities in decision-making (Singh et al., 2021). AI and ML find tremendous application in Earth Sciences as presented in Table 9, particularly in predictive modelling and analysis of data:

- Climate Modeling: AI and ML algorithms enhance the precision of climate models by analyzing large volumes of climate data and identifying patterns that may be neglected by traditional models (Singh et al., 2021)
- Earthquake Predictions: ML approaches have been able to predict earthquakes based on seismic data and its related precursors to the event (Academies & of Sciences, Engineering, & Medicine., 2022).

Table 9 Applications of AI and ML in earth sciences

Application area	Description
Climate modeling	Enhancing the accuracy of climate predictions using AI algorithms
Seismic activity prediction	Analyzing seismic data to predict earthquakes
Remote sensing	Monitoring environmental changes through satellite imagery analysis

- Remote Sensing: AI algorithms process the image data from satellites, with respect to environmental change analysis like deforestation, urbanization, and natural disaster occurrences (Li et al., 2024)

Among the promising directions of developing AI and ML in Earth Sciences is:

- **In Big data**: Merging AI and ML with big data technology to process and analyze large-scale Earth system data (Chang & Guo, 2020).
- **Real-Time Monitoring**: Design real-time monitoring systems for any natural disaster using AI in the warnings with respect to impact (Satheeshkumar et al., 2024)
- **Interdisciplinary research**: This encourages collaborative interaction between Earth scientists and AI experts in developing innovative solutions to address challenging environmental issues.

8 Hydrogeology, Water Resources Management, Geohazards, and Biogeochemical Cycles

8.1 Ground Water Exploration and Management

During recent times hydrogeology has undergone an evolution in the exploration and management of the ground water as shown in Table 10 and described below:

- **Geophysical Techniques**: Electrical resistivity tomography (ERT) and ground-penetrating radar (GPR) enhance the mapping of subsurface water resources. ERT gives an electrical resistance measure for the ground, aiding the identification of water-bearing formations, while GPR

Table 10 Advances in hydrogeology

Technique	Application
Geophysical methods	Mapping subsurface water resources
Modeling and simulation	Predicting groundwater flow and impacts of extraction
Contaminant transport modeling	Predicting movement of contaminants in groundwater
Water budget analysis	Analyzing balance between water inputs and outputs

gives a resolution imaging of the subsurface to identify groundwater resources as well as possible zones of contamination (Talukdar et al., 2024).

- **Modeling and Simulation**: Groundwater flow models have become sufficiently complex to simulate intricate problems, including extraction and recharge effects. These are mathematical simulations of the movement of water in porous media, enabling hydrogeologists to predict the elevation of the water table and furnish extractable rates that are sustainable. It also assists in the management of a water resource so that its utilization is never greater than sustainable limits, simulating recharge rates and groundwater dynamics.
- **Contaminant transport modeling**: This area has been crucial in the manner in which pollutants move in groundwater systems, hence the importance of advances in contaminant transport models. These models allow for the prediction of contamination spread by heavy metals or chemicals and are very important in the prevention of sources of drinking water from getting contaminated. Hydrogeologists use these models to come up with effective remediation measures and prevent further deterioration of groundwater quality (Smith et al., 2015).
- **Water budget analysis**: Water budget analysis is assessing the inputs, outputs, and storage of water within a given system. Hydrogeologists can track the amount of water entering the system through precipitation and recharge and the amount lost through evaporation, extraction, and discharge using this analysis. This helps in the proper management of water resources so that there is an equilibrium between supply and demand (Smith et al., 2015).

8.2 Emerging Technologies and Methods

A few emerging technologies are revolutionizing hydrogeology and water management:

- **Remote Sensing**: Satellite-based remote sensing offers large-scale monitoring of water resources. Hydrologists can assess the availability of water, track seasonal changes in water bodies, and detect signs of droughts or water scarcity using tools like Landsat imagery and synthetic aperture radar (SAR). These techniques can detect zones of pollution and monitor wetland ecosystems (Richter et al., 2018).
- **Artificial Intelligence (AI) and Machine Learning (ML)**: AI and ML algorithms are increasingly applied in the analysis of large hydrogeological data sets. It helps identify patterns, makes predictions about groundwater behavior, and optimizes water resource management. AI-based models may also detect anomalies in the water quality or flow pattern, thus responding quickly to emerging issues.

8.3 Geohazard Identification, Monitoring, and Risk Management

Geohazards, such as earthquakes, volcanic eruptions, and landslides, are a significant threat to human life and infrastructure. Therefore, monitoring and identifying these hazards is crucial for mitigating their impact:

- **Seismic Monitoring**: Seismometer networks, which comprise a sequence of sensors that detect ground movement, are widely used for monitoring seismic activity. Scientists can predict the likelihood of future events by analyzing the frequency and magnitude of earthquakes and issue early warnings. Such systems reduce damage by giving communities an opportunity to take precautionary measures before an earthquake strikes (Orion, 2019).
- **Volcanic Monitoring**: Volcanic eruptions can be predicted by the observation of volcanic activity, which helps save people living in its vicinity. Remote sensing, thermal scanning, and ground observation through sensors quantify volcanic gases, ground deformation, and temperature variation, among other indicators, to predict an eruption and provide timely warnings (Gong, 2023).
- **Landslide Monitoring**: Landslides most often result from heavy rainfall, seismic activity, or volcanic activity. Monitoring techniques include Interferometric Synthetic Aperture Radar (InSAR) and LiDAR (Light Detection and Ranging) for ground motion measurement. These technologies pinpoint landslide-prone areas before the slide and give one an early warning to minimize human life and property threat.

8.4 Applications in Earthquake, Volcanic Hazard, and Landslide Hazard Mitigation

Various advanced techniques and models are enhancing predictions and mitigation of geohazards summarized in Table 11 are explained as:

Table 11 Geohazard monitoring techniques

Geohazard type	Monitoring technique
Earthquakes	Seismic monitoring networks
Volcanoes	Remote sensing and ground-based observations
Landslides	InSAR and LiDAR technologies

- **AI-powered Early Warning Systems**: Early Warning Systems: AI and machine learning models are increasingly being used in the prediction of earthquakes and volcanic eruptions. Such systems analyze data from seismic stations, geological surveys, and satellite imagery to allow for the possibility of providing advance warnings of potential hazards. Through time, location, and magnitude forecasting, AI models help authorities evacuate populations at risk beforehand (Millar, 2020).
- **Risk Assessment Models**: The risk assessment models estimate possible geohazard impact. The types of probable disasters are thus predicted by these models for earthquakes, volcanic eruptions, and landslides that predict probabilities of the resultant impacts on people, structures, and the environment too. This data is useful in planning mitigation strategies and readiness plans (Sousa et al., 2021).

8.5 Understanding Biogeochemical Cycles

Biogeochemical cycles are the flows of essential elements such as carbon, nitrogen, and phosphorus in the Earth's atmosphere, biosphere, oceans, and geosphere. They are very important in maintaining ecosystems. Knowledge of these cycles is very crucial for managing ecosystems and solving environmental problems:

- **Carbon Cycle Monitoring**: Carbon is the central element in most climate change studies. Monitoring carbon fluxes or carbon moving through many environmental compartments can help understand better how ecosystems function and contribute towards or mitigate climate change (Albano & Sole, 2018). The monitoring will help deduce the amount of carbon being absorbed into or released by forests, oceans, and soil.
- **Nutrient Management**: Management of proper nutrient levels, especially nitrogen and phosphorus, is very crucial in reducing nutrient pollution as well as sustaining a healthy ecosystem. Excessive nutrient levels are usually from agricultural runoffs that cause harmful algal blooms, whereby an increase in nutrients results in more nutrient-enriched water bodies with oxygen depletion and loss of biodiversity (Singh et al., 2022).

Table 12 Key biogeochemical cycles

Element	Cycle description
Carbon	Movement of carbon through the atmosphere, biosphere, oceans, and geosphere
Nitrogen	Conversion of nitrogen between its various chemical forms in the environment
Phosphorus	Movement of phosphorus through the lithosphere, hydrosphere, and biosphere

Table 12 provides an overview of the key biogeochemical cycles. It highlights their role in maintaining Earth's ecological balance and supporting life processes

Emerging research areas include:

- **Microbial Biogeochemistry**: It is an important area of research, as microbes control all of the biogeochemical cycles of carbon, nitrogen, and other key elements. They are also in control of nutrient transformations, thus affecting organic matter decomposition; such processes directly impact the overall functioning and health of the ecosystem.
- **Advanced Sensors**: Researchers are developing sensors for real-time monitoring of biogeochemical processes. These sensors can track changes in nutrient cycles, carbon fluxes, and other critical parameters, helping scientists better understand ecosystem dynamics and the effects of human activity on biogeochemical cycles.

9 Conclusion and Future Directions

Remote sensing and satellite technology would continue to be leaders at the cutting edge of achievements in Earth Sciences by generating invaluable data and instruments, thereby contributing to an unprecedented understanding and management of the planet. The promising prospects of continued technological improvements imply enhanced accuracy, availability, and relevance of satellite-based observations toward solving a complex set of environmental and natural disaster management challenges. This will, however be achieved by persistent investment as well as further international cooperation along with adequate research on the effective data management policies. With the advancement of the satellite technology, integration of new technologies like AI and IoT will open more avenues that can be explored for further applications of this technology driving the advancement of Earth Science capabilities in the twenty-first century.

This chapter highlights the significant contributions of Earth Sciences to understanding and managing our planet's resources and hazards. Key areas include AI and ML applications, hydrogeology, geohazards, biogeochemical cycles, and future directions. The future of Earth Sciences lies in interdisciplinary collaboration, technological innovation, and sustainable practices. To address challenges and seize new opportunities, researchers in the Earth Sciences can contribute to a more resilient and sustainable world.

The Future Directions in Earth Sciences highlights the growing role of interdisciplinary and integrating advanced technologies for dealing with global issues related to climate change, resource management, and environmental sustainability. A few of the future directions have been given below:

- **Interdisciplinary Approaches and Collaborations**: Future research in Earth Sciences is will be more and more dependent on interdisciplinary approaches that involve knowledge of other disciplines as well to meet with the increasing complexity of the environmental challenge (Singh et al., 2022)
- **Technological Innovations and Their Impact**: Technological innovations such as AI, remote sensing, and big data analytics will continue to transform Earth Sciences, enabling more accurate predictions and better resource management (Singh et al., 2022)

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Integrating Deep Learning and IoT for Enhanced Monitoring and Sustainable Mining Practices

Md. Naimur Rahman and Kevin Lo

Abstract

Mining activities are associated with negative environmental, social, and economic impacts and require enhanced monitoring and detection systems. This chapter systematically reviews the Deep Learning (DL) approach in detecting and monitoring mining activities. It explores the development of DL techniques for analyzing remotely sensed data and enabling real-time observation of mining activities, incorporating Internet of Things (IoT) devices. The review also highlights key DL models like Convolutional neural networks (CNNs) and Recurrent neural networks (RNNs), which have been used in satellite imagery, UAV, and sensor networks. Additionally, the chapter examines case studies on illegal mining, focusing on their socio-environmental impacts and the effectiveness of DL in addressing these issues. Challenges related to data availability, computational requirements, and model size are explained, and potential future developments aimed at developing synergies with the help of other sophisticated technologies, including AI, IoT, and blockchain for improving mining supervision and resource utilization are explored. The current review focuses on offering guidance to researchers and policymakers on the opportunities and challenges in improving sustainable mining using DL and IoT.

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Keywords

Deep learning · Internet of things · Mining · Monitoring · Detection

1 Introduction

Mining plays a crucial role globally by providing the essential raw materials required for various industrial processes (Jones, 2023). However, traditional mining practices negatively impact the environment, economy, and social well-being of communities (Boldy et al., 2021; Shiquan et al., 2022). Growing global concern about sustainability and the environmental impact of mining activities has intensified (Shiquan et al., 2022). This has led to a growing demand for technologies capable of mitigating these effects. DL and IoT are transformative technologies with the potential to revolutionize the mining industries to boost efficiency while enhancing safety and reducing adverse effects on the environment (Khalil et al., 2021; Li et al., 2021).

In Deep Learning, the term 'deep' refers to the presence of numerous layers in the network architecture, rather than the model's ability to fully comprehend content (Chollet, 2021; Li et al., 2021). The classification of a network architecture as 'deep' is not universally defined, but it is generally considered to have at least two hidden layers, resulting in a total of four or more layers (Kavlakoglu, 2020). Deep Learning has garnered significant attention in recent years due to its outstanding performance on numerous problems, especially in computer vision enabled by large public data sets and the continuous enhancement of computational power. DL gained significant prominence in 2012 when the CNN called the AlexNet (Krizhevsky et al., 2012), of 'SuperVision' research group stood out from the competitors in ILSVRC (Russakovsky et al., 2015). Since then, Deep Learning has been applied to diverse research domains and

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tasks, expanding its objectives beyond object identification to include classification and other functions across various areas. However, DL implementations in other domains are characterized by a limited number of changes in architecture complexity; usually, modifications are performed in data sets and network training techniques.

IoT comprises interconnected devices that gather, process, and exchange data in real time, often facilitating monitoring and control operations (Verma et al., 2017). Devices like sensors, drones, and cameras are deployed across mining sites to gather data on equipment efficiency, environmental conditions, and worker safety (Zhang et al., 2023a). These IoT systems have become excellent tools for enabling mining activities (Kapoor, 2019). CNNs and RNNs have been successful in accomplishing certain tasks like pattern recognition, detection of objects, and anomaly identification for mining applications at different stages making them ideal for applications in mining (Sarker, 2021; Sengupta et al., 2020).

IoT and DL are extensively used for big data applications with geospatial observations to find mining deposits (Ghosh, 2023; Okada, 2021). Traditionally, exploration is time-consuming and resource-intensive (Okada, 2021). Moreover, data collection efficiency is achieved using DL algorithms in conjunction with available IoT-enabled devices such as satellite-based remote sensors and drones. These strategies are used to identify mineral signatures and geological features (Michailidis et al., 2020; Obi Reddy et al., 2023; Sudhakar & Priya, 2023). Therefore, this integration reduces exploration time and cost while improving the accuracy of ore body modeling (Allioui & Mourdi, 2023; Pujar et al., 2022).

For the identification and exploration of mining activity IoT and DL can make significant contributions (Al-Garadi et al., 2020). In real-time, IoT devices that collect and transmit the health and performance data of equipment allow operators to see problems before they become catastrophic failures (Kwon et al., 2016; Ray et al., 2017). Using DL models, data can also be utilized to predict the malfunctions of the equipment and perform predictive maintenance, which will reduce downtime (Serradilla et al., 2022). With the heightened awareness of safety measures at work mining sites and maintaining environmental regulations, this real-time approach is crucial for monitoring environmental parameters such as air and water quality, ground stability, and seismic activity at mining sites (Atif et al., 2021; Fijani et al., 2019; Wang et al., 2021).

IoT and DL have also been usefully deployed in integrated applications to detect and monitor illegal mining activities that are serious threats to environmental sustainability and socio-economic stability in many regions (Asharf et al., 2020; Labbe, 2021; Yu et al., 2023). Illegal mining incidents can be identified by combining and analyzing data from IoT devices like sensors placed on the ground, and aerial vehicles like drones (Reddy & Venkatesh, 2023). Thus, it provides timely measures to mitigate unlawful measures (Mohsan et al., 2023). For instance, through DL patterns, illegal mining can be detected within a short period which alerts the authorities to take appropriate measures and curb these unlawful operations (Mena, 2003). Furthermore, IoT-based environmental sensors can monitor wider socio-environmental impacts of mining, including deforestation and riverbank erosion (Gligor et al., 2024; Langhorst & Pavelsky, 2023). Despite the importance of DL and IoT models, there are few comprehensive reviews on their applications in mining activities. Jung and Choi (2021) examined machine learning (ML) within a diverse mining context and handled only 63 papers involving DL. Fu and Aldrich (2020) focused on mineral extraction, transportation, and processing, offering a concise summary of the DL methods applied in these fields. However, no study has specifically addressed the entire mining value chain, covering aspects such as illegal mining site exploration, planning, safety, and reclamation. Hence, this review seeks to systematically evaluate the role of IoT and DL in mining activities by examining their applications, effectiveness, and potential for improving sustainability. The specific objectives of this review are as follows:

- To provide a comprehensive summary of applications of IoT and DL technologies for mining at all stages including exploration, extraction, and environmental monitoring
- To identify the current advantages and challenges in the application of IoT and DL in mining (special focus on sand mining) consequences.
- To provide recommendations and a way forward for sustainable mining using DL and IoT.

This chapter begins by analyzing the spatiotemporal trends in publications on DL and IoT applications in mining practices. It then identifies the techniques employed under the workflow of DL and IoT. Subsequently, the chapter examines the utilization of DL and IoT in different mining scenarios, including mine exploration, extraction, ore preparation, and illegal sand mining site observation and its solution. It further explores the advantages and challenges associated with these technologies. Finally, the chapter presents recommendations and a way forward for achieving sustainable mining through the integration of DL and IoT.

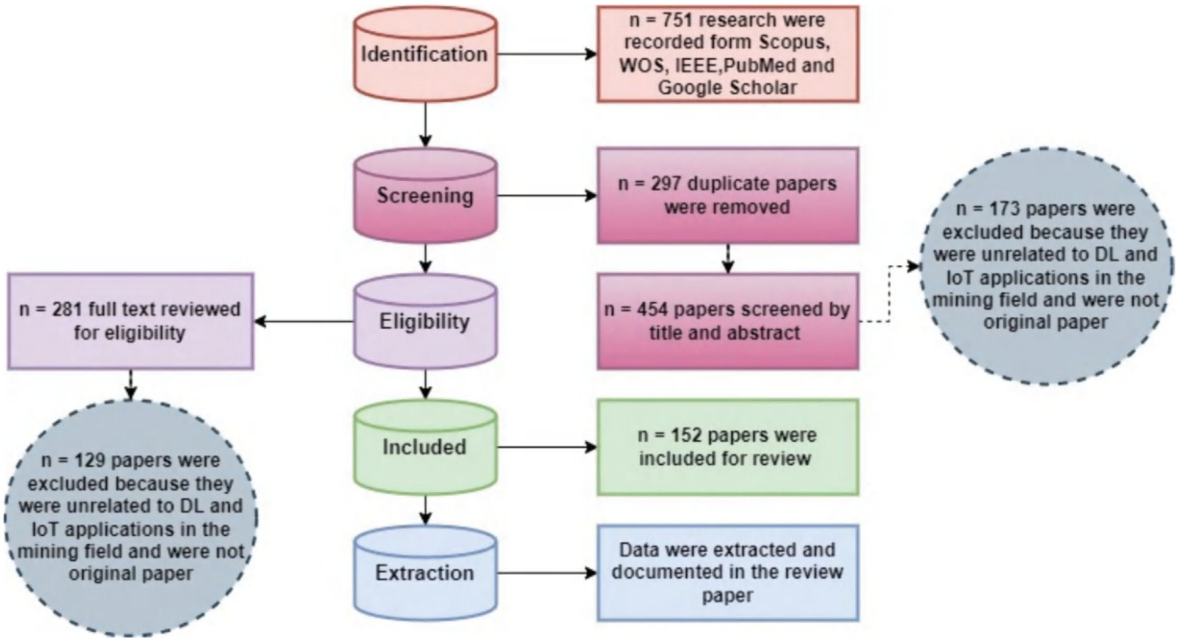

Fig. 1 PRISMA guideline for the data analysis of the review

2 Methods

This study was reported and designed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework (Shamseer et al., 2015). For adherence to the PRISMA guidelines, both the methodology and the findings were given in a clear and complete state (Fig. 1).

2.1 Search Strategy

We conducted a comprehensive review in line with PRISMA guidelines (Shamseer et al., 2015; Moher et al., 2014) which included DL and IoT-relevant studies contained in different journals published by Nature, IEE, Elsevier, Springer, Taylor & Francis, and John Wiley & Sons from 2012 up to October 2024. Key search terms included mining, sand mining, illegal mining, IoT applications, mining site detection, object detection, DL applications, IoT and DL process, and IoT and DL limitations. Additionally, references from the selected articles were reviewed to uncover further pertinent sources.

2.2 Inclusion and Exclusion Criteria

To ensure a comprehensive and accurate analysis, specific guidelines for selecting and excluding studies were established for this research. No limitations were applied regarding language, publication date, or study type. Originally published studies that were experimental or scientific investigations into the applications of DL and IoT on sand mining site detection, monitoring, and its real-time solution were selected as eligible studies. We included studies with valid statistical methods, robust models, reliable datasets, and accurate source data for the study region. Visualizations and quantitative metrics were presented for the investigation of the current state of DL and IoT applications on mining consequences.

Studies that did not conform with the stated criteria were excluded, including non-original research, duplicate publications, and journal preprints. Moreover, review papers or studies not directly on DL and IoT were not taken into account.

2.2.1 Type of Outcome

This review encompasses studies of the pertaining application of DL and IoT in the mining process and monitoring, current challenges and benefits of DL and IoT in the mining sector, recommendations towards the utilization of DL and IoT systems in mining monitoring, and illegal mining site and object detection in different areas around the world.

2.2.2 Study Selection

Extensive electronic databases were utilized to search for relevant articles, employing a variety of key terms to ensure comprehensive coverage. Initially, keyword-based searches were conducted using major databases such as Scopus and Web of Science (WOS). Moreover, PubMed and Google Scholar were associated due to their comprehensive coverage of the relevant literature. The retrieved studies were exported in CSV format and uploaded into Mendeley v1.19.8 to eliminate duplicates. Further screening was then conducted manually. Each study was reviewed by examining its title, abstract, and full text to evaluate its relevance and alignment with the objectives of the review.

2.2.3 Screening

During the overall preceding qualifying phase, 751 article titles and abstracts were reviewed and compared based on the established criteria. When discrepancies or uncertainties arose, a full-text review was conducted to address these issues. To make sure that the data is as accurate as possible, journal preprints and government report preprints were omitted. From all these, the analysis was limited to peer-reviewed papers only. This careful and thorough approach ensured that the studies selected for the review adhered to the highest standards of scientific research.

2.3 Data Eligibility

The identification screening and eligibility process of data are outlined below and in Fig. 1 of this paper. Firstly, 751 articles were retrieved considering the predefined filters. Out of the papers, 454 underwent initial title and abstract screening after excluding 297 papers found to be duplicates. Next, 173 papers such as pre-prints, not relevant to the DL and IoT applications on mining were omitted since they did not strictly fit the inclusion criteria. After that, the full text was reviewed and searched for the matched criteria, and subsequently 129 papers were excluded. Finally, 152 papers were included for the data extraction and inclusion.

2.4 Data Extraction

A file for extracting data was developed based on the identified variables to facilitate the systematic identification of relevant research data in the selected papers. The records included the first author, year of publication, sampling technique, study aim and objectives, and methodologies used. The first author was responsible for filtering titles and abstracts, followed by a full-text review and corresponding data collection. To eliminate duplicates, a rigorous process was followed: during the title and abstract screening, articles with similar titles and abstracts were cross-checked against previously saved entries using Mendeley and Microsoft Excel.

3 Results and Discussion

3.1 Spatiotemporal Trends of DL and IoT Studies in the Mining Sector

This review assessed a total of 152 research globally with a focus on the applications of DL and IoT models in the mining sector. The spatiotemporal findings of our study revealed that China, India, and the USA are applying the highest potential in the stated field comprising 55, 20, and 14 research respectively (Fig. 2a). These findings also emphasize China has reached a top position and other countries are far away from it. Therefore, the research gaps consist of regions that are not in a reasonable position in DL, and IoT-based study includes Bangladesh, Pakistan, UAE, Switzerland, Finland, Sweden, Singapore, Greece, Croatia, etc. with one or no notable research paper (Fig. 2b). Hence the recent trend in this field of research is increasing very rapidly, especially in the past 5 years, indicating the emerging revolution of increased research (Fig. 2c).

3.2 Deployment of DL and IoT Techniques in Practice

3.2.1 DL Techniques in Practice

DL techniques have been widely investigated in several different fields including geochemical mapping (Zhang et al., 2022a), earth sciences (Camps-Valls et al., 2021; Davy et al., 2024), cybersecurity (Dushyant et al., 2022), medical science and health care (Kumar et al., 2022; Saba et al., 2019), robotics (Soori et al., 2023), geophysics (Yu & Ma, 2021), and bioscience (Sapoval et al., 2022). To the best of our knowledge, there are limited studies on the application of DL in the mining sector especially in the automatic identification of illegal mining explorations (Asare et al., 2024; He et al., 2024). Moreover, Ji & Luo (2021) employed DL and remote sensing approaches to explore land use patterns from the mining area. DL methodologies have been applied to various problems that require different types of outputs, each depending on a certain application (Azhari et al., 2023). In the application context, DL tasks are often categorized as estimating, classifying, detecting, and semantic segmenting, each of which addresses distinct problem-solving needs (Fig. 3).

Different kinds of outputs are desired for each task in DL applications that attempt to solve specific problems, and each task has to be designed with a different set of features

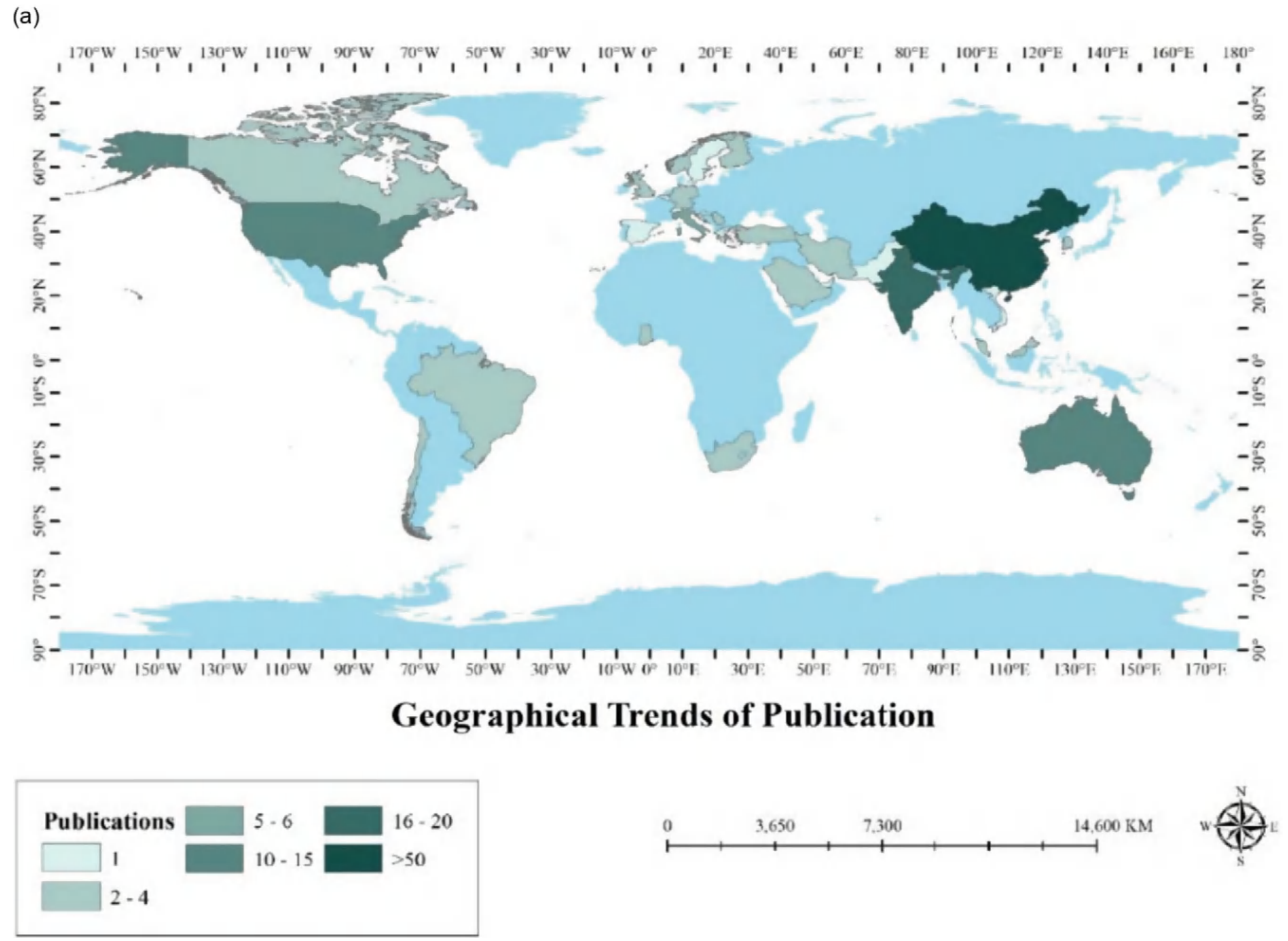

Fig. 2 **a** Regional trends of publication; **b** Publications based on different countries; **c** Publications based on different years

(Fig. 1). Estimation refers to forecasting continuous values as in regression operations, enabling the cost of an operation under particular conditions (Sun et al., 2021; Zhang et al., 2020). The classification includes grouped data into defined categories. For instance, DL can classify truck loading capacities into, empty, 25%, 50%, 75%, or fully loaded rather than estimating the precise weight (Sun et al., 2021)). The detection is about discovering objects in a dataset or environment such as oversized rocks in an image and their place/position (Loncomilla et al., 2022). Segmentation involves classifying each pixel or point in an image or point cloud into specific groups. For example, every pixel on a satellite image that's associated with a mine site can be separated from other areas (Wang et al., 2020).

3.2.2 IoT Techniques in Practice

IoT is an interconnected system of sensors, receivers, actuators, and internet-enabled devices that can be operated using a network with a common goal (Mouha, 2021). Radio-Frequency Identification (RFID) was the first IoT used to track objects (Srivastava, 2007). IoT systems rely on robust infrastructure, such as sensor technologies, communication, and data processing, to integrate networks at local, regional, national, and global levels, supporting a vast number of devices (Lea, 2018; Vermesan & Friess, 2013). An example of IoT use in the modern world is mobile phones and computer applications which receive data from connected sensors (Wortmann & Flüchter, 2015).

The generation of large amounts of data for IoT devices necessitates an advanced performance for real-time interactions and communications (Behnke & Austad, 2023). IoT systems are based in the cloud, which allows the connectivity necessary for fluid data transfer between devices and fast data processing and storage (Rani et al., 2023). Continuous monitoring of objects moving through cloud platforms allows IoT applications to provide highly accurate, real-time data insights and flexible resource allocation (Jeyaraj et al., 2023; Li et al., 2024; Raghavendar et al., 2023; Rani et al., 2023).

The mining industry, which has long evolved to meet the demands of changing times, is now undergoing a transformation, with IoT driving this shift (Pouresmaieli et al., 2023;

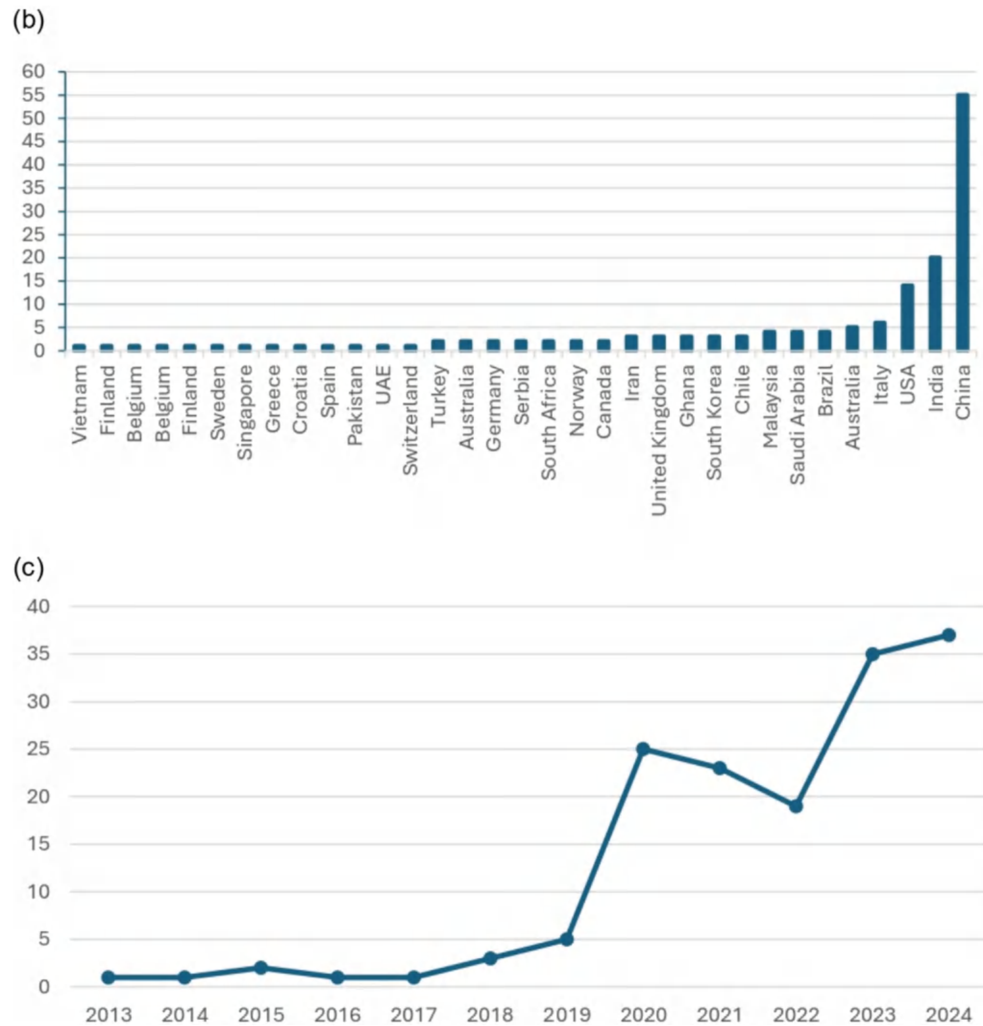

Fig. 2 (continued)

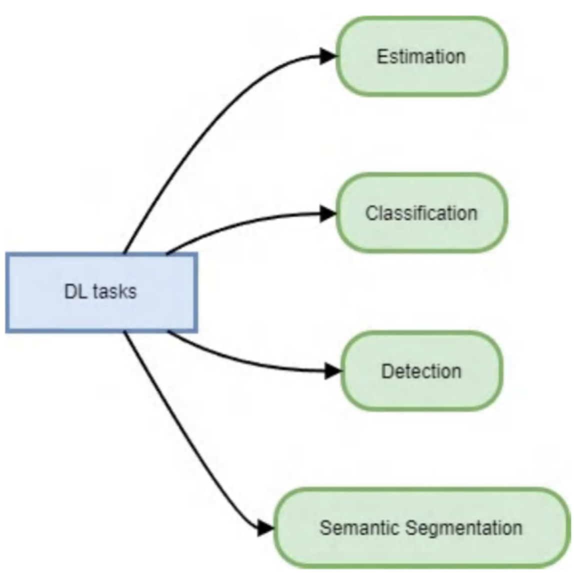

Fig. 3 Deep Learning task categories and their applications

Zhang et al., 2023b). Smart devices and connected systems have become essentially required given the dangerous nature of work in the mines and operational conditions (Onifade et al., 2023). In the mining area, the implementation of IoT offers great potential to improve operational efficiency through a reduction in equipment travel time (Cacciuttolo et al., 2023; Ikevuje et al., 2024; Onifade et al., 2023). As the industry gains momentum and embraces more advanced technologies, mining companies are turning to IoT to address operational challenges (Peter et al., 2023; Zhang et al., 2023b).

IoT applications are divided into two main categories. Firstly, industry-specific services are provided such as real-time healthcare monitoring devices (Chataut et al., 2023); construction and manufacturing (Ghosh et al., 2021; Singh et al., 2021); smart cities (Chataut et al., 2023); and smart Manufacturing (Abuhasel & Khan, 2020; Xu et al., 2020). Secondly, IoT products used across sectors include smart environments (Tan & Sidhu, 2022), smart energy systems

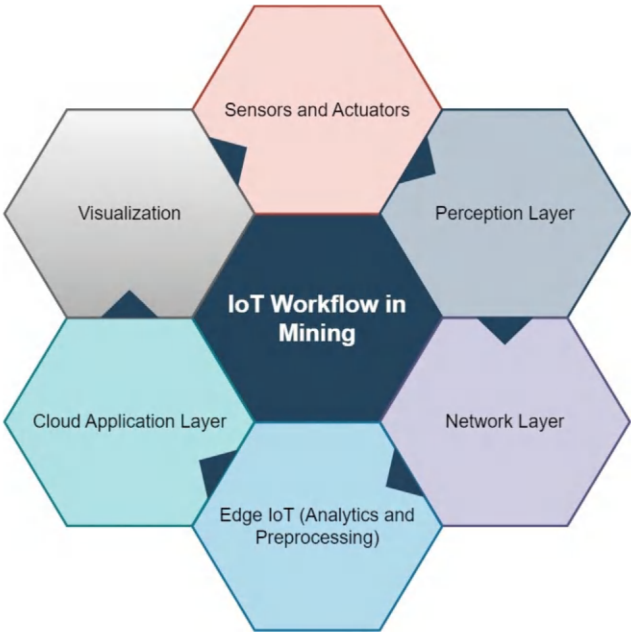

Fig. 4 IoT workflow in mining: data collection, transmission, and analysis

(Renugadevi et al., 2023; Rind et al., 2023; Vijayalakshmi et al., 2023), and risk management (Manoj et al., 2023; Nozari & Edalatpanah, 2023).

Regarding the application of IoT, Fig. 4 shows a visualization of the core components and IoT applications across different industries: mining, transport, energy, environment, etc. This figure illustrates the fundamental components of an IoT system, including sensors, actuators, communication networks, and data storage and analysis platforms, all working together to collect, process, and respond to data in real time. Real-time information collected from sensors and equipment is used by actuators to execute control responses in response to certain commands. After gathering this data, it is processed in the Perception Layer to make decisions around the detected physical parameters using the gathered information. The data then flows through the Network Layer, and then using an internet gateway it travels to the places where other processing will occur.

The Edge IoT Layer is particularly important when the data preprocessing and first analytics happen close to the data source to reduce latency and to be more operationally effective. It then submits the data to the Cloud Application Layer to be processed, using advanced analysis and storage with cloud platforms. The results are finally shown to the decision-maker's Visualization Layer, where the decision maker can read the data. The mining industry benefits from this comprehensive flow of IoT data from real-time collection to data analysis and visualization that supports better operational safety and production optimization (Ikevuje et al., 2024; Liang et al., 2023).

3.3 Application of DL and IoT

3.3.1 Application of DL in Mine Exploration

Table 1 summarizes the use of deep learning techniques in mine exploration, highlighting the methodologies applied and their specific applications. The Geochemical Data Mining model, a fusion of One Dimensional Convolutional Neural Networks (1DCNN) and Graph Convolutional Networks (GCN) is successful in identifying mineralization-related geochemical anomalies within geochemical data cubes (Zuo & Xu, 2024). A self-attention backpropagation neural network (SA-BPNN) utilizes quantitative data from hyperspectral remote sensing, geochemistry, and geophysics to predict ore prospecting targets for porphyry epithermal deposits (Liu et al., 2023). Furthermore, CNNs have been proven successful in a comparative analysis of graph deep learning algorithms for mineral mapping (Zuo & Xu, 2023).

Using Feedforward Neural Networks (FNNs) and one-dimensional CNNs in mine planning enables the estimation of copper ore grades to increase operational accuracy and operational feasibility (Olmos-de-Aguilera et al., 2023). Moreover, by applying Long Short-Term Memory Networks (LSTM) along with Bayesian optimization, and 3D micro seismic data used to predict water inrush incidents in mining (Zhang et al., 2023c). Recurrent Neural Networks (RNN) classify lithofacies patterns from well logs for geotechnical surveying (Santos et al., 2022). In mineral assessment, CNNs can differentiate ore from waste rock in borehole images (Jin et al., 2022), and segment minerals from resin in microscopic images (Filippo et al., 2021). Additionally, Fully Convolutional Networks (FCN) estimate capital costs of open pit mining concerning operation (Sun et al., 2021; Zhang et al., 2020), while CNNs classify the occurrence of ore in discretized areas of geological maps (Li et al., 2020). Deep learning can comprehensively increase the accuracy and efficiency of mineral exploration processes.

Although DL has improved exploration accuracy and efficiency, it is less used for identifying the environmental impacts of mining. The current models concentrate mostly on the operational and economic perspective rather than sustainability significance including reducing ecological footprints, identification of critical zones, and waste management. For more sustainable mining practices, future research may include environmental considerations, for example, land reclamation, automatic identification of vulnerable sites, water conservation, and ecosystem protection, into DL models.

Collaboration of technologists with environmentalists and policymakers is imperative in assuring sustainability. The mining challenges must be extended to ecosystem and community impact monitoring, helping to promote responsible practices in DL applications. Finally, the integration of local knowledge within DL models can increase transparency in mining operations.

Table 1 Application of DL in mine exploration

Category	Method	Specific application	References
Geochemical data mining	1D CNN and GCN	The hybrid deep learning model identified mineralization-related geochemical anomalies by extracting spectrum and spatial patterns from a geochemical data cube	(Zuo & Xu, 2024)
Mineral prospectivity	SA-BPNN	Forecasting potential locations for ore exploration in porphyry-epithermal systems involves leveraging quantitative insights derived from hyperspectral remote sensing, geochemical analyses, and geophysical measurements	(Liu et al., 2023)
Mineral prospectivity mapping	CNN	Comparative analysis of graph deep learning algorithms to showcase their effectiveness in capturing spatial patterns in mineral prospectivity mapping	(Zuo & Xu, 2023)
Mine planning	FNN and 1D CNN	Estimating copper ore grades using spatial information to enhance accuracy and improve mining operation feasibility	(Olmos-de-Aguilera et al., 2023)
Mineral prospectivity mapping	LSTM, Bayesian optimization	Predicting water inrush incidents in mining using 3-D micro seismic data, while denoising and identifying risks through clustering and consensus algorithms	(Zhang et al., 2023c)
Geotechnical surveying	RNN	Categorizing lithofacies patterns based on six properties derived from twenty well logs	(Santos et al., 2022)
Mineral assessment	CNN	Identifying and separating ore from waste rock through semantic segmentation of 900 borehole image segments	(Jin et al., 2022)
	CNN	Semantic segmentation of minerals from resin utilizing three datasets, each containing 556 microscopic image segments	(Filippo et al., 2021)
Cost estimation	FCN	Estimating open-pit mining capital costs considers annual production, stripping ratio, mill capacity, reserve grade, and mine lifespan	(Sun et al., 2021; Zhang et al., 2020)
Mineral prospectivity	CNN	Identifying ore presence within discrete image segments derived from geological mapping	(Li et al., 2020)

3.3.2 Application of DL in Mine Extraction

Table 2 presents a comprehensive description of DL application in the mine extraction process focusing on equipment management. The table section categorizes different techniques and illustrates how the relation between them is useful to efficiency and safety in the mining industry.

Various advanced DL architectures, including CNN, FCN, and DBN, have been utilized in multiple facets of equipment management, as outlined in Table 2. As one example, Wang et al. (2024a) examined the potential of image-based deep learning to detect faults in mechanical equipment, with a focus on the contribution of specialized image analysis to improved maintenance outcomes. As with offshore wind turbines, Xie et al. (2023) utilize the FFP-CNN model in fault diagnosis, showing the benefits of advanced CNN architectures

Table 2 Application of DL in equipment management for mine extraction

Category	Method	Specific application	References
Fault diagnosis for mechanical equipment	Image-based deep learning	Mechanical equipment fault diagnosis through special image deep learning methods	(Wang et al., 2024a)
Fault diagnosis	CNN	Employing the FFP-CNN model for fault diagnosis in offshore wind turbines (OWTs) improves both result accuracy and interpretability	(Xie et al., 2023)
Bearing fault diagnosis	CNN	Enhancing fault diagnosis accuracy with PGCNN on bearing datasets from case western reserve and Paderborn Universities	(Ruan et al., 2023)
Fault detection	CNN	Detecting and localizing symmetrical, unsymmetrical, and high-impedance faults in a distribution system	(Thomas et al., 2023)
Navigation line extraction in agricultural fields	FCN	The autonomous navigation of agricultural machinery in wheat fields utilizes advanced semantic segmentation to interpret the environment, identify field structures, and extract precise navigation paths	(Song et al., 2023)
Detection and classification	CNN	Estimating traffic density, real-time targets, and toll management in Intelligent Transportation Systems (ITSs)	(Berwo et al., 2023)
Vehicle detection and classification	DBN and YOLOv8	Detecting and classifying vehicles in aerial image sequences for smart traffic monitoring systems	(Al Mudawi et al., 2023)
Maintenance	CNN	Estimating machinery failures using four years of historical failure data	(Gomilanovic et al., 2022)
Unstructured VP identification	CNN	Detection of unstructured road vanishing points in self-driving vehicle applications	(Liu et al., 2021a)
Extraction	CNN	Identifying different rock-coal types in a collection of 6,000 images, which were enhanced from an original set of 300 images related to the shearer	(Si et al., 2020)
Extraction	CNN	Analyzing and categorizing the cutting patterns of a shearer drum using a dataset of 12,000 sound-derived images at 0.5 intervals	(Xu et al., 2018)

in increasing diagnostic accuracy while also increasing interpretability in complex systems. Ruan et al. (2023) also employ PGCNN for bearing fault diagnosis building off of datasets sourced from Case Western Reserve and Paderborn Universities, showing that tuned CNNs can significantly improve diagnostic accuracy in particular task classes. Moreover, Thomas et al. 2023) utilized CNNs to detect and localize different fault types including symmetrical and unsymmetrical faults in distribution systems.

Table 2 also shows applications that go beyond the ordinary fault diagnosis, like the work of Song et al. (2023) on the usage of FCN for auto extraction of navigation lines in agricultural fields, demonstrating the possibilities of DL for robotic navigation on agricultural fields. Berwo et al. (2023) focus on another field namely Intelligent Transportation Systems (ITS) that applies the DL approach for traffic density estimation and real-time target management. Mudawi et al. (2023) apply these applications to vehicle detection and classification using Deep Belief Network (DBN) classifiers as well as the YOLOv8 algorithm for analyzing aerial images used in traffic monitoring systems. The major findings of the stated studies indicate that deep learning approaches can significantly improve classification accuracy in very complex environments.

Maintenance applications involving CNNs utilize historical data to estimate machinery failures (Gomilanovic et al., 2022). Liu et al. (2021a) also explore the application of CNNs to unstructured road vanishing point (VP) detection in autonomous driving situations, showing the versatility of these approaches. Si et al. (2020) and Xu et al. (2018) focus on extracting processes utilizing CNNs to identify rock coal types and patterns of shearer drum cutting, respectively. These applications are an indication of DL's dramatic effect on the efficiency of the extractions, as well as an improvement in operational insight for mining activities.

Despite the promising applications, there are significant gaps in existing literature. Integrating real-time monitoring systems with DL techniques for predictive maintenance could enhance operational efficiency by proactively addressing potential infrastructure failures. Additionally, these models are generalizable to other mining environments, which have not yet been tested in other operational conditions.

To foster sustainability in the mining sector, the development of energy-efficient models of DL is necessary that minimizes resource consumption and thereby reduces a carbon footprint. Predictive maintenance systems can be implemented that optimize resource usage and extend the life of equipment used, therefore reducing the amount of new machinery demand. In addition, encouraging cooperation among miners, mining technology developers, and environmental NGOs, leads to guidelines that strike a balance between operational efficiency and environmental stewardship, and help to create a more sustainable future of mining.

Table 3 summarizes the application of DL in geotechnical management throughout the mine extraction processes using different methods and applications. Remote sensing (RS) is applied in sand mining, using a DL framework for object detection to map and quantify sand extraction in the Vietnamese Mekong Delta (Kumar et al., 2024). Another study utilized a dynamic mode of the Coulmann Graphical (CG) tool for stability analysis using side abutment loads and to assess the chain pillar stability in mining operations (Abdollahi et al., 2024). CNNs improved roof support safety in directional blasting and NPR anchor cable systems (Liu et al,. 2024a). In addition, Liu et al. (2024) have shown that the NGO-CNN-BiGRU-Attention model does well at predicting tunneling rockburst hazards, with 98% accuracy.

In predictive tasks, the stacking ensemble algorithm predicts the UCS of concrete from the borehole drilling data (Ling et al., 2024), whereas CNNs detected concrete damage during structural health monitoring (Arafin et al., 2024). Using data from Measurement-While-Drilling (MWD), Zhao et al. (2023) Predict key rock strength parameters through a deep neural network. Bayes-optimized CNNs (BOCNN) are used for hazard prediction of rock burst incidents in mining and hydropower projects (Li et al., 2023). In addition, CNN is applied to classify rock types, core sections, and dump images (Alzubaidi et al., 2022; Cai et al., 2022), while 3D-CNNs are used for the segmentation of fractures and joints from rock surface point clouds and photogrammetry data (Azhari et al., 2021; Battulwar et al., 2020). Moreover, CNN models are applied to image augmentation techniques to categorize rock types (Liu et al., 2020).

While recent progress has been made in using DL for geotechnical management, research has not placed sufficient emphasis on environmental sustainability. Future work should involve the consideration of eco-friendly practices, for instance, the identification and extraction of resources to minimize ecological impacts. In addition, collaboration with environmental scientists can help mining operations obtain better management and land reclamation. Expanding DL applications to track long-term environmental impacts will help promote responsible and sustainable mining practices.

3.3.3 Application of DL in Ore Preparation and Sand Mining

Table 4 showcases various applications of deep learning techniques in ore preparation and sand mining within mine extraction processes. For particle size and shape quantification, a combination of Generative Adversarial Network (GAN) and CNN synthesizes precision-focused imageries for segmenting and evaluating particle size and shape, surpassing traditional methods (Gong et al., 2024; Scala et al., 2024). In sandification degree classification, CNNs achieve a 91.4% accuracy in classifying sandy dolomite into four categories using a large dataset of images (Wang et al., 2024b). Seabed characterization benefits from a deep supervised semantic segmentation model (D4SC), mapping the seabed using sonar data for acoustic backscatter recognition (Arhant et al., 2024). Mask R-CNN detects sand particles and calculates size parameters through edge detection (Li et al., 2024b).

In ore characterization, R-CNNs achieve high precision in identifying quartz particles in iron ore images, while multilayer perceptron (MLP) networks enhance ore segmentation accuracy by reducing edge blurring (Ferreira et al., 2024; Sun et al., 2024). Further feature extraction is enhanced by R-CNNs for ore identification (Fu & Wang, 2024). In addition, CNNs monitor iron ore pellet sizes with lower computational cost than conventional models (Deo et al., 2024). Therefore, in real time, YOLACT automates granulometric measurements (Santos et al., 2024). Other applications include sand boil detection and segmentation in levee images (Santos et al., 2024), geogrid restraint quantification (Marx et al., 2023), and porosity estimation from grain size distribution via LSTM and

Table 3 Application of DL on geotechnical management in mine extraction processes

Category	Method	Specific application	References
Sand mining (SM) activities and budget estimation	DL framework for object detection	Mapping and quantifying sand extraction activities using RS and DL sources	(Kumar et al., 2024)
Stability analysis	CG	Coulmann Chain Pillar Stability Analysis (CCPSA) software for calculating side abutment loads and evaluating the stability of chain pillars in mining operations	(Abdollahi et al., 2024)
Roof support and pressure relief	CNN	The N00 mining method uses pressure relief through directional blasting (PRDB) and NPR anchor cable for roof support to enhance safety and reduce accidents	(Liu et al., 2024a)
Rockburst hazard prediction	NGO-CNN-BiGRU-attention model	Predicting the intensity level of rock bursts with an accuracy of 0.98, validated with real data from the Daxiangling Tunnel	(Liu et al., 2024)
Unconfined compressive strength (UCS) prediction	Stacking ensemble algorithm	Estimating UCS of surrounding rock at tunnel faces using borehole measurement-while-drilling (MWD) data	(Ling et al., 2024)
Damage condition assessment	CNN	Identifying concrete cracks and spalling in images for structural health monitoring (SHM)	(Arafin et al., 2024)
Rock strength prediction	Deep neural network (DNN)	Predicting rock strength parameters (Poisson's ratio, elastic modulus, and uniaxial compressive strength) based on Measurement While Drilling (MWD) data	(Zhao et al., 2023)
Rockburst prediction	BOCNN	Forecasting rockburst risks in mining, transportation, and water resource projects, with validation using data from the Jiangbian Hydropower Station	(Li et al., 2023)
Mass rock classification	CNN	Categorizing a drill core section as either intact or fractured using 74 images	(Alzubaidi et al,. 2022)
Dump material	CNN	Identifying and performing semantic segmentation of rocks within an image of dump material	(Cai et al., 2022)
Discontinuities	3D-CNN	Identifying and segmenting fractures and joints on rock surfaces	(Azhari et al., 2021; Battulwar et al., 2020)
Stability	CNN	They identify and categorize rock types from 1,034 images (expanded to 78,143 images through augmentation)	(Liu et al., 2020)

DEM (Anh et al., 2023). Various CNN models significantly contribute to sorting coal ash, mill materials, rock types, estimating ore production, and crusher utilization (Baek & Choi, 2020; Mustafa et al., 2020; Pan et al., 2022; Zhang et al., 2022).

However, consideration of environmental sustainability in DL applications to ore preparation and sand mining is infrequently envisioned. Future work should aim to combine DL models with sustainable activities such as minimizing resource utilizations, minimizing waste generation, and improving energy effectiveness in mine processes. In addition, DL models should be extended for monitoring environmental impacts like water usage and land degradation. To promote green mining technologies and make sure that DL

Table 4 Application of DL in ore preparation and sand mining within mine extraction processes

Category	Method	Specific application	References
Particle size and shape quantification	Combination of generative adversarial network (GAN) and CNN	Synthesizing high-resolution sand images and segmenting particles for size and shape evaluation, improving upon traditional methods	(Gong et al., 2024; Scala et al., 2024)
Sandification degree classification	CNN	Classifying sandy dolomite into four sandification degrees using a dataset of 5,729 images, achieving an accuracy of 91.4%	(Wang et al., 2024b)
Seabed characterization	Deep supervised semantic segmentation model (D4SC) using CNN	Automatically mapping the seabed using sonar data for acoustic backscatter recognition in mine countermeasures (MCM) operations	(Arhant et al., 2024)
Sand particle detection and parameter calculation	Mask R-CNN	Detecting sand particles in sample images and calculating their size parameters by using edge detection and segmentation techniques	(Li et al., 2024b)
Ore characterization	R-CNN	Identifying and segmenting quartz particles in iron ore optical microscopy images with a precision of 95.22% and an F1-Score of 91.72%	(Ferreira et al., 2024)
Ore image segmentation for beneficiation	Multilayer perceptron (MLP) with a feature pyramid network	Specific application: enhancing ore segmentation accuracy by mitigating edge blurring through efficient low-level feature extraction and a novel loss function, achieving 27 frames per second processing speed	(Sun et al., 2024)
Ore identification	R-CNN	Identifying lithological types in complex mining conditions by enhancing feature extraction and improving detection accuracy for efficient ore identification	(Fu & Wang, 2024)
Size monitoring of iron ore pellets	CNN	Detecting and measuring iron ore pellet size distribution under varying illumination with improved performance using fewer parameters and lower computational cost than conventional U-Net	(Deo et al., 2024)
Granulometric measurement of iron ore pellets	You only look at coefficients (YOLACT)	Detecting and segmenting pellets to automate granulometric measurement in real time during the pelletizing process	(Santos et al., 2024)
Lateral restraint quantification of geogrids	CNN	Segmenting particle outlines in transparent sand specimens to measure particle displacement and rotations under triaxial tests	(Marx et al., 2023)
Porosity estimation based on grain size distribution (GSD)	Long short-term memory (LSTM) combined with the discrete element method (DEM)	Predicting bed porosity using real-time images and GSD data, validated against experimental data	(Anh et al., 2023)

(continued)

Table 4 (continued)

Category	Method	Specific application	References
Sorting	CNN	Estimating coal ash content using 11,450 images generated from 4,595 original images through augmentation	(Zhang et al., 2022)
Milling	CNN	Classifying material types from images generated from 1,540 augmented sound and vibration signal datasets	(Pan et al., 2022)
Sorting	CNN	Semantic segmentation of five different rock types in images	(Yang et al., 2021)
Sorting	CNN	Semantic segmentation of an iron ore pile from 5,098 remote image patches derived from six images	(Mustafa et al., 2020)
Milling	CNN	Estimating ore production and crusher utilization using 9,072 data points collected over one month regarding truck haulage system operations and cycle times	(Baek & Choi, 2020)

applications do not only contribute to operational productivity but also to the ecological footprint reduction of mining, a collaboration between technologists and environmentalists is imperative.

3.3.4 Application of IoT in Sand Mining and Environmental Scenarios

In recent years, the integration of IoT technology in environmental monitoring and resource management has progressed significantly and facilitates the provision of real-time data that helps in making better decisions about mining, agriculture, and geotechnical engineering (Table 5). River basin management is one of the many applications of IoT and it has been the most useful application in areas that are prone to environmental degradation. For example, Liu et al. (2021)) employed IoT-based remote sensing and machine learning to monitor the ecological health of the lower Yellow River, to collect and provide highly accurate environmental data, and to support big data analysis for ecological management. They ensure the management of a river basin so that irreversible environmental damage would not happen as a result of human activities.

IoT-enabled soil moisture sensors and multi-sensor Synthetic Aperture Radar (SAR) have been used in the mining sector to augment environmental monitoring with high-resolution spatial estimates of ground moisture which are important for characterizing soil conditions across different weather patterns. Therefore, Antropov et al. (2024) highlighted the role of such technology in enhancing resource management, thereby being beneficial both to mining and agriculture since the models retrieve soil moisture robustly. Pelegri-Sebastia et al. (2024) describe how IoT-based environmental monitoring has been expanded also to beach management to improve tourist experiences and sustainable practices using real-time data on temperature and humidity. Moreover, IoT systems combined with fog computing and machine learning are used to predict soil moisture and nutrient levels in smart agriculture and mining, thereby allowing for optimal use of resources and their sustainability (Mohanty et al., 2024).

In addition, IoT has made mining damage control better; Zhu et al. (2022) improved the prediction accuracy of multi-core seam strip filling mining with the help of IoT, cloud computing, and data aggregation. This technology has been very effective in terms of minimizing ecological damage as well as surface subsidence. Likewise, IoT sensors have been used to monitor tailings dam stability, and real practice warning on dam integrity by critical parameters such as water level or deformation (Dong et al., 2017). In addition, the role of IoT in geotechnical engineering has also increased to provide real-time measurement of soil electrical resistivity aid in the design of civil engineering projects, and provide accurate data of soil condition (Kumar & Prasad, 2020). Most importantly, IoT-based systems like those of Ramya & kumari (2020) and Yan et al. (2019), have supported authorities in real-time alerts to combat illegal mining that can reduce false alarms and increase the detection of illegal sand mining, allowing for better environmental protection.

Despite all the advancements in IoT applications, there remain some gaps that need to be filled in the literature. Firstly, although research has centered on IoT systems on their technological prospective capabilities, few are concerned with

Table 5 Application of IoT in sand mining and environmental scenarios

Category	Specific application	Output	References
Mining environmental monitoring	Continuous ground moisture monitoring using in-situ soil moisture sensors and multi-sensor synthetic aperture radar (SAR) images	High-resolution spatial estimates of ground moisture, enhancing soil moisture retrieval models for various sediment types under different weather conditions	(Antropov et al., 2024)
Monitoring environmental condition	Using IoT-based sensors to monitor environmental conditions (e.g., temperature, humidity) for smart management of beaches	Real-time environmental data is provided to tourists via a mobile app, improving beach management and user experience	(Pelegri-Sebastia et al., 2024)
Smart agriculture and mining	Fog-assisted IoT system for predicting soil moisture and nutrient levels (NPK) using machine learning	Improved soil quality, irrigation efficiency, and slope stability, aiding both agriculture and mining sectors in resource management and structural safety	(Mohanty et al., 2024)
Mining damage control	Monitoring multicoal seam strip filling mining using IoT, cloud computing, and data aggregation to minimize ecological and settlement damage	Improved prediction accuracy (14.2% to 18.9%) and optimized mining processes by controlling surface subsidence and horizontal movement, enhancing sustainable mining operations	(Zhu et al., 2022)
Environmental monitoring in river basins	IoT-based remote sensing and machine learning for ecological data analysis in the lower Yellow River	Enhanced environmental data accuracy and a big data platform for ecological management and decision-making	(Liu et al., 2021)
IoT review in digitization	Implementing IoT for process optimization, machine health monitoring, worker safety, and asset management in the mining sector	Improved operational efficiency, enhanced safety, and better asset management, though challenges remain in communication and data infrastructure	(Rob & Sharifuzzaman, 2021)
IoT-based visualizations and predictions	Using IoT-based visualizations and data-driven predictions to digitally transform industrial processes in offshore production	Enhanced decision-making through noise reduction, material tethering, and triangulation, leading to more accurate process monitoring and management	(Østerlie & Monteiro, 2020)
Detection	Development of message service using IoT to detect illegal mining in land and rivers	Real-time alerts via SMS to local authorities, improving response to illegal sand mining activities	(Ramya & Kumari, 2020)
Mining platform development	A digital platform is developed to monitor and manage mining resources	Improved monitoring of water, soil, and sand mining impacts, with mitigation of environmental and social effects	(Salam, 2020)
Geotechnical engineering	IoT-based equipment for real-time measurement of soil electrical resistivity	Real-time soil resistivity data, aiding in the assessment of design parameters for civil engineering projects	(Kumar & Prasad, 2020)
Sand plug risk monitoring	Real-time monitoring of sand plug risks during petroleum fracturing, employing data mining and predictive algorithms	Improved early warning accuracy for sand plug risks, reducing false and delayed alarms through advanced data analysis	(Liang et al., 2019)
Monitoring illegal mining	Monitoring illegal sand mining activities using networked sensors and cloud-based data processing	Improved detection of illegal mining with reduced false alarms and enhanced environmental impact analysis	(Yan et al., 2019)

(continued)

Table 5 (continued)

Category	Specific application	Output	References
Mining system security	Applying IoT-based SCADA systems with a human machine interface (HMI) for real-time data acquisition, control, and system monitoring in mining operations	Improved system security by detecting and fixing HMI vulnerabilities, protecting mining operations from cyber threats	(Men et al., 2019)
Mining safety monitoring	Real-time monitoring and pre-alarm system for tailings dam stability using IoT sensors and a cloud platform	Real-time warning signals indicating the stability or danger status of the tailings dam, based on key parameters like phreatic line, water level, and deformation	(Dong et al., 2017)

long-term sustainability and environmental impacts. The literature rarely mentions the environmental costs of manufacturing maintaining and disposing of IoT sensors and related equipment. Further, studies are lacking in understanding how IoT systems can be effectively merged with existing policies to maintain compliance with environmental regulations in the mining and agriculture sectors. Additionally, data security and communications infrastructure pose serious challenges. According to Men et al. (2019), IoT devices are prone to cyberattacks, especially in remote places where the majority of mining and environmental monitoring is done. Moreover, data overload is an issue that is worth more attention from us, as IoT systems produce plentiful data that needs to be managed and interpreted efficiently to not oppress decisional processes in any way.

Several recommendations are crucial to ensuring the sustainable deployment of IoT in mining, agriculture, and environmental monitoring. To minimize the negative environmental impacts, first, the lifecycle assessment of IoT systems needs to be conducted to know exactly this environmental footprint from their production up to disposal. Secondly, monitoring responsible usage of IoT needs to be enabled through the integration of IoT systems into regulatory frameworks. Governments need to put policies in place that would enable sustainable use of IoT applications in social sectors like mining and agriculture. Thirdly, critical infrastructure should be secured through advanced encryption as well as real-time monitoring to guard such infrastructure from potential threats. In the end, solutions to the management and interpretation of the massive amount of data produced by IoT systems can be provided by utilizing big data analytics and ML models, so that the resulting data can be used in making decisions effectively.

3.4 Advantages and Challenges of DL and IoT

3.4.1 Advantages of DL and IoT

There are several reasons why deep learning models are so popular. One of the key strengths is their capability to automatically perform feature engineering (Mumuni & Mumuni, 2024). This distinguishes DL models from the usual ML models, which require manual feature extraction, and look to derive new features from raw data without specific instructions (Gatta et al., 2024; Radhakrishnan et al., 2024). Therefore, DL is especially well suited for use on large datasets that are unstructured (images, text, audio, etc.), and this capability also makes it excellent for efficient computational tasks. Moreover, DL models do best when the data being worked with is highly dimensional, for example, image recognition, and natural language processing (NLP), as well as autonomous systems (Olaoye & Potter, 2024). Besides, the scalability of DL models that make them uniformly able to handle different types of data and thus fit into multiple domains, the adaptation of DL models varies between different domains (Rang et al., 2024; Yu et al., 2024). In addition, the deep neural network has a layered structure that makes it possible to optimize parameters during the training to increase the prediction accuracy and apply them to various applications (Hanifi et al., 2024; Lei et al., 2024; Miikkulainen et al., 2024).

One of the benefits of IoT technology is the possibility of integration that can be achieved in industries such as mining, agriculture, and manufacturing (Gligoric et al., 2024; Logeswaran et al., 2024; Salam, 2024). The most significant benefit is that real-time data collection and monitoring make it an increasingly efficient and safe process of operation (Nižetić et al., 2020). The IoT systems are the interconnected sensors and devices that remain in constant monitoring of the equipment, working conditions, and worker activities (Häikiö et al., 2020; Misra et al., 2022; Mourtzis et al., 2021). This enables predictive maintenance in which the equipment's health is monitored in real time to reduce downtime and prevent unexpected breakdowns (Shamayleh et al., 2020). Real-time monitoring of assets not only improves resource utilization through reduction of dead time, it also prolongs the life of machinery thus saving costs and improving operational sustainability (Khan et al., 2022; Muhammed, 2024). For instance, accurate pixel-level classification of sand boils in levee images can be explored using transfer learning and achieving a balanced accuracy of 85.52% (Panta et al., 2023).

IoT is also critical to worker safety in high-risk industries like mining (He et al., 2023). Gas levels, temperature fluctuations, and structural stability can all be detected by sensors and alert operators to potential danger in hazardous environments (Esposito et al., 2022; Sunny et al., 2020). These applications including the automation system of IoT are creating harm-free environment and reducing the risk of accidents (Onesimu et al., 2021). Moreover, the ability of IoT to generate and process large volumes of data assists businesses in data-driven decision-making to optimize operation and improve productivity (Gupta & Quamara, 2020; Sestino et al., 2020). This is useful for industries in which resources and environmental conditions need to be managed very precisely.

3.4.2 Challenges of DL and IoT

Despite their benefits, DL models have some challenges. One important drawback is their dependency on large datasets in training (LeCun et al., 2015). Applying conventional methods to achieve better results has significant limitations as these models more often need access to massive amounts of data (Chen & Lin, 2014). The computational requirements for training also include high processing power, high-performance GPUs, and large storage (Jeon et al., 2021). Furthermore, deep learning models are sensitive to overfitting if the datasets are not rich and diverse enough (Algan & Ulusoy, 2021). Furthermore, DL models are known for a lack of transparency, also referred to as the 'black box' problem, in which the decisions and predictions made by models are not easily understood (Hussain, 2019). One of the difficulties with this opacity is that when errors are made it is hard to refine the models (Gao et al., 2022). Vulnerability to adversarial attacks is still a severe problem in real-world deployment (Irfan et al., 2021).

There are also many challenges associated with IoT implementation. A significant obstacle is the lack of infrastructure in remote areas, which is commonly encountered in sectors such as the mining industry (Aguirre-Jofré et al., 2021; Pouresmaieli et al., 2023). Without reliable communication networks and data transfer systems, IoT's real-time monitoring capability is not possible due to a lack of connectivity and system inefficiency (Nižetić et al., 2020; Shafique et al., 2020). Moreover, IoT generates huge amounts of data and the reality of its integrity and coherence warrants the use of powerful data storage and processing solutions (Makhdoom et al., 2018). Left unmanaged, data can easily take the industry down a rabbit hole, becoming a point of waste for analysis and decision-making (Molaei et al., 2020).

IoT systems can be attacked because they are interconnected, which is another concern in terms of cybersecurity (Saad et al., 2020). Such vulnerabilities can negatively affect operation efficiency and data integrity, resulting in safety issues and data breaches (Abiodun et al., 2021). Moreover, the cost of implementing, maintaining, and securitizing IoT can be prohibitive, especially for organizations operating in industries where technology adoption is traditionally slower (Jain & Chandrasekaran, 2020). As far as operation, the adoption of IoT may require training or upskilling of personnel, thereby increasing the complexity of the introduction of IoT into existing operations (Seet et al., 2021). However, the positive impact on safety, efficiency, and decision-making makes IoT a useful toolkit for any industry willing to risk extra expense to solve these issues.

3.5 Recommendations and Way Forward for Sustainable Mining Using DL and IoT

3.5.1 Integration and Implementation Strategies

- Integration of DL and IoT: The DL opportunities could aid in detecting legal and illegal mining explorations including transporting objects. For instance, illegal sand mining objects could be identified through DL and IoT technologies which also provide real-time solutions.
- Holistic Integration of DL and IoT: Creation of a complete framework that allows DL algorithms to be integrated into IoT, with the purpose of real-time monitoring and data analysis. An ideal blockchain integration in the mining business should cover all mining life cycles from exploration to extraction and environmental monitoring.
- Predictive Maintenance: Predictive maintenance using data stored from the analysis by IoT sensors could be done using DL models. It will aid in predicting when the equipment will fail, decreasing downtime increasing the life of the machinery, and, by extension, practicing sustainability.
- Real-Time Monitoring and Control: Provide IoT-enabled systems for continuous monitoring for example of bituminous mine activities. Environmental conditions within this may be characterized by air and water quality, ground

stability, and seismic activity. This data can make its way to DL models, which then can provide actionable insights and real-time alerts.

3.5.2 Sustainable Practices and Environmental Monitoring

- Environmental Impact Assessment: DL models are integrated to predict and monitor the environmental impacts of mining activities. Land reclamation, water conservation, and ecosystem protection are just a few of those areas. Data from environmental key indicators is gathered using IoT sensors and DL is used for data analysis and visualization.
- Illegal Mining Detection: Improving the ability to use drones and ground sensors that are IoT devices in detecting illegal mining activities. If the above-mentioned DL algorithms can recognize traces of illegal operations and alert the authorities.
- Resource Optimization: The use of DL and IoT to optimize resource extraction processes. This in turn includes improved accuracy of ore body modeling, waste minimization, and efficient use of mined resources.

3.5.3 Data Management and Computational Efficiency

- Big Data Analytics: To undergo numerous IoT device data processes, big data analytics platforms should be built with enhanced capacity. It is possible in this sector through proper analysis of the available data and processing of this data through advanced DL models.
- Energy-Efficient Algorithms: Concern for optimizing the utilization of computational resources towards the development of energy-efficient DL models. It will also help to limit the emission of carbon dioxide that results from data processing and model training.
- Edge Computing: Accelerate the use of a porting of edge computing to enable data preprocessing and preliminary data analysis at the source end. This minimizes delay, enhances functionality, and limits data transmission to central servers to a great extent.

3.5.4 Collaboration and Policy Development

- Stakeholder Collaboration: Promote dialogue between technologists, environmentalists, policymakers, and other local stakeholders. This will help in making sure that DL and IoT applications have better recommendations with sustainable development goals and the community.
- Regulatory Frameworks: Develop and implement policies that would support the sustainable use of DL and IoT in mining. This includes policies on data protection, waste disposal, mining frequency regulation, and standards of appropriate use of technology.
- Community Engagement: This means that locals should be engaged in systems that evaluate impacts or make decisions on them. With IoT and DL, it is possible to present relevant and easily understandable information on mining operations and the outcomes for the environment.

3.5.5 Training and Capacity Building

- Skill Development: Upskilling mining professionals are required to use DL and IoT technologies to exploit their full potential and therefore funding for training programs should be invested. This comprises data analysis technical training, sensor deployment, and predictive maintenance training.
- Research and Development (R&D): An R&D program initiative could be taken to identify and promote the use of DL and IoT applications of DL to the mining industry. Also facilitating collaborations with research organizations and academic institutions is needed towards fostering knowledge and advancing technology.

3.5.6 Case Studies and Best Practices

- Document Success Stories: The case studies of successful implementations of DL and IoT in sustainable mining are required to be compiled. It shares best practices and lessons learned so that future projects have some guidance.
- Benchmarking: The establishment of benchmarks and performance indicators is necessary to evaluate the effectiveness of DL and IoT applications to contribute toward sustainability goals.

4 Conclusion

The integration of DL and IoT technologies holds a transformative opportunity to improve monitoring and support sustainable practices for the mining industry. This review shows that these advanced technologies have the (potential to) change how mining is done across all levels, from exploration and extraction to environmental monitoring and resource optimization.

DL, specifically with models built around CNNs and RNNs has shown itself to excel in processing extremely large datasets, capable of accurate detection, classification, and segmentation tasks, the key to getting the most out of mining operations. DL, which is trained with large amounts of labeled data, is a good fit with IoT, allowing both technologies to form real-time data collection and monitoring. The combination of DL and IoT enables the process of real-time monitoring, predictive maintenance as well as decision-making processes and leads to improved operational efficiency and safety of the infrastructure. However, there are challenges in applying DL and IoT in mining. To fully exploit the potential of these technologies, issues related to data availability, computational requirements, and model scalability need to be resolved. Besides that, it is also of urgent necessity to embed environmental sustainability into DL models and IoT applications. Research in the future should be conducted to integrate eco-friendly ideas, maximize resource utilization, and minimize mining activity footprints on the environment.

To promote sustainable mining practices, several important recommendations reflecting the strategic integration of DL and IoT throughout the mining life cycle are outlaid. At first, comprehensive frameworks should be developed that amalgamate DL and IoT by utilizing predictive maintenance, decreasing equipment downtime, and fostering an IoT platform to continuously monitor the environment and conduct real-time data analytics. DL models for environmental impact assessments (like land reclamation, water conservation, and ecosystem protection) could be used to enhance sustainable practices and IoT devices and DL algorithms can also be used to improve the detection of illegal mining. Waste reduction requires optimization of resource extraction and ore body modeling. To process this massive amount of IoT-generated data, robust data management solutions are needed, including energy-efficient DL models and edge computing for low latency and better operations. Technologists, environmentalists, policymakers, and communities will need to collaborate to make sure DL and IoT can find their place in supporting sustainable development goals on one hand and with the help of regulatory frameworks and local engagement on another. The effectiveness of DL and IoT as a means to achieve sustainability in mining operations will be documented via case studies and benchmarks that will lead to a more balanced beneficiation between resource extraction and environment protection which needs to be addressed.

In conclusion, the strategic integration of DL and IoT presents significant potential to enhance the efficiency and sustainability of mining operations. By addressing current limitations and fostering collaborative, innovative processes, the mining industry can strike a balance between resource extraction and environmental stewardship, paving the way toward a more sustainable future.

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AI-Driven Insights into Fault Movements and Earthquake Dynamics

Shugufta Fatima, Sri Chandana Bangali, C. Kishor Kumar Reddy, and Anindya Nag

Abstract

Observations have revealed that Artificial Intelligence (AI) and Machine Learning (ML) algorithms have paved the way for many domains including, Earth Sciences. Interestingly, significant enhancements are seen in "AI and ML Empowered Insights into Fault Movements and Earthquake Dynamics." Further in this Chapter, we will examine how these technologies aid seismic activities, predict, forecast trending abilities and improve the results. Initially, the chapter explores current trends in Fault Movements and Earthquake dynamics. By approaching traditional methods, it is certain that huge amounts of big data cannot be processed, nor can they optimize results. To overcome the complexities of the traditional approach, AI and ML play a vital role in addressing large datasets and seismic networks. Not only do they analyse and predict, but they can also identify patterns and anomalies with exceptional accuracy. Furthermore, we discuss the difficulties which are related to the integration of AI and implementation of ML algorithms for seismic monitoring. With the aim of attaining quality datasets, integrating the model and validating the prediction. Building on that, we can direct proper research, develop the domain of seismic networks, and revolutionize better strategies to overcome disasters. In conclusion, we demonstrate the significant influence of AI and ML on the study of Fault Movements and Earthquake Dynamics. The chapter offers an overview of the prospects and findings in critical Earth Sciences and their effects on disaster management strategies.

Keywords

Predictive analysis · Artificial intelligence · Seismic activities · AI-driven insights · Seismic monitoring · Pattern recognition · Earthquake dynamics · Early warning systems · ML algorithms

1 Introduction

Comprehending the fault movements and earthquake dynamics is crucial for disaster preparedness, risk management control, and the development of effective early warning systems. Faults are basically small cracks in the Earth's crust where seismic energy can be discharged, which further leads to earthquakes. Monitoring these occurrences and mechanisms is essential to predict seismic events and analyse their latent ability to impact residents, infrastructure and ecosystems (Li et al., 2020). Traditional seismic analysis practices often rely on historical data and manual interpretation, which can be limited by the sheer volume of data generated by modern seismic networks (Khan et al., 2023).

In the last few years, advancements in technology have contributed to the emergence of Artificial Intelligence (AI) and Machine Learning (ML) as revolutionary tools in the field of Earth sciences (Rundle et al., 2022). These technologies are capable of handling huge amounts of data quickly and optimally, classifying complex patterns and trends that may not be distinguishable via conventional analytical methods (Wilson et al., 2018). By integrating AI and ML into seismic analysis, researchers can improve predictive capabilities, bringing about the improved perception of fault behaviour and more effective disaster management tactics (Jena et al., 2020).

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The code used in this chapter to predict the outcomes serves solely to demonstrate concepts and educational purposes. A review of case studies is provided and implemented to predict Fault Movements and Earthquake Dynamics. These studies depict the strengths and limitations concerning AI and ML technologies in Geographical Seismic Networks. Here, predictions are highlighted as they are monitored and improved using real-time datasets. These predictions are considered early warning systems.

Objectives of the Chapter: The primary objective of this chapter is to explore the applications of AI and ML in analysing fault movements and earthquake dynamics. Specifically, this chapter aims to: Scrutinize the current trends in geological activity and the adversities corresponding with traditional analysis methods (Rundle et al., 2022), feature case studies illustrating the effectiveness of AI and ML in predicting fault movements and seismic events. Review the integration of real-time monitoring systems by applying AI and ML for enhanced predictive analytics. Identifying some restrictions and challenges of implementing AI and ML techniques in seismic research and suggest future advice on upcoming initiatives. By meeting these objectives, this chapter aims to contribute to the apprehension of how AI and ML can revolutionize the field of earthquake research and refine disaster emergencies (Kühn et al., 2022).

1.1 Overview of AI and ML in Earth Sciences

AI and ML have been more widely adopted across various domains of Earth sciences, including climate modelling, remote sensing and geological analysis. In seismic research, these technologies facilitate the analysis of large datasets from seismic networks, enabling researchers to reveal patterns that could affect future earthquake activity. For instance, AI algorithms are capable of analysing and processing data from sensors that monitor and track ground shifts, helping to detect irregularities that may herald an earthquake (Wang et al., 2023). ML models can also be developed to discern patterns in historical earthquake records, refining the predictive models' capabilities for future seismic events. Additionally, with these technologies, it is possible for real-time data processing and analysis, which plays a vital role promptly in disaster response and risk mitigation (Khan et al., 2023). Incorporating the integration of AI and ML into Earth sciences signifies a paradigm transition, moving from reactive approaches to proactive strategies that can greatly aid us enhance our ability to comprehend and manage these seismic hazards.

2 Trends in Fault Movements and Earthquake Dynamics

The study of Fault movements and dynamics has evolved remarkably over the decades, changing from basic observational practices to sophisticated analytical techniques. Pioneering seismic investigations focused on visible effects such as building destruction, geological changes. However, the field has since expanded to explore the underlying mechanisms of seismic activity. Technical progress, including the invention of earthquake monitors and the emergence of machine learning, have transformed earthquake data analysis.

2.1 Historical Context of Seismic Studies

Seismic studies have seemingly evolved tremendously over the course of the past century, initially beginning with rudimentary observational techniques and gradually progressing to complex monitoring systems. Back in the ages, seismology primarily depended on the observation of tangible effects of earthquakes, such as structural damage and geological transformations (Wilson et al., 2018). Instruments like the seismometer emerged during the nineteenth century, which enabled the quantitative measurement of seismic waves. In the twentieth century, seismic research increasingly shifted its focus to comprehending the mechanics of fault movements and earthquake dynamics (Mousavi et al., 2019). Conventional methodologies involving manual data collection and analysis, researchers interpreted the seismic waveforms to determine earthquake sources and magnitudes. Nevertheless, these traditional approaches often struggled to efficiently handle large datasets produced by expanding seismic networks.

2.2 Limitations of Traditional Approaches

Despite notable progress, traditional approaches to seismic analysis methods continued to face various challenges, especially while dealing with the complexities of modern seismic data. One major drawback is their inability to process vast amounts of data promptly and efficiently (Petersen et al., 2024). Conventional methods often rely on manual data interpretation, which can be time-insensitive and susceptible to human error. Moreover, traditional seismic models often miss the intricate, nonlinear relationships among various geological and seismic factors. This limits the effectiveness of predicting power regarding earthquake behaviour and understanding fault dynamics. As seismic networks expand and data generation surges, the necessity of real-time data processing and interpretation adoption is even more required, highlighting the need for more enhanced analytical techniques.

2.3 The Role of Big Data in Seismology

In light of these challenges, big data has surfaced as a vital component of modern seismic research. The swift growth of seismic monitoring networks has led to an enormous influx of data, which demands innovative analytical strategies. Big data analytics empowers researchers to further process and handle intricate datasets, uncovering patterns and trends that traditional methods may fail to detect. In seismology, AI and ML technologies leverage in harnessing the potential of big data. By employing machine learning algorithms on vast datasets, researchers can detect the correlations between fault movements and seismic activity, enhancing the predictive models (Herrmann et al., 2013). For instance, as illustrated in the provided code in this chapter, AI techniques like Gradient Boosting and Support Vector Regression can effectively model and predict earthquake magnitudes based on geological features including latitude, longitude, and depth (Rundle et al., 2022). These advancements enable real-time monitoring and improve the ability to predict seismic events, ultimately benefiting disaster management and risk mitigation strategies.

3 AI and ML in Seismic Analysis

Artificial Intelligence (AI) and Machine Learning (ML) techniques have become essential in advanced seismic analysis, providing powerful tools for handling and evaluating huge datasets created by revolutionized seismic networks. Among the primary methodologies, Supervised Learning is the main approach, where models are trained on labelled data to make predictions based on input features and provided attributes. Leading methods used in Seismic Analysis include Gradient Boosting and Support Vector Regression (SVR). Gradient Boosting develops interactive ensemble models to improve prediction accuracy, while SVR identifies an optimal hyperplane to predict continuous outcomes, including earthquake magnitudes.

3.1 Overview of AI and ML Techniques

The role of AI and ML techniques has become very crucial in seismic analysis, providing effective tools in order to process and analyse huge datasets generated by contemporary seismic networks. The key approaches consist of the following Supervised Learning: This entails training models on labelled data to make prediction outcomes based on input features. The prominent algorithms in the seismic analysis included in this chapter are Gradient Boosting and Support Vector Regression. Gradient Boosting is an iterative ensemble that builds models to enhance prediction accuracy. Support Vector Regression (SVR) is a regression method that identifies an optimal hyperplane for fitting data, which allows the prediction of continuous outcomes, such as earthquake magnitudes (Takhtkeshha et al., 2022). Unsupervised Learning technique is applied in situations when labelled data is not available. It aids in uncovering patterns and groupings within the data without predefined outcomes. Clustering algorithms, such as K-means, are commonly used to detect groups of similar seismic events.

Deep Learning is a domain of ML that utilizes neural networks with multiple layers to model to capture complex relationships in data. Deep learning can be particularly beneficial for processing raw seismic waveforms and automating relevant features (Huang et al., 2021). These techniques help in improving to comprehend the ability of fault movements, enhance performance to predict seismic activity, and ultimately strengthen disaster preparedness. The workflow of AI and ML Analysis to predict a model is crucial to not miss out on steps to gain insights and comprehension of the particular dataset. The below picture depicts the working AI and ML model.

3.2 Data Acquisition and Processing

However, the success of AI and ML in seismic analysis mainly depends on the quality of data acquisition and processing. Raw seismic data needs to be cleaned and pre-processed to guarantee precise model training and predictions (Zhao et al., 2024). We need to load the seismic data, perform cleaning, and prepare it for analysis. The dataset needs to be imported using Google Drive by mounting it. The code has to import the Pandas library along with many other libraries respectively in Python to preprocess seismic data. It starts to load the data from a CSV file, merging 'date' and 'time' columns into one single column that is 'datetime'. The dataset is collected from Kaggle and executed using Google Colab Notebook. There are other ways to execute using Weka Software and Anaconda Jupyter. In order to execute and predict, we can observe in Fig. 1 the workflow of AI and ML Analysis to predict a model.

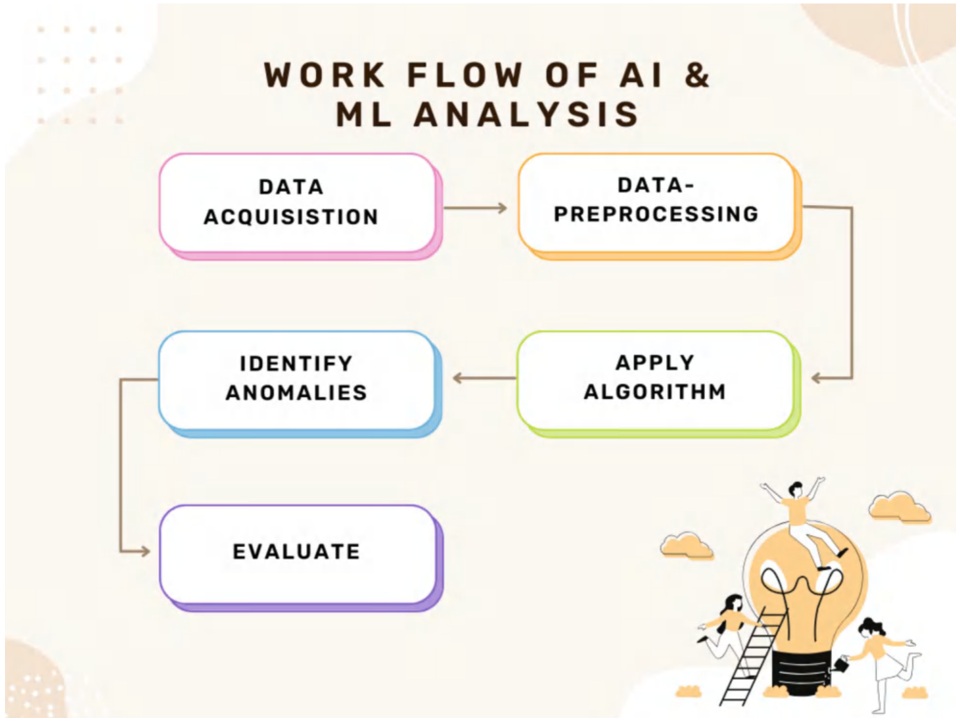

Fig. 1 Workflow of AI and ML analysis to predict a model

3.3 Identifying Patterns and Anomalies

Pattern recognition in seismic data analysis is essential as it helps in event detection. Other than that, it also enhances fault dynamics, uncovers recurring patterns and provides insights into fault behaviour over time. These patterns allow researchers to forecast future seismic activity and response strategies. Here, the main key three features ('latitude', 'longitude', and 'depth') and a target variable which is 'magnitude' from the dataset are considered. It will then display the initial rows for each of those variables. For Feature Selection and Target Variable, the following used for this dataset demonstrates how to select key features and set the target variable for recognizing the pattern. Pattern recognition is essential for researchers to identify trends, anomalies and correlations in seismic data analysis as that could signal future seismic activity. By exploring historical data, AI and ML algorithms can reveal patterns that inform forecasts of fault movements and earthquake behaviour.

For example, spotting anomalies in seismic signals can serve as early warning signs of potential earthquakes, allowing timely intervention and mitigation efforts. Recognizing these patterns is essential to establish robust predictive models. The code has to illustrate the process of selecting relevant features and defining the target variable for predicting and modelling earthquake magnitudes. This approach shows the reliability of predictions in seismic analysis.

3.4 Data Imputation and Scaling

The implementation data imputation and feature scaling are the main components in the preprocessing of a dataset. Data imputation is employed to handle missing values. Similarly, Feature Scaling standardizes the features to ensure that all the features contribute proportionately to the training model. Training on Gradient Boosting regressor on the dataset initially, we establish a preprocessing pipeline that first addresses missing values via the mean strategy, then StandardScaler to scale the features. This method ensures that our model training is resilient and not mitigated by missing data and discrepancies in feature scales.

3.5 Model Training Techniques

For AI and ML models, which hinge on implementation and evaluation to ensure their robustness in predicting seismic activity. Among the two commonly used techniques in seismic analysis, Gradient Boosting and Support Vector Regression (SVR) are mostly employed in this chapter. Gradient Boosting is a sophisticated ensemble learning technique that constructs models one after another in a sequential fashion, with each model attempting to correct the errors of the previous ones. This approach works well, particularly on regression tasks, such as predicting the size of the earthquakes. The imputed and scaled features are used where the model is trained, these features enable to discover the underlying patterns in the data

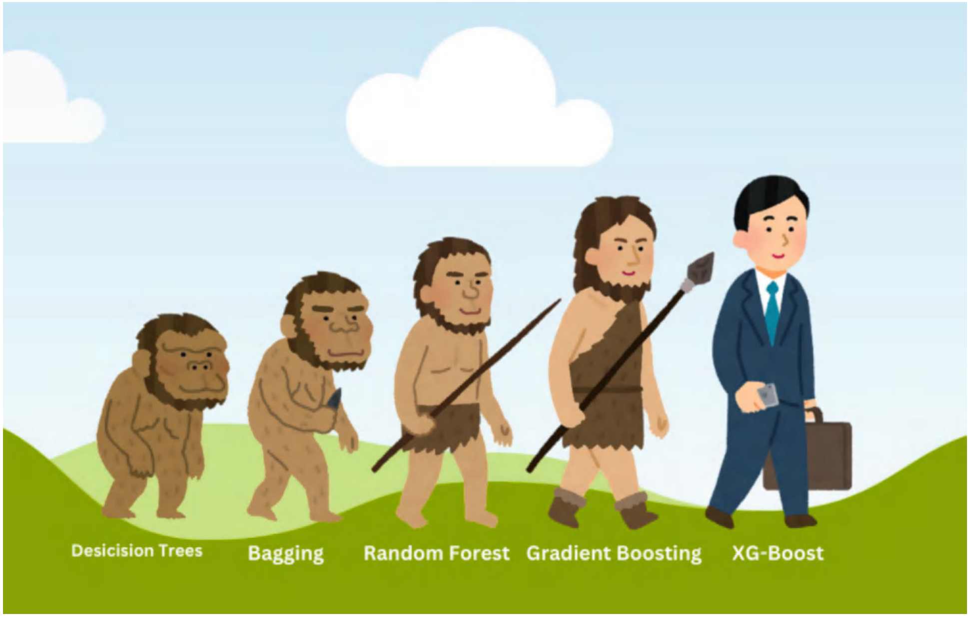

Fig. 2 The picture showcases the significance of Gradient Boosting compared to other algorithms

(Taha et al., 2020). Figure 2 picture showcases the significance of Gradient Boosting compared to other algorithms. To assess the model's performance, we can employ various metrics.

Some of them include Mean Squared Error (MSE) and Root Squared Error (RMSE), Mean Absolute Error (MAE), R^2 Score and Explained Variance Score. These metrics actually quantify the average squared differences among the values the ones that are predicted and actual. MSE reflects the average of absolute deviations, which provides a representation of the magnitude of errors. Whereas, R^2 Score speaks about the percentage of variance in the dependent variable that the model can explain. Lastly, the explained variance score evaluates the effectiveness model's ability to represent the data. These metrics provide insights into the model's accuracy and reliability. We can see that considering these metrics gives us a comprehensive picture of the model's ability and reliability.

The above-mentioned graphic Fig. 3 explains the relevance of Evaluation metrics to predict the model. After performing the Gradient Boosting model and evaluation metrics, the algorithm of the Gradient Boosting model is applied to the training dataset, makes predictions on the test dataset, and evaluates the model using standard metrics, thereby facilitating in order to assess its predictive capability. Support Vector Regression (SVR) implementation, which is another robust method for predicting earthquake magnitudes. SVR is operated by finding the best-optimal hyperplane that minimizes prediction error, which allows it to be suitable for complex, non-linear relationships in data.

Similar to Gradient Boosting, SVR is evaluated using MSE, RMSE, MAE, R^2 Score, and Explained Variance Score. These metrics help in understanding the model's performance in predicting earthquake magnitudes based on input features. So as to train the SVR model and to evaluate its performance. We apply, set up and train the SVR model, generate predictions on the test set, and evaluate its performance using the identical set of metrics as the

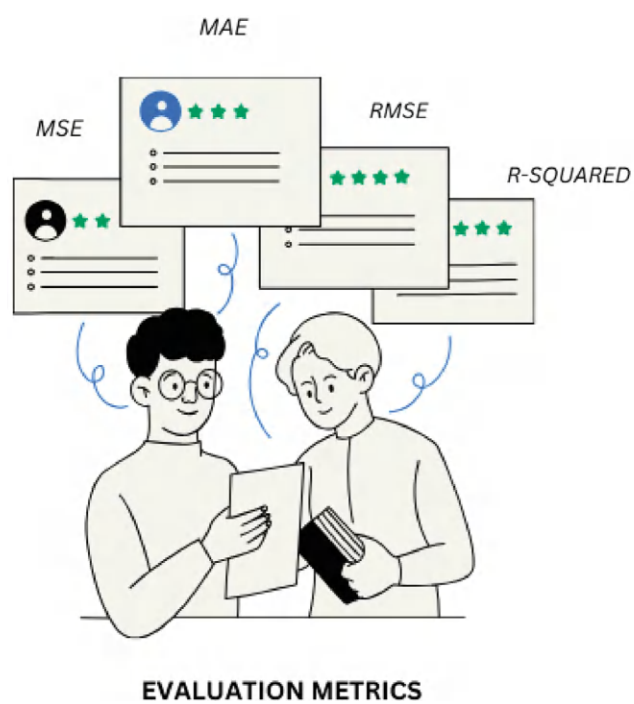

Fig. 3 The picture of evaluation metrics in order to predict the output

Gradient Boosting model, which allows for a direct comparison between the two approaches.

4 Case Studies on AI and ML Applications

The application of AI and ML in seismic analysis is demonstrated through two cases, showcasing their influence. Case Study 1: Predictive Analysis of Fault Movements highlights the use of Gradient Boosting for estimating earthquake magnitude based on features like latitude, longitude, and depth, attaining a Mean Square Error of 0.43 and an R^2 score of 0.31. The visualization representation using scatter and residual plots explains the model's reliability for identifying earthquake trends. Case Study 2: Early Warning Systems Development focuses on real-time observations, where AI employs Gradient Boosting and Support Vector Regression (SVR) process seismic datasets to send notifications promptly upon identifying anomalies to offer precise forecasts. These two cases showcase the ability of AI and ML to deliver accurate predictions and enable rapid responses to seismic trends and enhance seismic research and safety initiatives.

4.1 Case Study 1: Predictive Analysis of Fault Movements

Let us consider Case Study 1 as Predictive Analysis of Fault Movements in this chapter. In this case review study, we examine the application of AI and ML techniques in predicting fault movements and earthquake magnitudes (Greenfield et al., 2022). Using data from a regional seismic network, we implement the Gradient Boosting model to analyse and investigate the relationship between geographical features and seismic events (An et al., 2023). Coming to results and analysis, the Gradient Boosting model was trained on a dataset encompassing features such as latitude, longitude, and depth. The model's predictions were assessed against actual recorded magnitudes of earthquakes providing a comprehensive analysis. The model achieved a Mean Squared Error (MSE) of approximately 0.43, which produced reasonably accurate predictions overall. With an R^2 score of around 0.31, which indicates that the model captures a significant amount of the variance in earthquake magnitudes. These results were obtained by running the code on a Google Colab Notebook. As mentioned previously in this chapter, the visualization plots mentioned are for exclusive explanation and understanding purposes (Kühn et al., 2022). The following plot presents an actual earthquake magnitude with the predicted values generated by the Gradient Boosting model. Here, the scatter plot provides a visual assessment of the model's performance in predicting earthquake magnitudes.

In essence, the code gauges how well the Gradient Boosting model predicts alongside actual earthquake magnitudes. In terms of visual assessment, the closer the scattered points to the dashed red line the better the model. The residual compares actual earthquake magnitudes with the predicted values from the Gradient Boosting model. Supposedly the two plots assess the performance of a Gradient Boosting model in predicting earthquake magnitudes. The residuals plot reveals that the errors are randomly distributed around zero, implying that the model does not exhibit systematic tendencies over- or under-prediction, which reflects that it is a positive sign of model reliability (Figs. 4 and 5).

4.2 Case Study 2: Early Warning Systems Development

On the other hand, considering Case Study 2 which is Early Warning Systems Development, we emphasize the development of an early warning system using AI and ML technologies. The system is intended to monitor real-time seismic data and generate alerts based on predictive models. Information from multiple seismic sources is continuously gathered and processed in real time (Hoa et al., 2024). Machine learning models, including Gradient Boosting and SVR, are employed to analyse incoming data and predict potential seismic events. The early warning system was capable enough to issue alerts within seconds of detecting unusual seismic activity, greatly improving response times and safety initiatives in vulnerable regions.

4.3 Comparative Analysis of Case Studies

Comparative Analysis of Case Studies, both case studies showcase the efficacy of AI and ML techniques in seismic analysis. However, approaching the problem is from different viewpoints. In this chapter, Case Study 1 concentrated on predictive analysis utilizing historical data, allowing researchers to understand fault movements to gain deeper insights. While Case Study 2 emphasized real-time monitoring and early warning capabilities, showcasing how AI and ML support rapid disaster response. The key comparisons in the review are Case Study 1 drew upon historical data, while Case Study 2 relied on real-time data. The first case mainly depicts prediction accuracy, whereas the second highlights timely alerts and proactive measures.

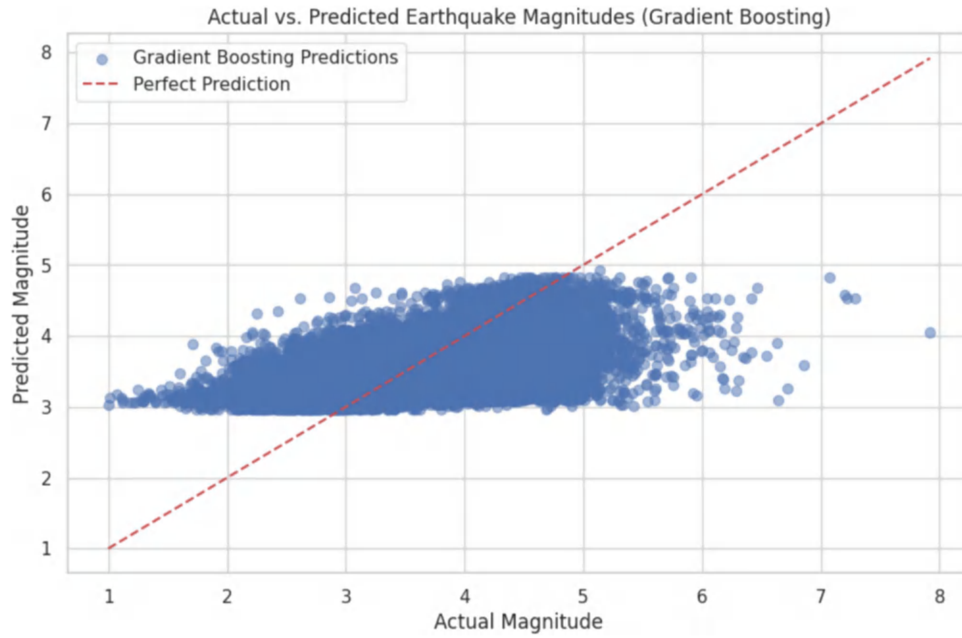

Fig. 4 Plot of visualization

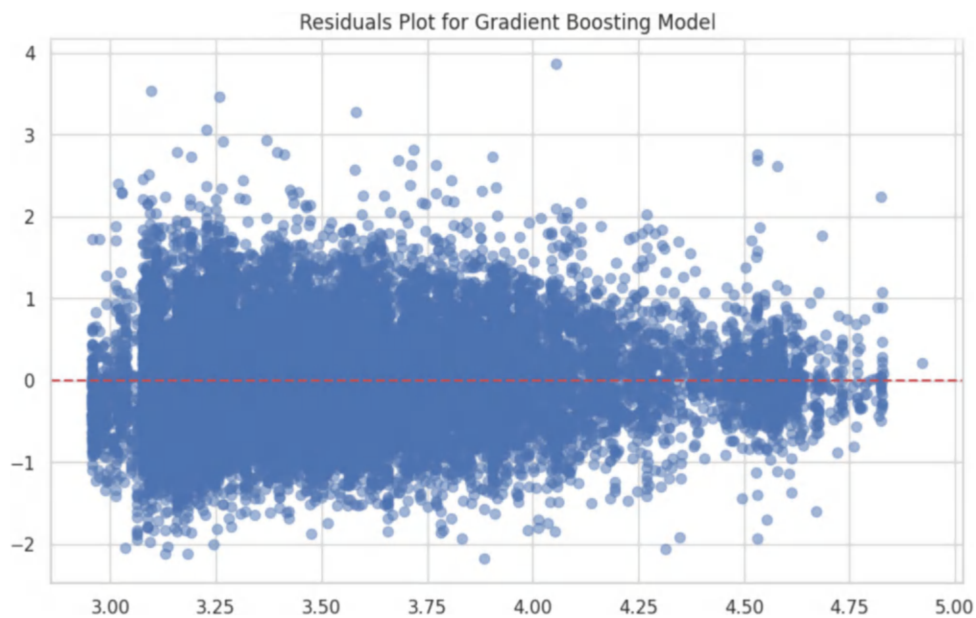

Fig. 5 Residual plot for the gradient boosting model

4.4 Strengths and Limitations of AI and ML Technologies

The strengths and limitations of AI and ML Technologies offer a wide range of advantages in seismic research. The capability to analyse huge amounts of datasets allows for more precise predictions of seismic events. In Real-time Analysis, AI systems can rapidly process incoming data, enabling timely alerts for early warning systems. Machine learning algorithms excel at detecting complex patterns that may be missed by conventional methods. The performance of AI and ML models relies heavily on the quality of the input data. Subpar or incomplete data can lead to inaccurate results. Interpretability of a variety of AI models, particularly deep learning networks, are often seen as "black boxes," complicating to understand how predictions are formulated (Dittmann, 2023). When Integration is Incorporating AI and ML into established seismic monitoring systems can be challenging, as it requires substantial changes in infrastructure and data processing methods.

5 Real-Time Monitoring and Predictions

A robust framework for live seismic data evaluation integrates ongoing surveillance, data processing, and predictive modelling using AI and ML methods. Real-time data from seismic sensors, GPS, and satellite visuals is refined, scaled and imputed to ensure optimal data for algorithms. These models examine historical and live data to identify trends and outliers of seismic activity. Automated systems generate prompt warnings to authorities and citizens, accompanied by accessible dashboards for visual insights. This framework facilitates timely alerts and disaster preparedness, enabling effective early warnings and crisis planning.

5.1 Framework for Real-Time Seismic Data Analysis

Developing a solid framework for real-time seismic data analysis involves several key components which combine data acquisition, processing, and predictive modelling using AI and ML technologies. The framework can be delineated in several ways. Continuous monitoring is conducted via a network of seismic sensors that collect real-time data on seismic activities, including ground motion, tremors, and other pertinent parameters (Jana et al., 2021). Integration of various data sources, like GPS data, satellite imagery, and geological surveys, serves to enhance the seismic dataset. Eliminating the noise and irrelevant data to provide high-quality input for the models. Handling missing values by using approaches such as mean substitution or advanced imputation methods. Scaling features to a uniform scale, allowing all parameters to contribute equal influence to the model's training.

Using AI and ML algorithms (e.g., Gradient Boosting, SVR) to scrutinize historical and real-time data. Developing training models on a significant number of datasets to uncover patterns that indicate potential seismic events. Ongoing analysis of incoming data through trained models aimed to predict seismic activity, automated systems designed for detecting anomalies and trends that signal earthquakes. Then alerting the mechanism, design of a notification system that activates alerts to issue relevant authorities and the public in response to predictive model outcomes. Incorporation of easy-to-use interfaces for visualization of seismic data and notifications. In simple words, notifications are nothing but seismic alerts. This framework promotes the timely analysis of seismic data, thereby improving the precision and responsiveness of predictions.

5.2 Implementation of Predictive Models

In general, predictive models can be successfully implemented in real-time monitoring scenarios to augment situational awareness and foster timely responses to seismic events. Essential steps for the implementation are required. Choosing suitable models based on the particular requirements of the monitoring scenario. Gradient Boosting and SVR are often preferred for their strong performance with sophisticated datasets (Taha et al., 2020). Models need to be trained using historical data to gain insight into the relationships between input features and seismic outcomes. To ensure reliability, Cross-validation techniques can be applied. Following training, models are deployed in a cloud or on-premise environment to be able to process and manage real-time data streams, which is deployment. By integrating with data acquisition systems, models can obtain live data for ongoing analysis. Ongoing monitoring of model performance under real-time conditions is fundamental. Key metrics like prediction accuracy and response time should be tracked consistently. Feedback loops can be carried out to retrain models periodically with new data, to maintain their precision and relevance. By effectively deploying predictive models, organizations can improve their ability to envision and counter seismic activities.

5.3 Enhancing Early Warning Systems with AI

AI technologies play a vital role in enhancing the competence of early warning systems for earthquakes. The artwork in Fig. 6 underscores the enhancement of early warning systems with AI.

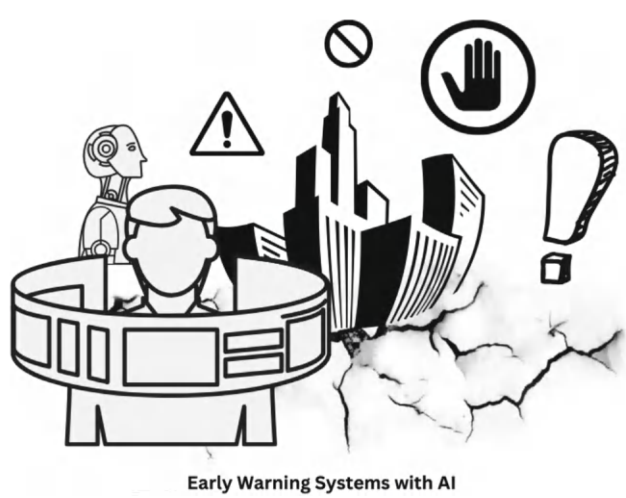

Fig. 6 Early warning systems with AI

Certainly, significant enhancements are that AI technologies can analyse extensive datasets to identify subtle patterns that may indicate impending seismic events (Llenos et al., 2024). This facilitates earlier detection and more dependable forecasts. Automated Alerts in AI can enable the automatic generation and dissemination of alerts derived from model predictions. This certainly minimizes response times and ensures that alerts quickly reach the impacted communities (Nezhadroshan et al., 2021). Adaptive Learning Machine learning models can tremendously learn from incoming data, adjusting to new patterns and progressively enhancing their predictive capabilities gradually. This is especially useful in turbulent surroundings where seismic activity can fluctuate. Incorporating AI can assist in designing user-friendly interfaces that present data comprehensibly, allowing emergency decision-making by the teams. Integration with Communication Systems in AI-enhanced early warning systems can connect with communication networks to verify alerts are sent via multiple channels (SMS, email, social media) to amplify reach. Lastly, by utilizing AI technologies, early warning systems can become more anticipatory, augmenting readiness and response to seismic events.

6 Challenges in AI and ML Integration for Seismic Monitoring

Incorporating AI and ML into seismic monitoring poses difficulties regarding data reliability, model development, data quality and network cooperation. Seismic data is frequently noisy, lacking, or inconsistently formatted demanding enhanced imputation methods and harmonization across data streams (Ni et al., 2023). Training models are challenged by insufficient reliable data, shifting seismic behaviours and the necessity of specific performance metrics to capture geological nuances. Moreover, the integration of AI demands strong system frameworks to manage vast amounts of datasets and live data streams. Surpassing these challenges requires cooperative action, continuous algorithm updating and cutting-edge computing resources to improve forecasting precision and strengthen seismic disaster handling.

6.1 Data Quality and Integration Issues

The potency of AI and ML models in seismic monitoring heavily depends on the quality and integration of the foundational data. Several challenges might emerge in this context. Seismic data can frequently be noisy or incomplete due to sensor failure or environmental disruption. High-quality, precise data is essential for developing robust predictive models. Various seismic networks may use differing formats, measurement units, and calibration benchmarks. Integrating data from multiple sources necessitates standardization to validate compatibility. Inadequate records may result in gaps in the dataset, impeding the analysis. Appropriate imputation methods must be used to address these missing values. The enormous volume of data generated by seismic sensors poses significant issues in terms of storage, computational capacity, and pace of analysis. Proficient data management and processing methods are required to handle massive datasets in real time. Tackling these data quality and integration issues is essential for constructing durable AI and ML systems in seismic monitoring and observation.

6.2 Model Training and Validation

Training and validating AI and ML frameworks leveraging seismic data brings forth numerous complications. Seismic data is commonly impacted by numerous elements, making it difficult to render the model. Earthquakes are naturally multifaceted, with various variables determining their occurrence and magnitude. As a result of a restricted amount of high-quality training data, models may be excessively tailored to certain datasets, causing poor generalization on new, unexamined data. Meticulous cross-validation and constraint techniques are mandated to alleviate this risk (Huang et al., 2021). Seismic trend patterns can transform over time, calling for continuous model adjustments. This entails a steady pipeline for retraining models incorporating recent data, which can be heavy on resources. Choosing appropriate evaluation metrics may pose challenges, as standard evaluation metrics might not completely reflect the performance of predictive models within seismic environments. Tailored metrics may have to be designed to embody the unique aspects of geological data. These challenges point out the requirement for thorough assessment and method in the model training and validation steps of model development.

6.3 Overcoming Barriers in Seismic Networks

To successfully integrate AI and ML into seismic observation, a range of techniques can be employed to surmount current barriers. Collaborative efforts within seismic system operators aid in developing uniform procedures for data collection, information retention, and sharing. This can promote seamless integration and interoperability across diverse platforms (Alemzadeh et al., 2020). Executing sophisticated imputation approaches can aid in addressing missing or incomplete data. Strategies, for example, multiple imputation or employing generative frameworks can augment data quality. Creating systems that integrate perpetual learning can help models adjust to emerging trends and patterns regarding seismic data (Naik et al., 2023). This could include establishing automated systems for model retraining and validating models. Enhancing hardware and software infrastructure to process substantial datasets and assist in live processing can boost the performance of AI and ML applications in seismic monitoring. Consulting with professionals from various disciplines such as Earth Sciences, data analytics, and software engineering can facilitate the formulation of more holistic models and remedies for seismic monitoring. By adopting these strategies, the incorporation of AI and ML technologies in seismic monitoring can be markedly elevated, yielding enhanced predictive capabilities as well as crisis management.

7 Future Directions and Research Opportunities

The evolution of seismic research lies in utilizing sophisticated AI and ML approaches, interdisciplinary collaboration coupled with novel emergency handling approaches. New advancements such as neural networks, transfer learning, deep learning and generative models provide opportunities to improve seismic studies via identifying detailed trends, producing artificial simulated datasets and boosting model performance for various areas. Interdisciplinary efforts between earth scientists, data analysts and crisis managers could improve Machine Learning frameworks, ensure responsible application and convert findings into practical crisis interventions. Such progress is set to redefine predictive reliability, deployment of resources and societal adaptability laying the foundation for better seismic monitoring and crisis management.

7.1 Advancements in AI and ML Techniques

The realm of AI and ML is rapidly evolving, offering new prospects that might notably advance seismic research. Cutting-edge deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are proving to be increasingly efficient for examining complex seismic data (Wang et al., 2022). These strategies can detect detailed patterns and temporal dependencies that standard established models could miss (Smith et al., 2021). Transfer Learning technique permits the models trained on a specific dataset to be modified for another, enabling the utilization of pre-existing models across various geographical areas or kinds of seismic information. Transfer-based learning can minimize the necessity for thorough retraining and increase model performance in areas with scarce information. As per Generative Models, approaches including Generative Adversarial Networks (GANs) are applicable for stimulating plausible seismic events, which can enrich training datasets. These frameworks can help in comprehending uncommon seismic events through the creation of synthetic data (Pierleoni et al., 2018). In Real-Time Data Processing, the combination of decentralized computing and real-time data analytics might increase the swiftness and productivity of geological monitoring systems, promoting prompt decision-making in the context of seismic events. Explainable AI (XAI) AI models increase in complexity, and the requirement for openness in their decision-making mechanisms grows. XAI techniques can help make earthquake forecasting models easier to understand, allowing researchers to grasp the factors impacting predictions. These innovations have the capacity to improve the precision and robustness of seismic assessments.

7.2 Interdisciplinary Collaboration

To fully harness the potential of AI and ML in seismic research, interdisciplinary collaboration is essential. Key areas for collaboration include perspectives from geologists and seismologists are essential for guiding model creation and grasping the geological context of Geological phenomena. Collaboration can aid in refining AI models to reflect real-life occurrences (Alemzadeh et al., 2020). Knowledge in data analytics, software engineering, and cloud services can promote the design of efficient algorithms as well as scalable systems for analysing large datasets. Collaborating with emergency disaster response professionals and legislative authorities can ensure that AI-generated insights are converted into actionable disaster management tactics. Collaborative endeavours can improve community readiness and adaptability. Tackling ethical issues as well as the social implications of AI in disaster management is imperative. Interdisciplinary teams can assist in guaranteeing that technologies are implemented ethically and fairly. By promoting interdisciplinary collaboration, scholars can design impactful strategies for seismic monitoring and crisis response.

7.3 Potential Impact on Disaster Management Strategies

Innovations in AI and ML possess the potential to transform disaster management tactics pertaining to seismic activities in multiple aspects. Enhancing Prediction Models, in simple terms refined predictive skills might contribute to more precise predictions of seismic events, permitting timely warning and leading to enhanced preparedness. AI can assist in resource allocation during crisis situations, enabling emergency services to allocate staff and assist more effectively guided by instantaneous data (Pierleoni et al., 2018). ML and AI-driven tools can improve clearer communication with the citizens, delivering transparent information and advice during seismic occurrences. This can bolster community resilience and emergency crisis efforts (Zhou et al., 2022).

AI technologies can assist in assessing the impact of seismic events, analysing damage patterns, and informing recovery strategies. This data-driven approach can improve future preparedness and mitigation efforts. AI can assist in different disaster management frameworks, encompassing early warning to disaster interventions, forming a cohesive framework that boosts overall efficiency. As AI and ML technologies continue to progress, their application in disaster response approaches can foster more adaptable communities and lead to better outcomes when confronted with seismic threats.

8 Conclusion

This chapter has investigated the game-changing role of Artificial Intelligence (AI) and Machine Learning (ML) in comprehending fault movements and earthquake dynamics. Some of the major findings are that the current trends in this chapter highlight the drawbacks of traditional seismic analysis methods and address the rising significance of big data in seismology. AI and ML technologies present considerable advantages in processing substantial datasets and uncovering correlations, resulting in improved forecasting of seismic activities. Speaking of the Applications in Seismic Analysis, Several AI and ML methods, like Gradient Boosting and Support Vector Regression (SVR), were reviewed. Case studies revealed the real-world applications of these methods in predictive analysis and the implementation of early warning frameworks. The chapter focused on critical challenges related to data quality, model training, and integration across seismic networks. Strategies for overcoming these obstacles were proposed, underscoring the need for reliable data management and cross-disciplinary cooperation. Forthcoming innovations in AI and ML, such as deep learning and generative models, were presented as potential revolutionizers in seismic installations. The importance of interdisciplinary collaboration was stressed to elevate research findings and confront the complexities of seismic activities.

The application of AI and ML into Earth sciences indicates a significant change which has the capability to enhance our insight into seismic activities and strengthen disaster management strategies. As these innovations continue to advance, they are likely to deliver profound comprehension of complicated geological processes, enabling timely and accurate predictions of seismic events. The consequences for future studies and practices are considerable. AI and ML can turn data into practical insights, empowering scientists and public authorities to take knowledgeable actions that improve community safety and adaptability. Nonetheless, it is important to take into account these progressions with careful consideration of moral ramifications and the societal repercussions of technology deployment. Ultimately, welcoming AI and ML in Earth sciences is not just merely an opportunity but a critical need to confront the pressing challenges caused by seismic hazards. Continued support for research initiatives, cross-disciplinary teams, and a determined commitment to ethical practices will be required to tap into the entire potential of these revolutionary technologies.

Appendix

Additional Case Studies

This part of the chapter provides supplementary case studies that showcase the utilization of AI and ML in seismic monitoring and earthquake prediction. These case studies are as follows. Case Study 3 about Machine Learning in Ground Motion Prediction Analysis. A study of how machine learning techniques have been applied in predicting ground motion parameters in various seismic zones, examining the methodologies, results and detailed approaches. Case Study 4 demonstrates AI-Led Post-Earthquake Assessment. A review of AI-based applications in evaluating damage and recovery efforts subsequent to noteworthy earthquake events, demonstrating how data-driven insights can shape recovery strategies (Murakami et al. 1970).

Code Repository

In this chapter, the code and syntaxes referenced for data analysis and modelling in this dataset can be found in an open-access repository across various platforms like Kaggle and GitHub for instance. The referenced code in this chapter can be executed using Google Colab Notebook, Weka Software, Anaconda Jupyter to conduct analyses, and the dataset has been acquired from Kaggle. The discussion provided is to fulfil educational objectives, furthering our knowledge of earthquake phenomena using AI and ML.

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Harnessing AI for Seismic Hazard Detection and Prediction: Innovations and Challenges

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Abstract

Advances in artificial intelligence have transformed seismic hazard prediction, addressing long-standing challenges in earthquake detection. AI-driven models have significantly improved the classification of seismic events, real-time data analysis, and risk assessment. Neural networks and hybrid systems have shown remarkable efficiency in processing vast seismic datasets, identifying patterns, and delivering precise predictions. Integration of advanced sensors with AI has enhanced the sensitivity and accuracy of seismic monitoring networks, ensuring detailed data collection and analysis. Automated response systems have revolutionized emergency protocols, enabling early warnings and minimizing potential damage. The application of predictive analytics has uncovered relationships within seismic data that were previously beyond the reach of traditional methods, offering deeper insights into earthquake mechanisms. These developments have paved the way for more effective monitoring and preparedness, particularly in regions with higher seismic activity risk. AI has reshaped how seismic hazards are studied and managed by fostering collaboration across disciplines. Despite the progress, challenges such as ethical concerns, resource limitations, and technical complexities remain significant. Addressing these issues has spurred innovation, leading to adaptive and resilient solutions for seismic hazard detection and response. This evolution underscores the vital role of AI in safeguarding lives and infrastructure, creating a foundation for more secure and prepared communities in the face of seismic risks.

Keywords

Seismic · Artificial intelligence · Neural networks · Monitoring · Automation

1 Introduction

Seismic hazards are the potential danger and impact of earthquakes, tsunamis, and other geological activities on human beings, infrastructure, and economic systems in general. Indeed, these nature-related calamities often lead to severe loss of human life, infrastructure destruction, and a large financial loss. Seismic activity has proved difficult for scientists to predict and detect due to the complexity and uncertainty of tectonic movement (Centeno et al., 2024). Historically, geological surveys, historical data, and seismic instrumentation were the basis for predicting and judging possible risks (Mokhtari & Imanpour, 2024). Such methods are mostly not precise, may not give real-time predictions, and lack the all-around understanding of interpreting data. Artificial intelligence has emerged as a game-changer for several industries looking into new ways data is processed and analyzed (Cen et al., 2024). Its integration into seismic hazard detection and prediction has added unprecedented opportunities for enhancing speed, accuracy, and scope in earthquake forecasting through the power to analyze large datasets and learn from historical patterns to evolve with new information to overcome better impediments associated with more

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conventional forms of seismic detection methods (Power & Roman, 2024). AI improves assessment concerning seismic risks, streamlines early warning systems, and consequently reduces impacts with applications of machine learning algorithms, deep learning models, and real-time data analytics (Espinosa-Ortega & Taisne, 2024).

1.1 Overview of Seismic Hazards

Seismic hazards comprise the diverse geological events directly linked to the movement of tectonic plates in the Earth (Gondaliya et al., 2024). The most widespread and destructive kind of seismic hazard is an earthquake, which is an event where the accumulation of stress along faults in the Earth's crust is released and takes the form of seismic waves that produce shaking ground effects by moving through all the layers of the Earth (Mai et al., 2023). The extent of structural damage and other calamities, such as landslides and tsunamis, depend on the severity of these ground effects (Flores & Rosa, 2024). Besides earthquakes, seismic hazards comprise other secondary events like aftershocks, liquefaction, and ground displacement, which could amplify the impact of an earthquake (Li et al., 2024). Seismic hazards are very important in areas characterized by tectonic plate boundaries, particularly the Pacific Ring of Fire. These areas are vulnerable due to the population density and the kind of infrastructure existing there. Countries like Japan, Indonesia, and Chile are all located in these high-risk zones and have created strong seismic monitoring and mitigation systems, yet uncertainty about earthquakes is still a challenge (Ejarque et al., 2022).

Seismic hazards can be classified into intensity, frequency, and type of tectonic activities. Thus, magnitude is one of the principal measurements of an earthquake, measured either by the Richter scale or moment magnitude scale, Mw; these two quantify the energy released in an earthquake (Chen et al., 2024). Seismic intensity, on the other hand, measures the effects of the earthquake through the Modified Mercalli Intensity (MMI) scale, including the intensity of shaking ground and the degree of damage. Magnitude and intensity are crucial for estimating the seismic hazard's potential impacts within a certain region (Ruggieri et al., 2024). Traditional seismic hazard assessment utilizes geological surveys, seismic instrumentation, and probabilistic models. These observation methods include fault line research, seismograph measurements of seismic activity, and the calculation of probabilities for events to happen in the future, considering the history of past occurrences (Albarbary et al., 2023). Though valuable insights have come from these methods, they cannot always predict an earthquake with precision. Seismic events are highly non-linear and involve several factors that cannot be modeled perfectly with available classical techniques alone. There has been an immense thrust for the inclusion of AI in the procedures used for seismic hazard assessment to enhance the accuracy of projections and improve time for early warning (Kumar et al., 2024).

1.2 Role of AI in Seismic Data Analysis

Artificial intelligence has turned out to be one of the strong tools in detecting seismic hazards mainly due to its ability to process large volumes of data and detect complex patterns that even traditional methods may miss (Romero et al., 2024). Frequently, the seismic data is large and unorganized-filed waveforms, ground motion measurements, and historical records of earthquakes (Albahri et al., 2024). AI-driven algorithms would be best suited to process such data and permit identifying trends and correlations not at all perceivable to analysts or common models (Galasso et al., 2023). In the last few years, machine learning and deep learning came to be understood as subfields of AI and have played an even more central role in the analysis of modern seismic data (Dey et al., 2022). ML algorithms, especially supervised learning models, are utilized to classify seismic events and distinguish between natural and human-induced tremors, where they predict the likelihood of future seismic activities (Devi & Govindarajan, 2024). Large datasets of earthquakes and geological records feed these models, educating them on determining specific seismic wave characteristics related to an earthquake (Natali et al., 2023). Other ML models applied, with great promise, to seismic detection include SVMs, decision trees, and random forests.

Deep models with CNN and RNN can adequately scrutinize intricate patterns in seismic waveforms (Nguyen & Truong, 2024). Convolutional neural networks have been applied in image-based seismic data analysis, for example, in processing satellite images and seismic tomography for fault line and tectonic boundary identification. RNNs, on the other hand, are adept at time-series data and have successfully been used in analyzing the temporal patterns of seismic waves for short-term earthquake forecasting (Firmansyah et al., 2024). It has also been useful in improving real-time seismic monitoring systems. AI can continuously evaluate data from a global seismic network to strip noise and irrelevant signals, yielding more accurate and timely warnings about a potentially occurring seismic event (Cerè et al., 2022). Systems rely on algorithms in ML and sensor networks to detect precursory signs of seismic activity and alert the affected population (Tazarv et al., 2022). Implementing AI in seismic hazard detection increases the data processing rate and reduces instances of false alarms compared to the traditional method of monitoring seismic events.

Another important application of AI is risk evaluation models for seismic hazards. Using AI to combine geological data with socio-economic factors would help create more holistic models of the potential effect that an earthquake may cause within infrastructures, communities, and the environment. These AI-based models can be utilized by governments, urban planners, and disaster management agencies as better mitigation strategies are put in place and allocating resources for adequate preparation for emergencies (Tsalouchidis & Adam, 2024). However, applying AI to analyze seismic data is a great challenge because of the large scale and quality of the datasets and models that can be generalized across different geological settings. Furthermore, patterns and correlations identified by AI in seismic data are essentially a product of ignorance of the fundamental physical process responsible for causing earthquakes, which makes it impossible for AI models to produce the most definitive predictions.

1.3 Key Challenges in Traditional Seismic Detection Methods

For a long time, traditional seismic detection techniques have relied on physical models of the moving tectonic plates, fault line mapping, and historical data of earthquakes on Earth. Even though helpful in understanding seismic hazards, traditional techniques have several weaknesses that have undermined the effectiveness of most of these techniques in accurately predetermining the moment an earthquake may hit and at what time. One of the biggest problems in the traditional detection of seismic waves is the uncertainty surrounding an earthquake event itself. Earthquakes result from extremely complex interactions between tectonic plates, and the build-up of stress on the faults may take decades or even centuries. Models in modern science can never predict with absolute precision where and when an earthquake will occur. The traditional approaches rely on probabilistic estimates, which can predict the likelihood of seismic activities happening in a particular area over a specified time frame but have no expectations of a specific event.

Another challenge in the determination of seismic hazard is dependence on historical data. The occurrence normally occurs in a rational and uncontrolled manner; therefore, past incidents are not good predictors of future seismic activity. Data limitation also arises if historical records are unavailable or seismic activity has not been of notable intensity over considerable periods. Precise models cannot be well established for such regions based on the limited data (Nabih et al., 2023). Reliable forecasts of earthquakes cannot be developed within such data limitations, and most regions remain susceptible to seismic events that may or may not be predictable. Traditional methods of detecting seismic activity also cannot employ the means applied in real-time monitoring and early warning systems. Current seismic networks have seismometers and accelerometers placed at different sites within the geographical area. Their sensitivities are also unevenly distributed. These factors may lead to partial or delayed data, affecting the alert generation process in the early warning systems. Traditional systems usually face issues in their ability to filter out background noise and sense minor tremors instead of significant seismic events, resulting in missed detections or false alarms.

Another challenge with the traditional models is that of complicating earthquake dynamics. On their own, several variables play critical roles in influencing seismic events, such as the crust's composition, the angle of the fault lines, and the depth at which tectonic activity occurs. Quantifying and integrating such variables into the models produces incomplete or oversimplified results. AI would fill in those gaps by enhancing data integration capacity, improving real-time monitoring, and developing better models for earthquake detection and risk prediction. Integrating AI in seismic hazard detection may promise more feasible solutions to these traditional methods (Sandhu et al., 2024). This process can be found in handling large datasets, learning from historical patterns, and the real-time realization of the data analysis aspects in seismic hazard prediction that are more revolutionized, hence periphery minimization risks due to earthquakes and other seismic events.

Objective of the Chapter: This chapter has sought to address the pressing need for more advanced seismic hazard detection and prediction methodologies by exploring the integration of artificial intelligence into this critical domain. The objective has included a comprehensive review of seismic hazards, looking at the problems presented by conventional prediction methods, which rely on geological surveys, historical data, and seismic instrumentation that often produce imprecise results and have limited real-time applicability. The chapter tried to focus on the transforming capability of AI in surmounting these limitations. Applying machine learning, deep learning, and real-time analytics enhances AI-based systems for better accuracy in classifying seismic events, accelerating data processing, and improving risk assessment capability. Exploration also includes the scope of predictive models that rely on AI, which could make sense of large datasets and recognize complex patterns to provide timely insight into seismic activity. The chapter has tried to show the role of AI in creating holistic models for disaster impact assessment and resource allocation by investigating its ability to integrate socio-economic and geological data. Challenges in deploying AI, such as data quality, scalability, and ethical concerns, have also been considered. The general objective has been to highlight AI as a revolutionary tool for reducing seismic hazards and impacts, thus providing greater safety and preparedness for vulnerable regions.

2 AI Techniques for Seismic Data Processing

Seismic data processing is acquiring, interpreting, and analyzing seismic signals to understand and predict various seismic activities like earthquakes. The complexity of seismic data, which encompasses both time-series ground movements and spatial data gathered by geophysical surveys, poses major challenges to accurate detection and forecasting. Traditionally, it depends on manual interpretation and deterministic models, normally failing to represent real complexity within seismic phenomena. Increasingly, more AI techniques are being implemented to process seismic data much more efficiently and with higher accuracy, based on machine learning and deep learning algorithms to handle large, multidimensional datasets (Roger et al., 2024). Advantages of AI over other traditional methods include learning from patterns in the data and the capability to improve its predictions over time. Since seismic data are dynamic and non-linear, they should be treated with algorithms that evolve and refine their model with each new input. AI techniques, such as machine learning and deep learning, can automate seismic data analysis to detect seismic events much faster and more accurately than before. These methods will also allow for real-time monitoring, a prerequisite for timely warning and, hence, reduced impact from seismic hazards. Applying artificial intelligence to processing seismic data renders the systems more predictive and adaptive. It will enhance the accuracy of earthquake prediction and warning systems. Particular techniques in AI are discussed in the succeeding subsections, ranging from machine learning algorithms for seismic detection, models using deep learning models of earthquake prediction, and real-time AI implementation in data analysis for seismic.

2.1 Machine Learning Algorithms for Seismic Detection

That class of algorithms only recently started to gain considerable traction in its route into seismic detection, which is machine learning algorithms, simply because they can easily analyze large chunks of seismic data in a way that traditional techniques often bypass. Such algorithms are excellent at classification tasks: distinguishing between natural earthquakes and human-induced tremors or differentiating between seismic noise and actual seismic events. One role in such processing is supervised learning, a sub-category of ML. In such learning, the algorithm uses labeled data, such as past seismic activity, to predict characteristics of future events given new data inputs. The SVM algorithm is commonly applied in machine learning-based seismic detection techniques. SVMs work by trying to find the best hyperplane that can separate different classes of seismic events in a multidimensional feature space. Mapping seismic data into such a space means that SVMs can classify them based on the proximity of new events to the decision boundary. SVMs are very useful in seismic detection tasks where the dimensionality is too high because they accommodate both linear and non-linear distributions.

Another popular algorithm for machine learning is the random forest algorithm, which constructs an enormous ensemble of decision trees during training and then predicts either the mode of the classes or the mean prediction for new input. Random forests make very robust seismic detection because they inherently can reduce overfitting and increase the generalizability of unseen seismic data. These models can analyze time series and spatial data and thus are apt for various seismic detection tasks ranging from micro-seismic activities to wide-scale earthquakes. Artificial Neural Networks have also been applied in seismic detection, particularly in pattern recognition jobs. ANNs mimic the basic structure of the human brain through many interconnected nodes or neurons that process seismic data in layers. The weights of those connections are adjusted to make the network acquire its ability to spot critical features in seismic data, such as frequency and amplitude of seismic waves; those two best describe the most important aspects to use for identifying an earthquake. Networks are especially helpful in complicated noisy datasets where they can learn how to filter out unwanted information and focus on key seismic indicators.

All in all, machine learning algorithms could dramatically improve traditional seismic detection methods. They allow for more accurate classification of seismic events, and the possibility to immediately analyze data in real time allows scalable solutions to deal with mass seismic data from global networks (Li & Gardoni, 2023). Evolving machine learning techniques would doubtless be used even more for seismic hazard detection, providing much more sophisticated tools for the early warning system and risk assessment models.

2.2 Deep Learning Models in Earthquake Prediction

Deep learning models have been a recent addition to earthquake prediction as the ability to analyze complex and nonlinear data structures inherent in seismic waveforms and geophysical signals. In contrast to the traditional models used in machine learning, deep learning techniques, specifically multilayer networks, can automatically learn high-level features from raw seismic data without any manual feature engineering. That ability for deep feature extraction has made deep learning models extremely effective for earthquake prediction, where the subtle pattern in seismic signals may be the difference between detecting an impending earthquake or missing all critical early signs. Another area of new adoption is CNNs, which have traditionally been used to analyze spatially correlated data: seismic tomography and satellite imagery of tectonic activity. The CNNs thus scan through seismic data at different resolutions. Images reveal features like fault lines, sub-surface fractures, and stress points that can be used to forecast probable seismic activity. CNNs are useful in identifying and analyzing secondary seismic events like aftershocks and forecasting their propensity for propagation and impact. Such large-scale datasets make them ideal for seismic research, typically involving the analysis of global seismic networks and satellite data in real time.

RNNs, or the LSTM networks, are also highly suitable for earthquake prediction because of their strength in processing time-series data. Seismic waves occur over time, and temporal dependencies between seismic events reveal valuable information about future activity. Another capability of LSTM networks is the long dependency on seismic data, which makes them predict seismic activities based on their former wave sequences. Therefore, LSTMs could provide real-time updates of seismic hazards with predictive powers that have not been possible by using previously traditional models. Autoencoders are another method of deep learning application that uses seismic anomaly detection. The autoencoders learn to compress seismic data so that any differences between the compressed and the reconstructed data could represent precursors of anomalies. The data corresponding to these anomalies would be seismic precursors, for instance, foreshocks or an alteration in deformation of the ground that may characterize an approaching earthquake. Thus, autoencoders are applied to unsupervised learning whenever the seismic data labeled is unavailable or insufficient. They can realize the patterns in seismic activity minus extensive human interference.

Deep learning models are promising and hold great potential for earthquake prediction, yet they still present a challenge. The big challenge is that these models require large, high-quality datasets to train the networks appropriately. Another reason is that earthquake occurrences are inherently unpredictable, so deep learning models need to be able to generalize well to unseen events of seismic activities. Despite all these challenges, rapid progress in seismic predictive approaches through deep learning is quickly arising because of rapid developments in computational power, increased availability of large datasets, and further innovations in the architectures of neural networks. Deep learning models will have a greater impact on the development of earthquake forecasting (Noureldin et al., 2022), providing detailed predictions and informed decision-making towards the mitigation of seismic hazards.

2.3 Real-Time Seismic Data Analysis with AI

Real-time seismic data analysis is an integral part of an early warning system and provides the lead time that will help mitigate the effects of an impending earthquake on the populations and authorities. The most important advantage of the application of AI in seismic hazard detection is the ability to process seismic data in real time. Most traditional seismic monitoring methods do not have the capacity for real-time analysis due to the sheer volume of seismic data resulting from global networks and the urgency of processing these data to issue early warnings (Wu et al., 2023). Advances in AI in machine learning and deep learning greatly increase real-time seismic data analysis speed and accuracy.

Seismometer or accelerometer-large arrays of sensors installed throughout areas with a history of earthquakes (Iuliis et al., 2024). The sensor captures ground motion and continuously transmits it to central servers for further analysis. With real-time AI algorithms, especially deep learning, it is now possible to filter through lots of such data at considerably high speeds and spot seismic signals amidst background noise. This ability to process large data streams in real-time makes seismic networks more sensitive because by observing minor tremors the traditional system would have missed, it is possible to adapt to these changes in seismic patterns as well by training on new data that comes to it to improve its predictive models. Adaptive AI models can update their parameters in real applications and carry out more precise forecasting of seismic events because of constant data streams. In areas where aftershocks are frequent or where tectonic activities prevail, there may be a requirement to update some predictions because of the fast developments in seismic patterns. AI systems can now be used to identify changes in patterns, which allows real-time tracking of how the risk of earthquakes changes.

Other areas that have implemented AI relate to improving the timeliness and accuracy of EEWS. The traditional EEWS is based on manual interpretation and preset thresholds as triggers for the alarm to be issued, which results in false alarms and delayed responses. AI-based systems continually learn from new seismic data and can dynamically change thresholds, reducing the chances of false positives and thus always recognizing real seismic events immediately. It is also possible to have more localized warnings to give region-specific alerts, considering and knowing the different seismic risks of other areas. AI-enhanced real-time seismic analysis is further weighted not only to detect damage but also to assess damage. The AI system would be able to provide real-time risk assessments of an event, indicating earthquake magnitude, depth, and proximity to population centers by the analysts to assist the emergency responders in prioritizing their efforts (Zheng et al., 2023). This would be more targeted in responding to seismic events, ensuring proper resource allocation to areas that are at the most risk. AI plays an important role in the real-time analysis of seismic data, particularly in making a difference in seismic hazard detection and moving toward faster, more accurate, and adaptive systems to mitigate devastating effects caused by earthquakes.

3 Challenges in AI-Driven Seismic Prediction

AI has led to an enormous improvement in seismic hazard detection and prediction. It is designed to significantly improve processing huge data volumes and identifying patterns often undetected by traditional methods. However, despite its promising potential, AI-based seismic forecasting faces various problems. These range from data availability, quality, and complexity to uncertainties in the forecasts and the sheer constraints imposed by computation. Overcoming these challenges would be significant in helping in advance and improving the accuracy of AI in predicting seismic hazards. These include the lack and quality of data for AI-based seismic prediction, uncertainty in earthquake forecasting, and computational power limitations utilized in the seismic models. Each of these challenges highlights the intricacies of putting AI into seismic hazard detection and the ongoing need for research and innovation to bridge this gap.

3.1 Data Availability and Quality Issues

Large, high-quality datasets are the major constituent in the success of AI models in seismic prediction. Seismic data could be provided through various sources such as seismometers, accelerometers, geophysical surveys, or satellite images (Sun et al., 2023). Although such sources are informative for seismic activities, the data is typically incomplete, noisy, or unevenly spread across geographic regions, which presents important challenges for training AI models since high-quality, labeled data forms an important basis for accurate predictions. The lack of labeled seismic data is among the significant challenges of applying AI in seismic prediction. Earthquakes, especially large-magnitude destructive ones, occur less frequently, leading to a relatively small quantity of corresponding labeled data. This constrains the ability of AI models to learn from past seismic events to predict with accuracy for the future. Another challenge is that in some regions, few historical records are available or insufficient, making it difficult for AI models to generalize on different tectonic settings.

Data quality is another major concern in AI-based seismic prediction. Seismic data normally has significant noise due to natural and anthropogenic sources, making it very difficult to isolate meaningful seismic signals. Noise sources that have appeared due to the vibrations caused by human activities like construction, transportation, or mining interfere with seismic data. Most traditional methods by which those noises can be filtered are incompetent because they may appear as actual seismic events. AI models, especially machine learning and deep learning algorithms are geared towards behaving well in clean data with accurate labeling. Noisy or mislabeled causes the wrong predictions to be made. Seismic data is often heterogeneous, a term used to refer to data from different sensors and sources, each with varying precision and reliability. For example, high-quality, almost real-time data may be available from seismic networks in well-monitored regions such as Japan and the United States, whereas sensor density might be scarce in low-income areas, with worse data quality and severe delay in transmission. This data quality inconsistency is another source of problems for AI models that depend on clean data to produce fairly accurate predictions.

Several approaches have been used to pursue this challenge. A possible solution is using a transfer learning-based approach. AI models are pre-trained on large datasets from well-monitored areas and fine-tuned to use smaller datasets from less-monitored areas. This enables a model to make predictions in limited or low-quality data based on knowledge gained through experience with high-quality data. Data augmentation may also produce more training data by synthetically generating seismic events or using simulation models to create virtual earthquake scenarios (Trani et al., 2022). Moreover, noise reduction algorithms and unsupervised learning techniques have been developed to improve seismic dataset quality. These filter out noise from datasets, identify mislabeled data and correct them to improve the reliability of seismic data. Enhancing data availability and quality would result in AI models that will be more accurate and reliable in seismic predictions.

3.2 Uncertainty in Earthquake Forecasting

One of the biggest problems with AI-driven seismic prediction is the uncertainty that comes along with earthquake forecasting. Earthquakes are chaotic, non-linear events influenced by many interacting variables, including tectonic stress, fault properties, and subsurface conditions (Liu et al., 2024). Many of these variables cannot be directly measured; sometimes, they are poorly characterized. The reason it's hard to model them with high accuracy is because of their inherent unpredictability. Statistical models have been used in seismic hazard analysis for a very long period because they enable the estimation of the probability of earthquakes against the backdrop drawn from history and known faults. Once again, such models only provide a probabilistic forecast and not a certain prediction. AI models, especially machine learning algorithms, added another dimension to earthquake prediction with an estimation of the timing, location, and magnitude of future earthquakes. Despite all these breakthroughs, AI-based earthquake forecasting remains with a scantly accurate usage.

One of the biggest uncertainties associated with AI-driven seismic prediction is the variability in earthquake precursors. Most earthquakes can be preceded by changes in seismic activity that are measurable and recordable, like foreshocks, ground deformation, or changes in gas emission, yet many occur without any evident precursors. Since AI models rely on these signals to make predictions, if some never have clear precursors, then some may never be predicted, and false positives can be generated even when there are no clear precursors. For example, a model fit to a training set that includes foreshocks may not perform well in regions that experience earthquakes without them. Other types of uncertainty arise from the complexity of the mechanisms by which earthquake triggering occurs. Even in relatively simple cases involving tectonic and fluid stresses, fault interactions are the triggering mechanism. Such factors vary from region to region and fault system to fault system, making it difficult to engineer one AI model that can adapt across all tectonic settings. For example, a model trained in a subduction zone where earthquakes are driven by the collision of the edges of diverging tectonic plates doesn't have anything to go on when operating with a strike-slip fault system where the lateral motion of plates is the dominant mechanism.

Earthquake dynamics are inherently non-linear, creating additional challenges to correctly predicting (Demertzis et al., 2023). Earthquake magnitudes are power-law distributed, with small earthquakes occurring very often and large ones occurring much less often (Abdalzaher et al., 2024). AI models trained using large datasets dominated by small earthquakes would have difficulty predicting large, less frequent events correctly. This bias in the data results in bad predictions as the model underestimates a larger earthquake and overestimates a smaller earthquake. To combat such uncertainty, researchers have devised a set of strategies. One way is through ensemble learning, in which several AI models are assembled to produce robust and reliable predictions. Ensemble methods successfully reduce individual model error by averaging multiple models' outputs, such as random forest and gradient boosting. Another would be to integrate AI models with physical models of earthquake dynamics so that AI learns from a combination of data-driven patterns and conceptual understanding of earthquake processes. Despite all these efforts, uncertainty is also one of the basic challenges to developing AI-driven seismic prediction. Although AI promises to improve earthquake forecasting accuracy, it does not guarantee it will hit the perfect level because earthquakes are inherently unpredictable. However, by adding probabilistic approaches, increasing model generalization, and AI integration with physical models, continued effort has helped researchers get closer to making reliable and accurate earthquake forecasts.

3.3 Computational Limitations in Seismic Models

Seismic hazard detection and prediction involves much computational power to analyze huge and complex datasets. In other words, AI models, in general, and deep learning algorithms, in particular, demand immense computing powers, memory, and storage capacity to be developed and deployed. These computational limitations are the major hindrances towards scaling and efficiency in AI-driven seismic prediction systems dealing with real-time data from global seismic networks. These huge datasets include continuous time series, thousands of sensors, satellite imagery, geophysical surveys, and historical records from previous earthquakes (Wang et al., 2024). It is easy to imagine that more than a terabyte of data for one day alone could be presented by one day of global seismic network data. Any hardware will be tested in real-time processing of such volumes of data if algorithms are not highly optimized for data handling. AI models, especially deep architectures CNNs and RNNs, become computationally intensive in training and inferential phases.

The major computational challenge for this paper is the training time taken to produce AI-based deep learning models for seismic prediction. A week or more of training will be required for large-sized datasets and complex models; training a deep learning model on seismic data is not a problem. Sometimes, this extended training time restricts the testing of various architectures and the tuning of hyperparameters. Such models also commonly require training to be done on high-performance computing (HPC) clusters or specialized hardware, such as graphics processing units (GPUs) or tensor processing units (TPUs), that might not be readily accessible for every researcher. The other computational challenge relevant to seismic prediction is latency. Real-time seismic prediction deals with a very significant challenge coupled with latency since this lateness means that earthquake early warning systems cannot inform the populations sufficiently to allow them to respond to the pending disaster by evacuating the place or doing whatever else is necessary. AI models in such systems must process incoming seismic data within milliseconds to raise alerts quickly. Deep learning models incur computational overhead, which introduces delays that can slow the delivery of early warnings. Algorithmic efficiency and hardware resource optimization are necessary to reduce this latency.

Seismic datasets often contain large data volumes that are difficult to store and manage (Donato et al., 2024). Huge amounts of historical seismic data must be accessed to train AI models. These amounts have to be stored, retrieved, and processed efficiently. For this purpose, cloud-based storage solutions have increasingly been used as a fix to store and access seismic data remotely. However, large datasets lead to latency or time delay in the model's training and inference process. The cost of storing and processing a huge dataset in the cloud can be costly, according to the viewpoint of some research institutes and other organizations. Researchers have proffered various solutions to tackle these computational limitations. One such approach was distributed computing, which splits the computational workload amongst various machines or nodes connected in a network. Distributed training of AI models allows for parallel processing and reduces train times with deep learning models on massive seismic datasets. In that regard, the new protocol has been very effective in training models on cloud-based platforms because it accounts for the dynamic resource allocation based on the computation needs of the task.

Another interesting solution is model compression techniques, including pruning and quantization, to reduce the size and complexity of AI models without losing any accuracy: pruning is the removal of connections in a neural network that are unnecessary or redundant and, in some cases, redundant weights; quantization reduces the precision of the model's parameters, lowering memory requirements. Such techniques were proven effective at significantly lowering the deep learning models' computational footprint, making them applicable to real-time seismic prediction. It has also been the case that hardware acceleration, including better graphics processing unit (GPU), tensor processing unit (TPU), and field-programmable gate arrays (FPGA), increases the efficiency of AI-driven seismic prediction systems. It is particularly hardware solutions geared towards speeding up the training and inference of AI models to carry out huge datasets about seismic very efficiently with reduced latencies in real-time applications.

4 Innovative AI Models in Seismic Hazard Prediction

AI turned out to be the revolutionary technology in seismic hazard prediction. This science has developed complex systems using innovative AI models for scientists engaged in the field, which can deal with the complexity of a prediction regarding earthquakes, which frequently involve enormous datasets along with intricate, non-linear patterns. Unlike traditional seismic monitoring, where the approach was highly based on physical models and records, AI-driven approaches increase the precision of the predictions by learning from data at both structured and unstructured levels. Such includes seismic waveforms, satellite images, fault line data, and real-time sensor readings. Because of this ability to analyze various data types, AI systems can detect patterns that might otherwise be missed and improve the reliability of early warnings and hazard estimations. Neural networks and hybrid AI systems have made immense contributions to this field. Neural networks are primarily of two types: CNNs, specifically Convolutional Neural Networks, which do exceptionally well in pattern recognition, and RNN or Recurrent Neural Networks, especially suited for the analysis of sequences of data. These two forms are critical to understanding seismic phenomena. Meanwhile, combining several algorithms and methodologies, hybrid AI models show improved prediction accuracy by overcoming the defects of individual methods. This section discusses neural network application in the classification of seismic events, AI-based models for seismic risk assessment, and the development of hybrid AI systems to enhance the performance of seismic hazard prediction models.

4.1 Neural Networks for Seismic Event Classification

Application of Neural Networks Neural networks have made seismic event classification what it is today, the modern system used in predicting an earthquake. Neural networks are unique in processing large and complex datasets, leaning on patterns inherent in seismic waveforms to classify events. Convolutional neural networks were originally designed for analyzing images but had already been successfully adapted to process seismic waveforms. A CNN holds a series of convolution layers, wherein the system scans through the seismic data automatically to retrieve the most critical features, such as wave peaks, depths, and amplitudes. This feature extraction process makes it possible for CNNs to classify and assign seismic events into categories such as natural earthquakes, aftershocks, or human-induced tremors with an appropriate level of accuracy. For instance, CNNs can be deployed in a learning set that was developed using datasets labeled seismic events so that they can notice even future events that originate from real-time seismic data. Thus, after training, such networks can learn to distinguish between normal tectonic activity and events that may represent a more serious seismic hazard. Detecting these seismic hazards is crucial in densely populated urban areas where even minor tremors can have serious implications. CNNs can also be used for micro-seismic event detection, which traditional methods cannot easily detect but could trigger larger earthquakes.

Recurrent neural networks, especially long short-term memory (LSTM), have been used for classifying seismic events. While CNNs are excellent at spatial pattern recognition, RNNs are designed to process sequences like time series seismic waves. Of particular great interest among the traditional RNNs were the LSTMs able to study the fundamental relationships between seismic wave events in time points. Through these sequences, LSTMs can improve the prediction of seismic events to give early warnings that may impact minimizing the effects of earthquakes. Autoencoders are another type of neural network used for anomaly detection through seismic data, which learns to compress and reconstruct seismic signals, including deviations that could represent seismic anomalies or precursors to an earthquake. Autoencoders provide an advantage of unsupervised learning, meaning they do not need labeled data, which could sometimes be below. The use of neural networks in seismic event classification has completely transformed the classification process by allowing higher accuracy and speed for real-time monitoring systems. Their ability to be used on large amounts of complex data improves the capacity for early detection of disasters and contributes to adequate preparation and disaster relief responses.

4.2 AI-Based Risk Assessment Models

Risk assessment models based on AI are very crucial for determining the various impacts that seismic hazards could have. Such models use machine learning algorithms to process large volumes of data, including seismic activity records, geo-spatial information systems data, and socio-economic factors and provide detailed risk profiles for various regions potentially exposed to earthquakes (Berhich et al., 2022). Unlike most traditional risk assessment methods, AI-based methods can continuously update risk estimates in real time by including novel data collected on any new seismic activity. Such real-time ability enhances the accuracy and timeliness of earthquake risk evaluations; at the same time, such evaluations are becoming increasingly important for decision-makers of urban plans, emergency response, and disaster mitigation.

Random forests, decision trees, and SVM algorithms are common algorithms used in AI-based models for assessing risks. Such models have been used to analyze seismic data from the past so that patterns used to infer the intensity of an earthquake and its impact can be developed. For example, the decision trees manage to approximate pretty complicated relations between seismic factors like the intensity of ground shaking, depth of earthquake, and distance from fault lines. Similarly, an ensemble learning method called a random forest combines several decision trees to increase the strength and predictability of seismic risk. These AI-based models can also incorporate non-seismic variables, including population density, building resilience, and socio-economic vulnerabilities, in the risk estimation (Zhang et al., 2024). By accounting for more variables, AI models can offer a better holistic view of the risks emanating from seismic events. For instance, an AI-based risk assessment model could predict that the calamity from an earthquake of a given magnitude would be much worse in a highly populated urban center with older, inappropriately maintained infrastructure than it would be in a sparsely populated rural area with new building structures well-designed to withstand earthquakes. Such detailed risk assessments will enable policymakers to make much better allocations of resources and strategize the framework of preparedness and response to natural calamities.

In seismic risks, AI-based models are very beneficial in managing secondary hazards such as landslides, tsunamis, and aftershocks. Based on historical patterns of secondary hazards paired with topographical data analysis, cascading effects resulting from seismic events can be predicted. This ability is pivotal in coastal areas because tsunamis frequently follow catastrophic earthquakes. By integrating AI into seismic hazard forecasting, the precision and scope of seismic hazard prediction have dramatically increased, and thus, their mitigation becomes easier and more applicable. Any government or organization could use these models to prioritize better-retrofitting work, enhance early warning systems, and allocate resources toward areas and regions most at risk.

4.3 Hybrid AI Systems for Improved Accuracy

Hybrid AI systems are the latest frontier of seismic hazard prediction as they integrate multiple AI techniques and more traditional approaches to achieve higher accuracy, speed, and robustness in earthquake forecasting. Hybrids are systems that can incorporate different algorithms' strengths and thus make it possible to overcome weaknesses from individually operating models that face constraints related to an application. Hybrid systems incorporate machine learning, deep learning, and statistical modeling to deal better with the data characterizing the complex phenomena under consideration, namely seismic hazard prediction (Mukesh et al., 2024). Hence, a bigger predictive power is obtained, especially in environments with very irregular patterns of seismic activity and highly interacting factors. Physical models of tectonic activity may be combined with machine learning algorithms to implement hybrid AI systems. The physical models rely soundly on well-established scientific principles of fault mechanics and stress accumulation. Still, the inability of these models to account for predictable signatures of unpredictability in seismic events makes them inadequate. Machine learning algorithms are excellent at identifying patterns in seismic data but lack a physical understanding of the reasons behind why certain events happen. Hybrids will couple both approaches to provide even more accurate forecasts based on insight drawn from data-driven processes and physical laws.

A great example would include a hybrid system where that uses a specific type of machine learning model that has been thoroughly analyzed using real-time seismic data to predict the probability of having an earthquake, while a physical model is used to provide context because it simulates the way stress builds up along fault lines with time. The hybrid system can better fine-tune its predictions to minimize false positives and negatives. Hybrid systems of this type have worked especially well in regions of sophisticated seismic activity, such as subduction zones, where the Earth's crust is broken due to the interaction of several tectonic plates and can cause earthquakes through a collision.

An extremely important constituent of a hybrid AI system is ensemble learning, which combines predictions of many models to enhance the final accuracy. An ensemble approach in seismic hazard prediction could be used where different types of machine learning models, including neural networks, decision trees, and support vector machines, could be used. The outcome of each model was aggregated to give the final forecast. Because aggregation occurs, the resulting final prediction will be more accurate than any of the predictions given by individual models. This approach is very effective with the uncertainty that always accompanies seismic prediction, as it allows the system to draw on a diverse range of models for better decisions. Hybrid AI systems overcome challenges caused by data scarcity using transfer learning and data augmentation techniques. In areas with few documented local seismic occurrences, limited historical data would exist to be used to train an intelligent model. Transfer learning addressed the challenge by utilizing a well-trained model using data from another region to fine-tune performances that may enhance predictions where there are few records of seismic occurrences. This is another important feature of hybrid AI systems: in principle, they can be integrated to combine real-time monitoring with long-term forecasting. Some AI models are better prepared to detect and respond immediately to seismic events, while others are more suitable for long-term hazard assessment.

Other techniques for data augmentation, namely the generation of synthetic seismic events, would increase the diversity and size of training datasets so that hybrid systems can generalize better to new seismic events. Hybrid systems can be a combination of both, using real-time seismic activity detection and providing long-term earthquake risk predictions. For instance, AI may use historical data for the long-term risk of aftershocks or secondary hazards like tsunamis, while real-time data from the network of seismometers was used to detect an earthquake's early warning signals. Hybrid AI systems, therefore, provide large improvements compared to traditional seismic prediction methods and single-model AI approaches. The system's improvement from the multi-algorithm, multi-physical model, and multi-machine learning approaches makes seismic hazard predictions more accurate and robust. Therefore, its applicability for both long-term and real-time monitoring provides benefits for immediate disaster response and future risk assessment. As technology advances, hybrid systems will be even more developed to find a solution to the risk hedging of seismic hazards.

5 Technological Advancements in AI for Seismic Prediction

Artificial intelligence's technological aspect is quite advanced in seismic prediction. AI can process amounts of data and learn complex patterns through experience, making it an invaluable tool in seismology (Noureldin et al., 2022). This approach to seismic hazard prediction has embraced AI from traditionally physical models with historical data into more improved real-time monitoring, hazard detection, and risk assessment. These changes make it easy to deal with the complexity of earthquake forecasting through better predictive models and effective response systems. Technological advancements in AI algorithms, the integration of AI with advanced sensors, and the automation of seismic response systems have been the driving factors that ultimately enhanced the process efficiency and accuracy of detecting and predicting an earthquake. These developments carry unique advantages in seismic hazard mitigation and help protect vulnerable populations and infrastructure. This section discusses major technological leaps, especially concerning AI algorithms, sensor integration, and automated seismic response mechanisms, on how AI has changed seismic prediction.

5.1 Breakthroughs in AI Algorithms

Some of the latest breakthroughs involving AI algorithmic innovations have revolutionized seismic data processing, analysis, and interpretation. Traditional approaches to earthquake prediction have relied almost entirely on deterministic models, which, although useful, fail to exploit the complexity of the process involved. Their more sophisticated approach-the AI type, especially based on ML or DL- appeals to the detection of subtle patterns and correlations in seismic data inaccessible to them. Such algorithmic advances refine the detection of a seismic event and the predictive capacity of earthquake forecasting systems.

Recent breakthroughs in AI algorithms for seismic prediction include developing neural networks, including convolutional neural networks, CNNs, and recurrent neural networks, RNNs. CNNs have demonstrated an exceptional ability to analyze waveforms and identify spatial patterns that might indicate fault lines and sub-surface fractures. This feature extraction ability of CNNs has reduced manual data processing, and hence, fast, accurate seismic event classification is possible. In contrast, RNNs and the specific case of LSTM networks performed exceptionally well in analyzing time-series data for seismic occurrences in the form of wave propagation. LSTMs particularly excel at capturing the temporal dependency of seismic events, thus enabling the continuous monitoring of seismic signals and tracking them in the case of earthquake prediction tasks.

The other AI algorithm breakthrough applicable to seismic prediction is transfer learning in seismic prediction. There is a transfer learning where an AI model trained on one region or tectonic setting can be used in another, and this proves particularly critical for areas with minimal records of seismic activities. This way of doing things enables the AI system to generalize differently across different geographical regions, thus offering a better prediction for the area with sparse data. The other promising area was the application of ensemble learning techniques, which are popular today because they combine the outputs of multiple AI models to generate a more robust prediction. Ensemble methods reduce the uncertainty related to individual model predictions by aggregating outputs from different models, providing more reliable forecasts (Razmi et al., 2023).

Another key advancement is in unsupervised learning techniques applied in seismic analysis. Most importantly, unsupervised models, clustering algorithms, and autoencoders can discover hidden patterns in seismic data using unlabeled training data. It proves especially useful for identifying seismic anomalies or earthquake precursors: finding an anomaly or precursor might not be similar to that in history. Autoencoders can compress and reconstruct seismic signals to pinpoint deviations indicating impending seismic events (Wang et al., 2024). These advances in AI algorithms have greatly contributed to seismic prediction, with more accurate and real-time detection of the occurrence of earthquakes and risk assessments.

5.2 Integration of AI with Advanced Sensors

AI and advanced sensor technology have greatly enhanced seismic hazard detection and monitoring possibilities. Seismic sensors, among them seismometers and accelerometers, have existed for decades to measure how the ground moves (Saqib et al., 2024). However, these sensors have limited usefulness since processing and making sense of large amounts of data proves challenging. The AI approach has helped answer this limitation by enabling real-time analysis of sensor data, among them, the quicker handling of events thanks to their immediacy and accuracy. These have, in turn, made seismic networks more sensitive and able to capture smaller events that would otherwise go unnoticed. Modern seismic networks use advanced sensors. Advanced means they can capture wide ranges of seismic data. They even include ground motion, pressure changes, and temperature fluctuations. AI systems can process these multi-sensor data to identify patterns of tectonic activities or fault line shifts. For example, by incorporating machine learning algorithms, AI systems may identify microseismic events, otherwise tiny tremors that may precede major quakes. Real-time analysis of data coming from accelerometers opens up the possibility of informing people beforehand, thus potentially saving numerous lives and minimizing damage by giving populations an extra window of time to respond to seismic threats.

Another innovation that improves seismic monitoring is satellite-based sensors integrated with AI, like the interference synthetic aperture radar (InSAR) technology. InSAR sensors can detect slight ground movements caused by tectonic movements within the Earth's surface. AI algorithms can process this data to find ground deformation patterns that may precede an earthquake. The impact of satellite data analysis by AI becomes notable in out-of-the-way places with sparse populations, where ground-based seismic sensors are somewhat inadequate. With ground-based and satellite sensors, AI systems provide a wide-angle view of tectonic activity; this broadens short-term earthquake prediction and long-term hazard assessment. Another critical success in sensor-AI integration is the development of IoT seismic networks. IoT technologies allow the deployment of huge populations of low-cost, networked sensors in seismically active regions. Those sensor networks generate enormous amounts of data, which AI algorithms can mine to identify seismic events in real time. By filtering the data to only focus on the relevant seismic signals, AI minimizes false alarms and ensures that major seismic events are intercepted. Combining IoT-enabled seismic networks with AI-driven analysis provides a scalable solution for monitoring large areas of geography and is, thus, ideal for use in earthquake-prone regions with complex tectonic environments.

A real quantum leap from the current and individual detection of seismic hazards, incorporating AI with advanced sensors leads to more accurate real-time observations of seismic activity as it combines the capability of state-of-the-art sensors to gather data and the analytics power of AI. This technology not only develops better early warning systems but aids in a much more detailed seismic risk assessment, allowing governments and organizations to prepare themselves better against future seismic events.

5.3 Automation of Seismic Response Systems

Automated seismic response systems hold potentially greater promise with AI. In the conventional seismic response system, people usually interpret data sets, determine the intensity of an event, and organize responses. The obvious involvement of human beings in these processes may occur at a lag that defeats the purpose of early warning systems, especially fast-moving seismic events such as earthquakes. It can eliminate these delays to provide more prompt and coordinated reactions, potentially minimizing the destruction caused by the earthquake and automating critical aspects of the seismic response, from real-time data analysis to activating early warning systems and coordinating emergency services (Ismail et al., 2022). For instance, AI algorithms can continuously monitor seismic sensor networks and detect seismic events instantaneously, classify them into their magnitudes, and locate them precisely. The AI system can then automatically trigger early warning alerts to the public and relevant authorities based on predefined thresholds (Sandhu et al., 2023). In earthquake-prone regions, a few seconds of warning can make all the difference in terms of people taking cover, utility companies shutting down critical infrastructure, and emergency services preparing for incoming requests.

AI systems can also play a pivotal role in the post-earthquake response. Following an earthquake, AI-driven systems can analyze the information gathered by ground sensors and satellite imagery, together with social media, to assess the impact of the disaster and identify areas where the effort to respond to emergencies should be concentrated (Nautiyal et al., 2022). For example, a model of extreme damage in one area can be predicted using AI based on the magnitude, depth, and location of the earthquake in terms of population concentrations. Information can aid emergency responders in directing their best efforts to where the neediest and most damaged locations are. In addition, AI can be linked directly to drones and other automated systems to execute expedited damage assessments with real-time data regarding building integrity, infrastructure damage, and hazards such as fires or gas leaks.

Another application of AI in the automation of seismic response has to do with critical infrastructure management. Systems may be designed such that power grids, pipelines carrying gas, and transportation networks will be switched off immediately upon an earthquake to prevent further damage and limit the risk of secondary hazards like fires or explosions. AI algorithms could immediately analyze real-time seismic data to conclude whether a damaging earthquake is likely. Such automation could allow an entire building or other structure to shut down automatically without human intervention. Around critical failure points, such immediate response would be extremely valuable in areas of dense population and complex infrastructures. AI-driven automation also provides long-term seismic preparedness. These systems can continue to analyze the data.

Consequently, patterns and anomalies can be diagnosed, which may signify increases in seismic risk. Risk assessment will be automatically updated, thus keeping decision-makers informed regarding potential hazards. This system can also be coupled with smart city infrastructure, enabling cities to adapt dynamically to changing seismic conditions. For example, AI may divert traffic flow or reroute public transport in the event of an earthquake so that affected regions can be accessed for emergency activities.

6 Conclusion

AI is also relevant in the seismic hazard prediction domain and has moved significantly forward in precision, speed, and efficiency. Some of the recent advancements in AI algorithms, particularly neural networks and ensemble learning, have driven immense progress in the classification and prediction of seismic events. Enhanced data gathering and real-time processing become more feasible when AI uses more advanced sensors. Automatic systems have been inducted to further enlarge the early warning mechanisms and response strategies during an emergency. Despite ongoing challenges, such as lack of data availability and computational limitations, the role of AI in seismic hazard prediction is continually evolving to offer more robust solutions for mitigating earthquake risks. The continued development of AI-driven technologies promises to enhance disaster preparedness and reduce seismic events' human and economic toll.

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AI Techniques for Remote Monitoring

Jasneet Chawla and Harmanjeet Singh

Abstract

Remote Monitoring is the field of administering, following, and controlling the system or activities distantly with the aid of tools and technologies. It has a pivotal role in numerous sectors, allowing organizations and administrators for decision making without being physically present. The traditional remote monitoring methods depend considerably on manual observations using simple sensor. With the use of basic wired communication methods, the collected data was transmitted from remote locations to the central control station. These methods were laborious, susceptible to human error, and possessed insufficient real-time capabilities. The incorporation of Artificial Intelligence (AI) based techniques into remote monitoring has significantly transformed the ways in which the surveillance was conventionally performed. This chapter examines the profound impact of the technology on the domain of remote monitoring, exploring the advance methods that have enhanced the real-time effectiveness of the system in varied domains. Beginning with the description of remote monitoring and its evolution, the chapter highlights the role of AI in the process of automation of data analysis, recognizing the irregularities in data, and allowing the prediction. With the continuous advent of AI, technology has significantly impacted various sectors, ranging from remote healthcare monitoring to environmental surveillance, from security monitoring to applications in the agriculture sector, remote monitoring plays an indispensable role in modern society. The chapter further addresses the key challenges experienced during the integration of the technology for remote monitoring. Followed by a discussion on the forthcoming trends and associated future prospects.

Keywords

Artificial intelligence · Computer vision · Edge computing · Deep learning · Machine learning · Remote monitoring · Remote surveillance

1 Introduction to Remote Monitoring

Remote monitoring is a technology-based method that facilitates the observation and management of systems, environments, or processes from a distance, typically employing sensors, communication networks, and data analytic tools. It supports real-time or near-real-time data collection and processing, aiding in the detection of abnormalities, performance optimization, and safety assurance across diverse industries like healthcare, industrial operations, environmental management, and security. Remote monitoring improves efficiency, minimizes manual oversight, and delivers timely insights for decision-making by employing sensors to collect data from distant locations, transmitting it through wireless or satellite networks, and processing it with sophisticated algorithms, frequently driven by artificial intelligence. It is important in numerous sectors to initiate a quick intervention to prevent from malfunctions or to forecast crucial situations that include medical equipment, industry devices (Lee et al., 2015), environmental monitoring, and surveillance. With the advancement in technology, remote monitoring advanced simultaneously. It provided more automation, improved scalability, and enhanced accuracy.

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The capability of governments, merchandises, and humans to see, administer, and command numerous systems, processes, and surroundings without being in person at place has been changed by the comprehensive technical method called as remote monitoring. It requires accumulating, transmitting, and interpreting the real-time data gathered from a far-off or unreachable place with the aid of devices like sensors, communication networks, and data processing tools. Remote monitoring has become necessitous in fields ranging such as medical, business operations, environmental management, agriculture, security, and smart cities.

With the incorporation of cutting-edge technologies like edge computing, Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT), Remote monitoring has become more capable, automated, and intelligent. In earlier times, analog sensors needed human assistance to gather and process data, manual inspections, and early wired communication systems have all obstructed the capability of remote monitoring. In industrial, medical sector, and urban infrastructure, large-scale system management and monitoring is viable due to this evolution. These methods have been susceptible to mistakes, lack the ability to offer insights in real time and were time-consuming. However, as an outcome of the advancement of technology, the field of remote monitoring has drastically transformed.

Explicitly, it has now become possible to deploy networked sensors and devices that acquire massive amount of data from physical systems and transmit it through networks with the integration of technology, thus, allowing automated control and real-time monitoring. The considerable developments in the area are employing AI to monitor distantly. Processing of enormous datasets gathered by remote systems intelligently can be done with the aid of these technologies. Human observers may overlook but Artificial Intelligence-based systems can identify the anomalies, forecast the trends, and spot the patterns for better data analysis. AI-driven predictive systems, for instance, can help monitor the machine's performance in industrial setups and recognize early indicators of wear or failure can assist in reducing downtime and lower costs.

Similarly in the healthcare industry, AI-governed remote monitoring systems possess the ability to surveillance patient data like blood pressure, glucose levels, and heart rate, etc. These systems may help in identifying potential health risks and notify medical experts for immediate assistance. In the discipline of environmental management, remote monitoring is necessitous for keeping a record of changes in ecosystem, tracking wildlife, and quantifying environmental indicators like quality of water and air. Remote sensing devices like satellites, drones, and ground-based sensors assist in gathering data across wide geographic areas and impart information related to concerns like pollution, deforestation, and the repercussions of variation in climate (Islam et al., 2023).

Another crucial use of remote monitoring is the security-surveillance systems that are deployed in monitoring social spaces, residential places as well as other crucial infrastructures. Often such systems employ Artificial Intelligence to drive video analytics to identify trends, breaches, or threat in a video stream in real time. The next frontier of remote monitoring is smart cities where computers are embedded in networks of interconnected sensors to control energy, traffic, etc. Remote monitoring also aids to optimize the use of resources, increase security, and improve the population's quality of life across smart cities in general. For example, in store systems capture data on vehicle movement and traffic density via cameras and sensors to inform city managers to Physical Traffic Management of the flow of traffic and reduce the overall travel time. On the same line, smart grids, for instance, monitor energy usage and adjust the network for electricity supply from one moment to the other to prevent overloading and ensure optimal energy utilization. Water and waste management also require tracking and monitoring of resource usage in order to identify both consumption as well as loss and ensure optimal utilization in Smart Cities also relies on remote monitoring. These systems collect information, which is analyzed, to generate relevant information that can improve the operation of cities and make it more efficient and efficient.

- Sensors: Sensors may be installed in remote locations whereby they collect different information, location, vibration, temperature, pressure, humidity, etc. These sensors should be tasked with the responsibility of collecting measurements of the environment or physical characteristics of an object and converting these measurements into electrical signals that, may be further processed.
- Communication Networks: Communication networks are very essential in passing data from the sensor to the monitoring system. However, there are many other ways data can be transmitted, for example through radio frequency, satellite systems, cellular systems (4G, 5G), though wireless networks such as Wi-Fi and Bluetooth, wired networks, and others. Early interventions can be made due to the flowing real time or near real time information between monitoring stations and the remote site as made possible by this link.
- Data Processing and Storage: Data collection is followed by data handling and data security. Cloud-based solutions are known to be integrated into many advanced contemporary systems of remote monitoring, as an efficient tool for data processing and storage. This makes handling big data possible and flexible at scale. To be processed, the data is analyzed with the help of algorithms which are often based on Artificial Intelligence and Machine learning: to detect the outliers, predict the trends, and generate the outcomes. It is needed for early decision making for timely responses.

- User Interfaces and Alerts: Real-time monitoring data and insights from the monitored environment are presented in the form of readable consoles, or graphical user interfaces (GUIs), which operators and managers can access to monitor the environment remotely. A lot of these systems come with some alerts that notify management whenever there is something out of the norm, something strange, or an event that ought to receive attention. The relevant parties will also be informed as soon as possible through alerts that can be sent in the email, SMS or by connected applications.

1.1 Remote Monitoring in Earth Sciences

Remote Monitoring performs a transformative role in analyses, management, and handling of natural and ecological processes, in real time. With the support of technologies such as remote sensing using satellites, drones, and other grounded sensors, continuous changes in environment like climate shift, deforestation, etc., can be tracked. Early and timely forecasting of natural calamities like forest fire, floods or earthquakes can aid in damage estimation and preparation of evacuation plan. This can act as a life saver in critical conditions. With the promotion of sustainable utilization of natural resources, remote monitoring helps in optimal resource consumption. It also tracks habitat changes and helps in preserving the endangered species from being extinct in order to conserve biodiversity. Furthermore, human activities like industrialization, urbanization impacting the surroundings can be assessed and monitored. By assessing the real-time data, remote monitoring empowers researchers, policymakers as well as disaster management personnel to cope with challenges related to earth sciences.

1.2 Role of AI in Remote Monitoring

Due to advancements in AI technology, remote monitoring has become an essential aspect with immense potential to enhance the ability to address a diverse category of industries' challenges efficiently and more systematically. The earlier forms of remote monitoring were predominantly residual, acquiring data with basic instruments and interpreting it with operators. At the same time, these systems had their weaknesses as far as the capability to process huge volumes of data instantly, detect complex patterns, and make forecasts regarding the future. However, the use of AI makes remote monitoring a more effective tool where the concerned data analysis can be undertaken automatically, the possibility of problems can be predicted in advance, various processes can be carried out efficaciously reducing the role of humans to a great extent. A few of the major domains for AI in remote monitoring are: Predictive maintenance, Anomaly detection, Automation of processes, Real-time decision making, and scalability.

- **Predictive Maintenance**

The largest implementation of AI in remote monitoring is in the practice of predictive maintenance. Large operational costs losses can be observed when equipment fails in industries such as manufacturing and energy, transport industries. Two traditional maintenance models, preventive maintenance carry out equipment maintenance irrespective of the condition the machinery may be in, or the failure, where equipment is repaired after it has failed. Both approaches are ineffective: The proactive maintenance approach may entail resource wastage through unnecessary changeovers or replacement while the reactive maintenance approach may lead to machine breakdown hence unnecessary time wastage (Tsvetanov, 2024).

Thus, to overcome these difficulties, predictive maintenance employing results of analyses of signals from the sensors for minor signs of wear or malfunctioning before they cause a fail are used. They are developed based on data history, which contains information on the performance of the equipment, failure characteristics, and working environment, and machine learning. These models can therefore predict how much more useful life the components have and they also recommend the correct maintenance schedules. For example, AI systems can analyze the vibration data of an industrial machine to detect signs of mechanical failure at the early stage and then plan repair to occur when breakdown is least expected. This strategy optimizes the expected, average, and useful life of equipment, decreases the costs of their maintenance, and reduces non-operational time.

- **Identification of Anomalies**

AI's another most useful capabilities is its ability to identify outliers in giant data sets, which is valuable to remote supervision systems. Identification of unusual characteristics or outliers in data that signify issues or potential concerns is referred to as anomaly detection. It was difficult for the operators in the traditional systems to identify every abnormality from the data since it required a lot of effort in paging through big volumes of data. AI, on the other hand, performs this on its own by scanning the data feeds and analyzing them with advanced machine learning algorithms in order to detect any outliers from the normal range if any available.

Thus, to overcome these difficulties, predictive maintenance employing results of analyses of signals from the sensors for minor signs of wear or malfunctioning before they cause a fail are used. They are developed based on data history, which contains information on the performance of the equipment, failure characteristics, and working environment, and machine learning. These models can therefore predict how much more useful life the components have and they also recommend the correct maintenance schedules. For example, AI systems can analyze vibration data of an industrial machine to detect signs of mechanical failure at the early stage and then plan repair to occur when breakdown is least expected. This strategy optimizes the expected, average, and useful life of equipment, decreases the costs of their maintenance, and reduces non-operational time.

- **Automation and Optimization of Processes**

Another useful competence of AI is its ability to identify outliers in giant data sets, which is valuable to remote supervision systems. Recognition of unfamiliar characteristics or outliers present in the data that signifies potential concerns is termed anomaly detection. In the traditional systems, it was burdensome for the operators to identify abnormalities existing in the data as a lot of effort was required to broadcast through enormous data. On the other hand as a consequence of intervention of AI, scanning the data feeds and analysing them with advanced machine learning algorithms in order to detect any outliers from the normal range if any available has been performed (Lee et al., 2015).

In application areas such as healthcare, security, and environmental monitoring Anomaly detection plays a very important role. As an illustration, the use of artificially intelligent remote monitoring healthcare systems employs the technology to record various vital signs, like blood pressure, oxygen saturation, and heart rate. On a continuous basis for patients who are discharged from the hospital may alert a medical team if any kind of anomalous behaviour is observed. For instance, if the oxygen saturation value dips suddenly to a low level abnormally, or if the heart rate instantly elevates higher than usual on a trending graph, with the assistance of artificial intelligence-based monitoring system, an alert may be sent to the medical team can initiate the desired action on time before things turn out of control. Likewise, sensor data about the quality of air and water acquired from stations maintained by government agencies or non-profit organizations, critical locations near residential neighborhoods, or picnic spots, technology can help to analyse, detect dangerous situations or increase in pollution levels that may warrant a quick response. Furthermore, the video streams from security cameras or motion sensor data to improve the effectiveness of security systems can be analyzed. Since it can detect anomalous behaviour faster than human operators, for example bursts of unexpected activity in a visual frame or unusually erratic motion sensor recordings, it can also alert security personnel to an unusual event ahead of time so that the team can take quick action and nip the situation in the bud.

- **Real-Time Decision Making**

AI-powered real-time decision-making improves remote monitoring systems' capacity to act quickly, which is essential in situations where harm must be stopped, safety must be guaranteed, or performance must be maximized. Due to the prior data requirement, transmission to a central location, and then followed by examination by human operators, traditional monitoring systems consume lot of time. On the contrary, AI based systems possess the ability to analyse locally acquired data in the cloud or through edge computing, which permits for faster decision-making and lower latency.

AI-assisted remote monitoring systems can serve to determine in real time the best available treatments for patients in the healthcare industry depending on their concerns (Islam et al., 2023). For patients under home monitoring systems, an emergency response team or medication adjustment can serve as the measures that the AI system can advise if their levels fluctuate. In an industrial setting, AI-based real-time data monitoring from machines and prompt modifications can be implemented to maximize efficiency, and cut down on energy usage, or avoid equipment breakdowns. Artificial Intelligence can stabilize the supply and demand in energy networks by making adjustments to avoid overloads or blackouts on the basis of evaluation of real-time data taken from power plants and customer usage.

In domain of environmental monitoring, dispensing the early warnings for natural disasters like floods, wildfires, or hurricanes by artificially intelligent real-time decision-making can assist save lives of millions. Likelihood of disasters can be predicted by the Remote AI systems that allows authorities to take pre-emptive actions, such as circulating of evacuation orders, deploying of emergency response teams, with the help of evaluation of data collected from satellite images, weather stations, and ground sensors.

- **Big Data Management and Scalability**

Remote monitoring systems give rise to the huge amount of data, thus, posing data management and analysis as a key challenge. Artificial Intelligence possess the capacity to process, filter, and analyse large-scale datasets at a speed and scale that is significantly faster than that of humans. With the use of machine learning models, deeper insights into the systems under consideration can be gained. AI based models can be trained using big datasets in order to identify hidden patterns and the existing correlations that would be difficult to analyse otherwise.

Further, these intelligent systems aid in dealing with the enormous influx of data and drawing insightful details to assist numerous sectors such as manufacturing and energy in which millions of sensors may spread across to facilitate. With regard to the smart grids AI based algorithms can consider the data collected from the millions of sensors and meters present across the grid in order to recognise the ineffectiveness, forecast the demand, and enhance the distribution of electricity optimally. Since these remote systems are scalable, this can be appointed in situation which is complex or over wide geographic areas, rendering data that is reliable and useful.

AI has the capacity to gain an understanding from the data and permits the remote monitoring systems to eventually advance in intelligence. As they process more data and enhance the algorithms, Remote systems increase their accuracy, reduce the errors of being identified as false positives, and become more equipped at forecasting future well. With this learning process, remote monitoring systems become capable of adjusting to changing situations and steadily become productive.

- **Enhanced Decision Support and User Experience**

AI enabled remote monitoring systems provide an enhanced user experience through intelligent dashboards, data visualization, and decision assistance tools. These AI-powered dashboards possess the capacity to show complex data in a comprehensible. These systems employ AI to prioritize alerts, weed out false alarms, and show users just the most pertinent information, in order to minimize the overload. In this manner, the operators can make well-informed decisions more expeditiously.

On the basis of the evaluation of the present and past data, these AI systems render decision support, to recommend the course of action from the anticipated results. The technology can further assist doctors, by suggesting appropriate treatment plans to patients based on the disease history, past treatments and real-time monitoring data. In industrial settings using AI's predictive analytics, systems can propose the best maintenance plans or operational adjustments accordingly. Additionally, these decision assistance technologies can provide users the ability to make more informed choices for improvement the productivity.

2 Artificial Intelligence Based Techniques in Remote Monitoring

With the expansion in development of reliable models that are capable to analyse volumes of data, recognise the abnormalities, forecast, and offer assistance in real-time decision-making, artificial intelligence has completely transformed the field of remote monitoring. Many AI enabled models ranging from sophisticated deep learning architectures to conventional machine learning algorithms are employed to ameliorate the performance of remote monitoring systems in varied domains.

- Machine Learning Models

Machine Learning, a subset of Artificial Intelligence, focuses on producing algorithms and statistical models that allow machines to learn from acquires data and use that for decision-making. Traditional method involves coding explicit instructions to perform tasks, whereas ML algorithms analyse datasets to identify existing patterns. This allows them to increase the performance over time without explicit programming. Machine learning have numerous techniques, such as supervised learning that entails training models using labelled data; unsupervised learning that focuses on recognising concealed patterns present in unlabelled data and in reinforcement learning, agents learn optimal responses through trial and error in dynamic situations. ML offers number of applications that include diagnosis of disease in healthcare, detection of fraud in finance, segmentation of customer in marketing, the domain of remote-monitoring, etc. Figure 1 presents the classification of ML approaches on basis of learning strategy.

Logistic Regression: Logistic Regression is a analysis method that is used to produce ML models when the dependant variable is binary in nature. It is used to characterize the connection that pertains among a dependent and multiple independent variables. The nature of independent variable may be nominal, ordinal or internal. LR obtains the identification from the log function, that is a sigmoid in nature and the outputs values lie between 0 and 1 (DeMaris & Selman, 2013). LR executes the work by learning from the training dataset, the vectors of related weights and the bias term.

$$z = \left(\sum_{i=1}^{n} w_i x_i \right) \tag{1}$$

"z" passes from sigmoid function represented by $\sigma(z)$ to create probability. The Sigmoid function is commonly referred to as Logistic function.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

To generate probability, it must ensure that $P(y = 1|x)$ and $P(y = 0|x)$ sums to 1.

$$\begin{aligned} P(y = 1|x) &= \sigma(w.x + b) \\ &= \frac{\exp(-(w.x + b))}{1 + \exp(-(w.x + b))} \end{aligned} \tag{3}$$

For the classification process, 0.5 is termed as decision boundary.

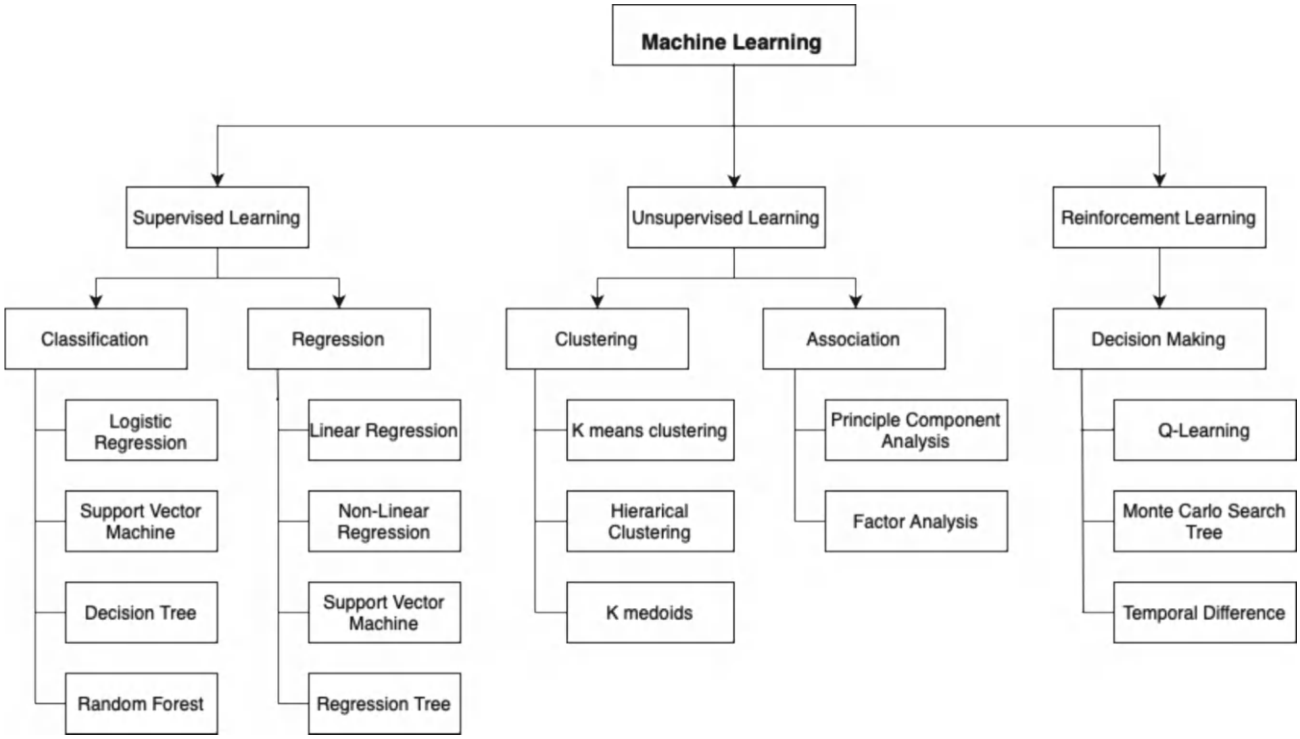

Fig. 1 Classification of ML approaches

$$\text{decision}(x) = \begin{cases} 1 \text{ if } P(y = 1|x) > 0.5 \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

Equations (1) to (4) represents the logistic formula (DeMaris & Selman, 2013).

ML Algorithms are widely applied onto the domain of remote-monitoring for applications such as anomaly detection, pattern recognition, and predictive analysis.

Support Vector Machines: A supervised ML technique, Support Vector Machine, classifies the data by recognising the ideal hyperplane which optimizes the separation between each class in an N-dimensional space. The classification task is choosing the most suitable hyperplane that maximizes the distance between the closest points of two distinct classes. The dimensionality of the input data affects whether the hyperplane will be a line in two-dimensional space or a plane in multi-dimensional space. The method determines the optimal decision boundary between classes to identify the ideal hyperplane from the given possibilities, the lines following the selected hyperplane are called as the support vectors (Chowdhary et al., 2020). SVM algorithm can be used to handle linear as well as non-linear classification problems. Figure 2, illustrates the diagrammatic working mechanism of a Support Vector Machine.

In remote monitoring, these algorithms are used to differentiate between conventional and abnormal behaviour of the system.

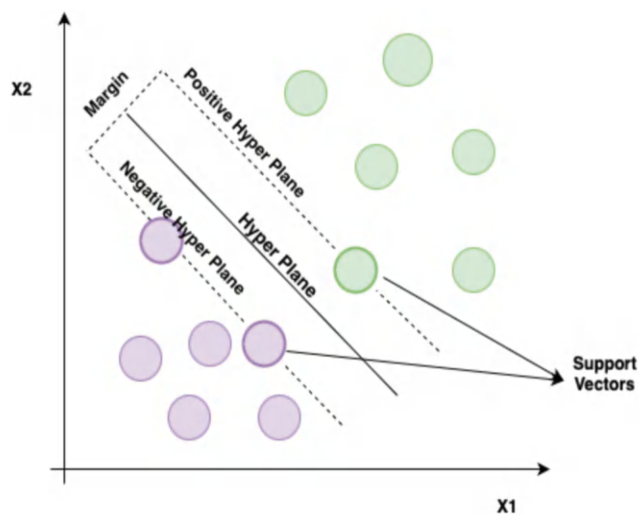

Fig. 2 Support vector machine

Decision Tree: Decision Tree (DT) is a supervised model that does not employ any parameters. DTs may be used for tasks related to classification as well as regression. The structure of the object can be delineated like a tree, central trunk, extended branches, mediatory nodes, and terminal leaves. Decision Trees simplifies the classification and regression concerns through an intuitive approach in modeling (Suthaharan & Suthaharan, 2016a).

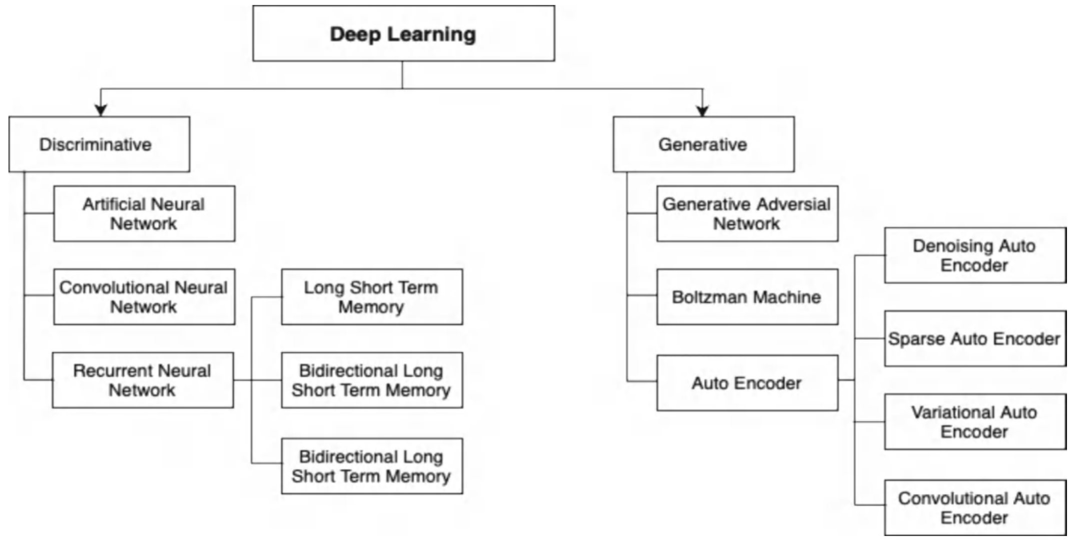

Fig. 3 Classification of deep learning approaches

DTs are implemented for classification as well as regression-related tasks. These also provide a visual illustration of decision-making process. Further, DTs can also help in identifying the basic reasons responsible for the occurrence of anomalies and forecasting the future malfunctions.

Random Forest Classification: Another prominent classification model, Random Forest (RF) Classifier, an improved bagged decision tree, is a supervised machine-learning technique used for accurately classifying and making informed decisions. During the input phase, a collection of decision trees is treated as a single entity, while the resulting output consists of several decision trees. To classify the new object within an input vector, position that input vector beneath all of the trees. The inaccuracies in the classification arise from the interplay between many trees and the individual strength of each tree within a forest. In order to minimize the error rate of the forest, it is essential to lower correlation among the trees and simultaneously enhance the individual strength of each tree. A tree with a low error rate is regarded as a robust classifier (Rigatti, 2017).

Random Forest is a highly versatile model, particularly effective when applied to large databases. This is an ensemble learning technique that boosts prediction accuracy by combining several decision trees. In remote monitoring systems, random forests are used to improve anomaly identification, risk assessment, and fault detection.

Deep Learning Models: DL is a subbranch of ML which revolutionized branch of AI by using neural networks with multiple layers called the deep neural networks to replicate and enable development of highly complicated models for the interpretation of composite data. The term "Deep" in DL signifies the implementation of NN with multi-layers. The NNs are created for replication of the way the human brain works and process the information by using the neurons that apprehend the intricate patterns present inside the data.

DNNs contain multi layers with interlinked nodes. Every layer is built on the prior layer in order to ensure refinement and improvement in the forecast process. The movement of computation in the forward direction in network is known as the forward propagation. Data is ingested in the network through input layer and the resulting prediction or result is received from the output layer, these layers are termed as the visible layers (Mathew et al., 2021). Figure 3, presents the classification of Deep Learning models on the basis of learning algorithm.

For the analysis of complicated and unstructured data, such as videos, images, and time-series data, deep learning models are especially useful. Since the multi-layered models possess the capability to identify complex patterns and features from sizable datasets this makes them appropriate for remote monitoring applications.

Convolutional Neural Networks (CNNs): CNN is a type of Deep Learning Neural Network Architecture. These connections are specialized for processing and analysing visual data collected as images. Thus letting them most appropriate in the field of CV (Bhatt et al., 2021). CNNs suits according to most of the tasks involving image recognition, video recognition, along with its segmentation and classification as it possess the capability of automatically learning special hierarchies of various features from the input image.
Key components of CNN include:

- Convolutional Layer
- Pooling Layer
- Activation Function
- Fully Connected Layer

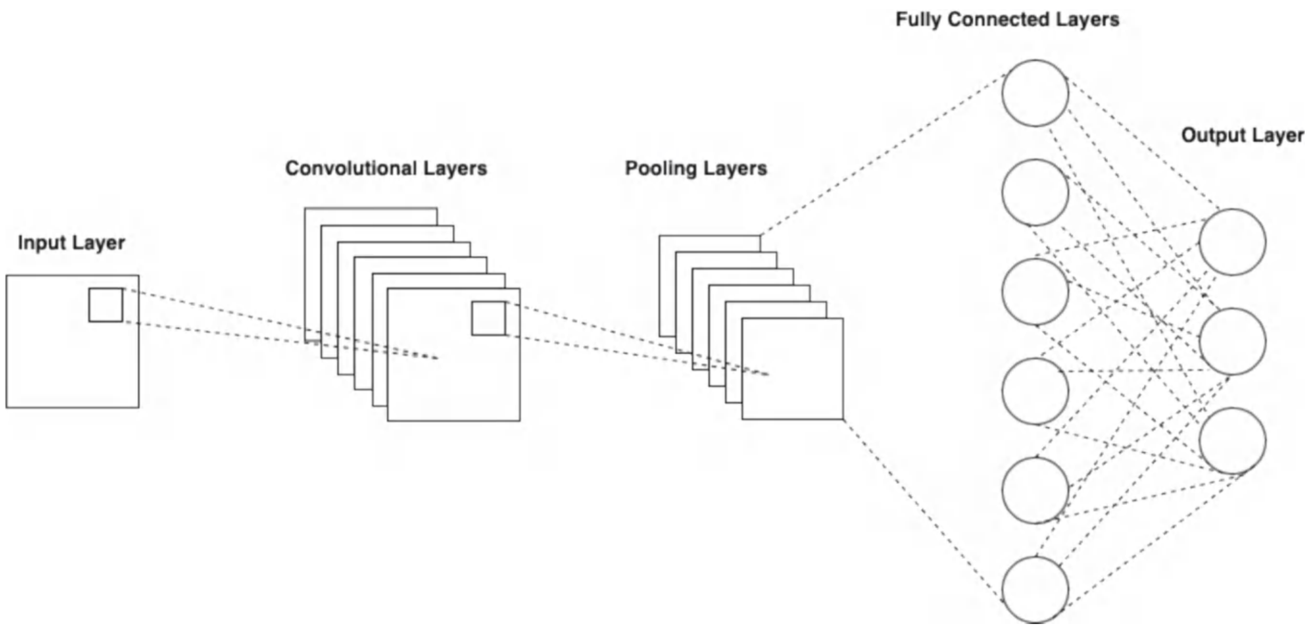

Fig. 4 Architecture of convolutional neural network

Figure 4, presents the design of a Convolutional Neural Network.

In remote monitoring CNNs are used for the visual inspections including finding anomalies in medical imaging, flaws in industrial equipment, and fractures in infrastructure.

Recurrent neural networks (RNNs): Residual Neural Network popularly known as Residual Network or ResNet are a type of CNN that are suitable for applications related to image processing and image recognition. In ResNet, the weight layers learn residual function from the input layer. To create a network, it stacks residual blocks over one another. Conventional deep networks often faced a problem of vanishing gradients or exploding gradients because of which the gradients which are used to update the network weight become too small or large. This resulted in a difficulty to train layers effectively. ResNet overcomes the issue by introducing residual learning that use shortcut connections by skipping multiple layers. Connections permit network for learning residual function with reference to the input layer.

Mathematically, if $H(x)$ represents the mapping, allowing layers to adjust residual mapping $F(x)$, then

$$F(x) = H(x) - x \tag{5}$$

which implies,

$$H(x) = F(x) + x \tag{6}$$

This helps the network during training by diminishing the degradation issue.

ResNet is often suitable for key point detection tasks where the aim is to locate some specific points on the object present in an image. The common ResNets are ResNet34, ResNet50, ResNet101, and ResNet152.

These are applied in time-series analysis as they handle sequential data well. In remote monitoring, RNNs aid to identify the patterns in sensor data, forecast system conditions, and recognise the irregularities over time.

- **Generative AI Models**: On the basis of patterns acquired, Generative models produce synthetic data and is capable to forecast potential future situations. Data augmentation and recreation under various situations in remote monitoring is the major strength of these models.

Generative Adversarial Networks: Generative Adversarial Networks (GANs) have two networks, one acting as a generator and other as a discriminator. They are employed to produce realistic synthetic data that can enhance training datasets for remote monitoring applications, hence boosting the model's resilience in identifying rare occurrences.

Variational Autoencoders: VAEs are a class of generative models that ascertain the fundamental distribution of the data. They can generate fresh data samples that mimic the original data, hence improving the training process for anomaly detection systems.

- **Ensemble Learning Models**:

The techniques to merge multiple machine learning models together to generate a single model is called ensemble methods. The basic idea is that by merging the predictions of several models, the comprehensive performance of ensembled model is enhanced, bias as well as variance is reduced (Mohammed & Kora, 2023). Some important terminologies include:

Base or Weak Learners—First level in ensemble learning architecture, these are trained to make predictions.
Meta Learners—These are in second level, and are trained on the output of base learners.

Ensemble models works on the strengths of distinct models and reduce their weaknesses, often lead to generalized predictions on unseen data. Popular Ensemble Techniques include Bagging (Bootstrap Aggregation), Boosting (Ganie et al., 2023), Stacking (Yoon & Kang, 2023) and Voting. Ensemble learning models integrate various machine learning algorithms to enhance accuracy, stability, and robustness in remote monitoring applications. These models utilize the advantages of distinct algorithms to enhance performance.

- **Hybrid AI Models**: The Hybrid models are the advance deep learning systems that integrate various machine learning architectures, or DL models with ML models for enhancement of the performance. Hybrid models are more powerful than Ensemble models. These models consider the strengths of different models to handle complex problems efficiently, thus leading to enhancement of performance of the model (Jena et al., 2021).

  There are different types of Hybrid Models:

- Different Neural Networks: This category of hybrid deep learning networks are combination of different types of neural networks. This includes CNN-RNN Hybrids that are combined to use best of their strengths. CNNs have the capability to capture spatial features present in the images whereas RNNs handle sequential data well. When this hybrid model is used for an application like video analysis, CNN can extract spatial signals from each frame whereas RNN can capture the temporal dependencies between the frames. Another example is CNN-LSTM Hybrids. LSTM is a kind of RNN that is capable of managing sequences (Rashid et al., 2018).
- GANs with Other Networks: Generative Adversarial Networks is an unsupervised neural network. It is used for variety of tasks like generating realistic images, synthesizing the images from text, and creating new images etc. To enhance capabilities of GANs, hybrid models can be created. This includes Autoencoder-GAN Hybrids, that use Autoencoder to pre-process the data and reduce the noise before feeding to GAN. Due to the improved quality of data, the overall performance of GAN is enhanced. Another example include GAN-RNN Hybrid. This hybrid model has been effective for generating sequential data. The GAN ensures generation of realistic sequence, and RNN handle temporal dependencies (Sharma et al., 2024).
- Attention Mechanisms in various architectures: Attention mechanisms focus at important input elements. In case of large dataset, that is difficult to model as whole, attention mechanisms allows to concentrate on essential part. It includes Attention based CNNs that allows to focus on important part of the image. Another example includes Transformer CNN Hybrid. Transformer is yet another strong attention mechanism. When combined with CNN, it improved the tasks that needed local feature extraction and global context understanding (Nguyen et al., 2018).
- Deep Learning with Machine Learning: The deep learning models if combined with traditional machine learning models can generate hybrid networks with improved ability to interpret complex patterns at the same time traditional algorithm's interpretability. For an example deep feature extraction with classical algorithms. Deep Learning model such as CNN can be used to retrieve features from raw data that can be fed into classical ML models like SVM, Random Forest. Apart this ensemble models can also be combined with deep learning models to improve its performance (Mohammed & Kora, 2023).

Hybrid AI models integrate many AI methodologies to capitalize on the strengths of each approach, resulting in more resilient and adaptable systems for remote monitoring. These models can amalgamate machine learning with rule-based methodologies to enhance decision-making processes.

- **Reinforcement Learning Models**: Reinforcement learning (RL) is a category of machine learning in which an agent acquires decision-making skills through interaction with its environment. Reinforcement learning techniques are especially appropriate for remote monitoring applications that require real-time decision-making and adaptive control.

Q-Learning:

A value-centric reinforcement learning methodology that facilitates the optimization of decision-making by identifying the most advantageous action in a specific situation. These models are primarily used for adaptive control systems as well as real-time process management.

Deep Q-Networks:

Deep Q-Networks (DQNs) can manage extensive state spaces by approximating the action-value function through neural networks as it combines Q-learning with deep learning. DQNs render them appropriate for intricating into the remote monitoring tasks.

3 Embedding AI into Remote Monitoring Systems

Artificial intelligence powered remote monitoring systems aim to enhance the capacity of systems while gathering, analysing, and responding to data in real-time. Automation and the ability of these systems to make data-driven judgments come as a consequence of incorporation of AI technology. Diverse sectors have been facilitated with the ongoing surveillance, anomaly identification, predictive upkeep, and effective operational management.

- **Internet of Things (IoT) and Artificial Intelligence**
  - Data Acquisition: AI-driven remote monitoring systems depend significantly on Internet of Things (IoT) sensors to gather data from diverse sources, including industrial machinery, environmental factors, healthcare instruments, and others. These sensors continuously collect substantial amounts of data and communicate it to centralized or edge-based AI platforms (Mohammadi et al., 2018).
  - Real-Time Data Analysis: AI systems analyse data instantaneously to detect patterns, trends, and abnormalities that may elude human operators. AI and IoT together allows remote systems to adopt and respond well to situational change autonomously.
- **Edge Computing and On-Device AI Processing**
  - Edge AI: Amalgamation of Artificial Intelligence with edge computing has done wonders in the areas of remote monitoring, it has enabled data processing locally near the source of data for an example at network's edge. This aids in prompt decision-making, reducing the latency, and generating more agile systems.
  - Reduced Data Transmission: With the ability to process data locally, the technology when embedded into edge devices decrease the need of sending significant amount of data to centralized servers. This in turn enhances the efficiency and cost-effectiveness of remote systems by reducing the bandwidth consumption and data transmission outlays.
- **Machine Learning and Deep Learning Integration**
  - Pattern Recognition: Artificial Intelligence based Machine Learning techniques are used in the remote monitoring to identify patterns present in the data. In industrial and environmental sectors, these use of these algorithms can help to recognise anomalous patterns in machine's performance prior to failure.
  - Predictive Analytics: With the use of historical and real-time data, Deep Learning models can be employed to forecast future trends. These models can prognosticate failures in equipment, energy requirement, or probable security violations, permitting implementation of preventive measures.
- **AI-Powered Computer Vision System**
  - Visual Data Analysis: Computer Vision when integrated into remote monitoring systems can assist in the evaluation and interpretation of visual data obtained from the cameras and sensors. Applications like as security surveillance, industrial automation, and environmental monitoring use the technology extensively.
  - Anomaly Detection: For the analysis of images or video feeds for anomaly identification, like unauthorized access, product flaws, alterations in ambient conditions, or atypical movements in monitored regions, AI based models are applied. This improves the system's capacity to address faults instantaneously.
- **Natural Language Processing (NLP) in Monitoring Systems**
  - Human-Machine Interaction: Incorporation of Natural Language Processing into remote monitoring systems promotes the communication between the system and its users. In this way, operators can engage users with AI-driven systems through natural language, allowing them to issue commands and receive explanations in a user-friendly way.
  - Data Interpretation: AI based remote systems also embed natural language processing to evaluate and interpret textual data like log reports and warnings. This helps in deriving important insights from unstructured data, thus allowing better and informed decision-making.
- **Embedding Explainable AI (XAI) Techniques**
  - Transparency in Decision-Making: Methodologies incorporating Explainable AI (XAI) when unified into AI-powered remote systems helps to improve the system's transparency. With this, AI process for decision making becomes more comprehensible to users. By enabling them to discern the rationale behind particular alerts or recommendations.

  – Regulatory Compliance: Sectors such as healthcare, banking, etc. where adherence to regulatory and compliance is mandatory by delivering transparent elucidations of AI-driven actions is a major support.
- **Automation of Alerts and Response Mechanisms**
  – Automated Alerts: Upon the detection of anomalies or irregularities, AI powered systems in the domain of remote monitoring can autonomously generate notifications. In accordance to the severity of the issue, alert alarms are prioritized, promising that crucial situations obtain sudden response.
  – Automated Decision-Making: Remote AI systems are intended to detect concerns and then apply the specified steps for the solution of the problem. If a machine, for an instance, is about to get overheating, the AI enabled system can independently turn it off or adjust its operational parameters to avert from damage.
- **AI-Driven Predictive Maintenance**
  – Failure Prediction: Another crucial application of AI in remote monitoring is the predictive maintenance. On the basis of examination of sensor data and previously available maintenance records, AI models aid to forecast potential failures that allows pre-emptive repair before breakdowns occur.
  – Cost Reduction: On integration of the technology into remote monitoring for predictive maintenance eliminates the operational expenditures. This is done by reducing unanticipated downtime and prolonging the longevity of machinery and equipment.

4 Application of Remote Monitoring Along with the Impact Analysis of AI

- **Healthcare**: Popularly called telemonitoring, remote monitoring in this field enables medical personnel to keep tabs on a patient's vital signs and health issues from a distance. The facility is helpful for senior citizens having mobility concerns, patients who need post-operative care, and the patients with chronic conditions. Remote devices like the wearable sensors, smartwatches and trackers continuously measure blood pressure, oxygen, glucose levels, heart rate, and blood pressure. The data collected from these devices can be used to recognize and identify the abnormalities thus serving as early indicators, offering timely healthcare assistance (Islam et al., 2023). The application could be witnessed during the recent pandemic COVID19 (Vaishya et al., 2020).
  – **Impact of AI in Remote Healthcare**: Remote patient health monitoring systems aids in continuous and real-time follow up of health of the patients suffering from chronic and serious ailments. AI-enabled wearable gadgets and sensors gather vital data like heart rate, blood pressure, glucose levels, etc.
  – **Use Case**:
    Predictive Health Analytics: AI can be used to forecast the future health problems by analyzing the patterns and insights in patient data. These AI algorithms are capable of assessing the key disease related parameters and recognize the peculiarity prior to the development of conditions leading to early and timely diagnosis (Tsvetanov, 2024).

    Anomaly detection: As soon as any significant variations in a patient's vital signs is observed by the AI systems, medical professionals are notified to initiate an appropriate action.

    Telemedicine Support: On the basis of evaluation of patient's vitals acquired by monitoring device, telemedicine consultations can be organized in order to provide remote assistance.
- **Industrial Monitoring**: Industries such as manufacturing, energy production, and oil and gas, employ AI powered remote monitoring systems to supervise machinery, assess operational performance, and forecast maintenance needs. Sensors can be used to keep a measure of temperature, vibration, and performance indicators on machinery for tracking wear and tear. AI-powered predictive maintenance can analyze the data points enabling preventative maintenance. In this way, the operational efficiency is enhanced and downtime as well as maintenance cost is lowered. In energy sector, remote monitoring of turbines, pipelines and grids guarantees maximum performance and early identification of problems (Lee et al., 2015).
  – **Impact of AI in Remote Industrial Monitoring**: AI-driven remote monitoring system rely on data acquired from sensors employed with the help of Industrial Internet of Things (IIoT) (Mohammadi et al., 2018). This offers real-time tracking of machinery and equipment in industrial settings. The two primary areas of focus are predictive maintenance and automation.
  – **Use case**:
    Predictive Maintenance: Data gathered from the sensors that track a machine's temperature, pressure, vibration, and other factors can be analyzed using AI based algorithms. The technology be used can predict the break-down of a machine by spotting anomalous patterns, enabling proactive maintenance and reducing downtime.

    Operational Efficiency: Real-time data analysis by Artificial Intelligence systems help to make automatic adjustments. With this, efficiency can be maintained in industrial processes. Optimized use of resources like energy, water, or raw materials is maintained.

Irregularity Identification: AI can provide assistance for the detection of irregularities in the normal functioning of machinery. This may point to future malfunctions or breakdowns. Further, identification of unusual characteristics that might be precursors to failure is done.

- **Environmental Monitoring**: Remote devices for environmental monitoring can be used for the management of natural resources, tracking the climate change, and wildlife. Sensing devices are used by the systems in order to measure features related to levels of pollution, temperature, moisture content of soil, and air and water quality. The data is acquired using devices like satellites, drones, and other IoT devices which are used to monitor biodiversity shifts, urbanization, and deforestation. AI-based algorithms by using large datasets collected from these sensors can perform patterns recognition, simulate climate change and issue alerts for natural disasters like floods etc. The beneficiaries include government policymakers and environmental conservation activity planners (Mohammadi et al., 2018).
  - **Role of AI in Remote Environmental Monitoring**: Consistent tracking of environmental indicators like quality of air and water, forecasting of natural disastrous events frequently use AI based remote monitoring systems.
  - **Use Case**:
    Air Quality Monitoring: With the data acquired by satellites, drones, and ground-based sensors, Artificial intelligence (AI) systems can measure the quantity of pollutants in air. These systems can further assist in policy making by identifying pollution sources and predicting pollution patterns.

    Monitoring Water Quality: With the examination of data extracted from the sensors near the water bodies, Artificial Intelligence based systems can predict the contamination level. Water resources can be protected in a timely manner if early contamination is identified.

    Timely Warnings: By interpreting the trends in weather and other related data, natural disasters can be predicted by AI models. In this manner, precautionary actions to reduce damage can be taken, thus, saving lives by issuing early warnings.
- **Agriculture**: Real-time remote data monitoring systems have transformed the agriculture sector. From data related to the soil conditions, health of the crop, weather patterns, and pest activity have revolutionized the farming operations. Images related to crop health are captured by drones fitted with cameras and sensors, and sensors positioned in fields track the amount of moisture and nutrients in the soil. The resultant includes maximizing the fertilization of land, proper irrigation, and pest management. In this way, farmers can save resources and increase crop yields. Remote Monitoring offer a more sustainable way of modern farming considering climate change and food security.
  - **Role of AI in Remote Agriculture Monitoring**: Smart agriculture using remote monitoring devices provide real-time data on crop health, weather, soil conditions, and resource utilization. Artificial Intelligence has transformed the agriculture in the modern day.
  - **Use Case**:
    Crop Health Monitoring: AI-powered drones and satellite imaging can gather early indicators related to crop illnesses or infections. This allows farm care takers to initiate appropriate action before damage.

    Irrigation Management: With the implementation of AI based remote irrigation systems, irrigation schedules can be optimized. This will be helpful to make sure that crops receive timely and proper quantity of water, minimizing waste and increasing agricultural yields.

    Resource Optimization: Artificial Intelligence remote system helps to optimize the use of agriculture related resources like water, herbicides, and fertilizers, etc. This results in the optimal use of resource and better evaluation of real-time data on soil and environmental conditions.
- **Security and Surveillance**: Another benefitted field is intrusion detection and surveillance in the field of security. Modern systems for monitoring public areas, vital infrastructure, and private properties are AI-powered video analytics and Internet of Things (IoT) sensors based. Data from motion sensors and video cameras is accumulated at central monitoring center (Alzubaidi et al., 2021). Video feeds to look for threats, unauthorized access, or unusual activity are examined using AI algorithms.
  - **Role of AI in Remote Security and Surveillance**: AI powered remote monitoring in the security and surveillance has by allowed real-time data processing via cameras, sensors, and drones.
  - **Use Case**:
    AI-Powered Video Analytics: Real-time video footage is analysis can be performed to identify any kind of suspicious actions like prolonged and unauthorized access, or unusual movement patterns by AI systems. The timely and desired reactions can result in effective surveillance.

    Biometric monitoring and facial recognition: AI based face recognition systems can be implemented to identify people in busy public places or restricted areas as well. This will help to enhance security in critical locations.

5 Challenges and Considerations

Along with the several advantages the integrating Artificial Intelligence with remote monitoring systems provides, it also entails some obstacles and considerations that must be addressed for efficient deployment.

- **Data Quality and Accessibility**
  The effectiveness of AI based remote system largely depends upon the quality of data. Some key challenges are:
  - Inconsistent or Incomplete Data: The data acquired from sensor may be unreliable, and compromised. This may result in false AI predictions.
  - Data Latency: Fast data processing is a key functionality required from a real-time monitoring system. Any kind of delay in data transmission can adversely affect the efficacy of AI-driven decision-making (Dong et al., 2021).
- **Scalability Issues**
  Extensive Data acquired from numerous sources is fed into an AI-driven remote monitoring systems for processing. Sometimes a huge volume of data from numerous sensors or devices, is received, which may lead to scalability problems. The key challenges are:
  - Significant Computational Expenses: As the number of AI models are required to analyze data from several sensors in real time increase, computational expenses and heightened energy usage also elevate substantially (Tsvetanov, 2024).
  - Network Bandwidth Limitations: Considerable bandwidth is needed in order to transmit significant quantities of data from remote sites to centralized processing units.
- **Security and Privacy Concerns**
  While incorporating AI into Remote monitoring systems, data security and preserving user privacy are essential are major concerns. The main challenges are:
  - Data Breaches: If the sensitive information is accessed in an unauthorized manner, this can result in privacy violations and the exposing of confidential data (Islam et al., 2023).
  - AI Vulnerabilities: AI models are prone to adversarial attacks where malicious inputs can be employed to manipulate the system's predictions.
- **Algorithmic Bias and Ethical Implications**
  The presence of bias in AI systems can lead to erroneous and false predictions. Addressing the concerns related to biases, AI-powered remote monitoring systems can yield equitable and impartial results (Sarker, 2024). The key challenges include:
  - Training Data Bias: Skewed and imbalanced datasets may lead to development of AI models that yield biased outcomes. These models fail to generalize effectively across many contexts.
  - Ethical Implications: Domains like healthcare, security and surveillance have certain ethical considerations. Automated decision-making by AI systems provokes significant concerns, erroneous predictions in these systems may yield in severe repercussions.
- **Cost of Implementation and Maintenance**
  AI-based remote monitoring systems can possess substantial initial investment and maintenance cost. This includes direct and indirect cost related to hardware installation, software, data management, and technical proficiency. The challenges may include:
  - Huge Initial Investment: Considerable expenditures on hardware, software and well qualified operational personnel are required for the implementation of AI technology enabled systems.
  - Maintenance and Upgrades: To guarantee the effectiveness, security, and alignment with the latest technology enabled systems, timely upgradation and maintenance are essential.
- **Real-Time Decision-Making**
  In the primary remote monitoring applications areas like industrial automation, healthcare, and smart grid management, real-time decision-making plays a very crucial role (Suthaharan & Suthaharan, 2016b). These AI-enabled remote systems must possess the capacity to efficiently process gained data with high precision for developing insights in time-sensitive scenarios. The primary challenges are:
  - Processing Delays: The efficacy of real-time decision-making systems depends on the data processing delays. The prolongated obstructions may result in safety hazards.

Challenges related Scalability: With rise in the data volume, real-time processing may encounter certain challenges and concerns related to capacity to scale.

6 Discussions and Future Scope

The advancement in the technology has significantly impacted the remote monitoring sector. These systems perform so by acquiring, assessing and analyzing the remote data gathered using certain tech-powered remote devices that may use technologies such as IoT, Edge Computing etc. By delivering prompt insights and actions derived from real-time data streams, this integration has revolutionized multiple areas like healthcare sector, energy management, environmental monitoring, and industrial automation, etc. The plethora of AI algorithms ranging from traditional machine learning to advanced deep learning models, the systems possess the capability to recognize essential patterns in data and forecast the faults and anomalies. The upgradations have resulted into development of robust and resilient technology-powered system offering consistent remote data analysis and reliable monitoring systems adhering to the standards laid by the agencies like General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) for safeguarding customer data.

The advancements in Artificial Intelligence are directly impacting the remote monitoring sector. With the Explainable AI based methodologies, more transparent and reliable remote decision-making systems can be generated. This transparency establishes better user trust and ensure endurance to ethical implications. The research is likely to concentrate around the adaptability of AI systems to varied contexts. This may incorporate advancements in decentralized learning methods like federated learning. Further, AI models capable of functioning effectively on resource-limited devices may be explored.

Artificial Intelligence have to capability to induce some noteworthy changes across numerous sectors. This can include advancements in predictive capabilities, operational efficiency, and decision-making time with focus on sustainability, scalability, and other related ethical implications. Artificial Intelligence based remote-monitoring systems will facilitate the generation of novel opportunities assisted with innovation and research, leading to more intelligent, adaptive, and robust solutions in an evolving environment.

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Role of AI in Estimating Potential Aftershocks During Earthquake

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Abstract

One of the most significant developments in seismic hazard assessment and disaster preparedness is the role that Artificial Intelligence will play in the estimation of the aftershock potential immediately following earthquakes. Generally speaking, aftershocks are the smaller earthquakes that follow the main shock of a bigger seismic event, occurring as adjustments of the Earth's crust take place along the fault line of the primary quake. The study of aftershocks provides insight into the mechanisms of fault mechanics and seismic wave behavior, improving predictive models and reducing uncertainty with respect to future seismic activity. Traditional methods of aftershock prediction involve statistical models and/or historical data and usually carry limited predictive power. The coming-of-age of AI, more precisely machine learning, made it a strong tool to enhance such prediction through real-time analysis of complex seismic data sets. The allowance of the integration of AI into seismic monitoring and response frameworks will provide better estimates of aftershock probabilities to help with emergency response efforts, optimize resource allocation, and ultimately reduce the impact of subsequent seismic events on affected communities. This chapter speaks to the importance of methodologies that will revolutionize aftershock estimation through AI. In this work, we walk through some techniques, such as supervised learning, neural networks, and ensemble methods, and their applications in seismic data analysis. The AI models recognize patterns and correlations, beyond the realm of traditional and manual processing, by ingesting real-time earthquake data, historical seismic records, and geological information. Such models can dynamically update predictions at every new data availability with far better accuracy and timeliness. We further detail how AI integrates into current seismic monitoring systems, those cases in which AI-driven predictions have successfully informed emergency response strategies and risk management practices. We further discuss overcoming challenges in data quality, model interpretability, and computational demands, as success for these AI models is bounded by quality and quantity since training datasets drive the accuracy; poor or biased data will yield unsuccessful, biased predictions. Much more important is the fact that AI in typical seismic monitoring systems should be integrated with due care for transparency and interpretability regarding algorithms to make sure that the predictions are reliable and understandable for human operators.

Keywords

Artificial Intelligence (AI) · Machine learning · Aftershocks · Seismic hazard assessment · Seismic wave behaviour · Predictive models · Real-time data analysis · Supervised learning · Neural networks · Ensemble methods · Seismic data analysis

1 Introduction

Smaller seismic occurrences known as aftershocks occur after a major earthquake defined as the main shock. Aftershocks can have a significant influence even if their magnitude is

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usually lower. They might happen days, weeks, or even years after the primary event. With the greatest recurrence rates observed soon after the main shock, their frequency usually declines with time. These events occur as a result of the earth's crust realigning itself after the main shock-related stress release, which causes more seismic activity to occur until the geological structures stabilize. For the purpose of evaluating continuous seismic risk, it is essential to comprehend the behavior and patterns of aftershocks since they can exacerbate the damage already done to infrastructure and make emergency response operations more difficult. Additionally, research on aftershock dynamics aids in the creation of predictive models.

1.1 History

The study of earthquakes has experienced a remarkable evolution from stories in antiquity to the current scientific methods that are applied. In ancient times, myths and religion were believed to have an impact on natural calamities like earthquakes. People from many cultures around the world, such as Greece, China, and Japan, connected the earthquakes and their aftershocks to the actions of vengeful gods or otherworldly entities.

This mythology was widely accepted then. The majority of these explanations were based on observed patterns rather than a methodical analysis of the phenomenon. The nineteenth century saw a shift in the scientific understanding of earthquakes, which was aided by numerous developments in observational equipment. The invention by John Milne and later by Charles F. Richter of the seismograph gave a footing for more quantitative analysis of seismic activity. An earthquake magnitude scale introduced by Richter in 1935 would make the measurement of earthquake magnitude possible and provide a clearer picture of what was released in terms of energy during a seismic event. Early theories and models aimed to explain aftershock behavior were also formulated within this period, though based on very limited empirical evidence.

A rock burst is defined as the sudden underground collapse of rocks in mine excavations, which causes great risks to miners. In this paper, a long-term prediction of rock bursts will be developed using accuracy enhancement and machine learning, hence minimizing the risk of subjectivity (Pu et al., 2019). The other development for the field came in the form of statistical models in the late twentieth century with Omori's law, which laid the framework for understanding the frequency and decay of aftershocks as a function of time since a main earthquake. The results, which Omori published in 1894, revealed that the rate of occurrence of aftershocks decreases as a function of time, but still very much rested on historical data and assumptions that failed to activate all the variables.

The dawn of the twenty-first century spelled an entry of a completely new era in seismology with the advent of AI. The incorporation of AI and machine learning techniques into the analysis process enables real-time data analysis with more dynamic and accurate determinations of aftershock activity. These advances have obviated some of the limitations of earlier statistical models by using vast volumes of real-time data and sophisticated techniques for computing, thereby enabling the prediction of aftershock with greater precision. This is a promising front in earthquake science that may save lives or at least soften impacts through more effectively predicted preparedness strategies.

2 Aftershock Shedding Process and Normal Prediction Methods

Smaller seismic events known as aftershocks occur after a larger one because the first seismic event causes the Earth's crust to adjust to new stress conditions. Predictive models and the study of earthquake dynamics both benefit from aftershock analysis. Aftershock behavior and forecasting are theoretically based on the mechanisms that generate them as well as by statistical models that attempt to explain their patterns.

2.1 Aftershocks and Failure Mechanism

By using dense seismic data and derived aftershock hypocenters and their focal mechanisms, the authors of the paper came to a conclusion that the aftershocks tend to happen in fractures surrounding the main shock fault rather than on the fault plane itself. It was found that the thickness of the distribution at 1.0–1.5 km was greater than the fault damage that was seen in the field. In contrast to earthquake swarms in geothermal locations, which are propelled by fluid migration, main shock heterogeneity explains the majority of aftershocks in terms of co-seismic stress variations. The findings point to distinct processes for aftershock and swarm development (Yukutake & Iio et al., 2017). The primary cause of aftershocks is the Earth's crust failing mechanism. A powerful quake puts a lot of stress on the crust. Instead of being almost evenly distributed, the stress is more concentrated in the areas close to the fault plane. More seismic activity in the area could be caused by the initial rupture along the fault line, which creates a complicated stress field.

The stress redistribution theory states that tension in the fault plane and its surrounds redistributes following the main earthquake. This might be big enough to break through the rocks' local resistance, cause more rupture, and cause aftershocks. Occasionally, this process can be explained by the idea of static stress transfer, in which variations in stress brought on by the first shock Occasionally, this process can be explained by the idea of static stress transfer, which holds that variations in stress brought on by the first shock increase the possibility of subsequent failures in nearby faults or areas of the same fault system. By estimating the changes in stress based on the fault's geometry and the crust's material properties, redistribution of stress may be described using elastic theory. Dynamic triggering is another key idea in the interpretation of aftershocks. Dynamic triggering occurs when the main shock's seismic waves pass through the crust, interacting with different fault systems and perhaps setting off other aftershocks along non-contiguous sections as a result of the initial stress change events. The phenomenon is caused by complex interaction between fault structures that are already present and seismic waves. In order to predict aftershocks, scientists utilize a number of statistical models. Over time, these have evolved. Models use patterns that emerge after some other earthquakes to estimate the frequency, magnitude, and temporal distribution of aftershocks. The 1989 Loma Prieta earthquake's aftershocks do not fit into traditional models for main shock-aftershock interaction because their slip orientation suggests a nearly uniaxial stress field in which the maximum principal stress acted almost normal to the main shock's fault plane, as opposed to responding to changes in stress from the mains hock.

This further implies that the main shock's stress decrease was almost complete and that the fault's strength relaxation had a significant impact on the aftershocks production. Further highlighting the complexity governing aftershock behavior, the main shock rupture was limited to areas of the fault where there were pre-existing shear loads capable of initiating slip (Al Banna et al., 2020). Omori's Law, put forth by Fusakichi Omori in 1894, is among the most established and generally recognized statistical models. Omori's Law computes the aftershock frequency decrease over time after the main shock. According to the model, $N(t)\ \partial\ 1/(t + c)p$, where $N(t)$ is the number of aftershocks at time t and c and p are fitting parameters, the number of aftershocks is a function of time that follows the power law diminishing.

P is a parameter derived from actual data. This law reflects the experimentally established trend that aftershocks are most often generated soon after the primary shock and subsequently diminish over time. The Omori's Law was refined and changed to incorporate aftershock rate and magnitude variation in Ito's Law and the Utsu-Ogata model. Early in the twentieth century, Ito's Law was created, which more precisely combines the presentation of correction factors for empirical data in specific places. From here, the Utsu–Ogata model expands on Omori's Law with additional parameters, accounting for the main shock magnitude and the features of regional seismicity. Another significant advancement in the field of aftershock prediction is Bath's Law, which establishes a correlation between the main shock's magnitude and the anticipated number of aftershocks. Larger main shocks typically produce more aftershocks, which is indicative of a greater amount being released and maybe a more severe reactivation of a fault system.

The modern development of AI has been accompanied by the infusion of learning. A model that uses interactions between strong and moderate earthquakes in a region. Applied to Southern California for $M \geq 6.4$ earthquakes from 1932 to 1979, the algorithm successfully predicted 9 out of 10 events with an average spatial accuracy of 58 km and an average delay of 9.4 years. Following this period, from 1980 to 1988, four significant earthquakes occurred, with three—Coalinga (May 1983), Chalfant Valley (July 1985), and Superstition Hills (November 1987)—successfully predicted by the algorithm, demonstrating its ongoing relevance and accuracy in earthquake forecasting (Prozorov & Schreider et al., 1990). These methods educate algorithms to recognize intricate patterns and produce more precise forecasts by utilizing massive datasets of seismic activity. The predictions provided by statistical models are set at their historical assumptions and parameters, but machine learning-based models can dynamically update their forecasts with fresh real-time data. Given in different ways, the study of aftershocks addresses the mechanisms that govern failure inside the crust of the Earth and utilizes statistical models to predict their behavior. Theoretical understanding of dynamic triggering and stress redistribution complements empirical models created for aftershock activity forecasting. Advancements in technology and computing techniques additionally amplify the precision of aftershock prediction computations about seismic readiness and risk mitigation. Table 1 illustrates the different types of prediction models by various researchers.

3 Mechanism and Historical Models: Fundamentals of Artificial Intelligence and Machine Learning

The study of historical models and underlying ideas that have influenced the development of artificial intelligence (AI) and machine learning (ML). Machine learning (ML) focuses on algorithms that learn from data and get better on their own, whereas artificial intelligence (AI) aims to build systems that can do jobs that require human-like intellect.

Neural networks, which emulate brain activity, are examples of advanced models that were made possible by earlier models like rule-based algorithms and symbolic reasoning systems. Deep learning's comeback in the twenty-first century has transformed fields like computer vision and natural language processing.

Table 1 Different prediction models

Prediction method	Description	Paper	Author
Rule-based methods	To produce predictions, these systems use pre-established rules that are drawn from expert knowledge	Application of Artificial Intelligence in Predicting Earthquakes: State-of-the-Art and Future Challenges	Al Banna, M. H., Taher, K. A., Kaiser, M. S., Mahmud, M., Rahman, M. S., Hosen, A. S., & Cho, G. H. (2020). Application of artificial intelligence in predicting earthquakes: state-of-the-art and future challenges. *IEEE Access*, *8*, 192880–192923
Shallow machine learning	Algorithms that can examine data and identify patterns, such as decision trees, support vector machines, and linear regression		
Deep learning algorithms	These make use of neural networks to handle big datasets and identify intricate patterns that conventional techniques could miss		
Analysis of time series	Predicts the earthquake magnitude for the following day by using past magnitude data as time series input	Artificial neural networks for earthquake prediction using time series magnitude data or Seismic Electric Signals	Moustra, M., Avraamides, M., & Christodoulou, C. (2011). Artificial neural networks for earthquake prediction using time series magnitude data or seismic electric signals. *Expert systems with applications*, *38*(12), 15032–15039
Seismic Electric Signals (SES)	SES is used as input data to forecast the timing and magnitude of earthquakes		

3.1 Overview of Machine Learning

A significant area of artificial intelligence (AI) is machine learning (ML), which is the creation of algorithms that automatically learn from data and generate predictions based on it. Whereas statistical models relied mostly on pre-programmed rules and assumptions, machine learning (ML)-based algorithms extract predictive power from datasets through repeatedly iterated learning processes. This distinction enables machine learning (ML) to identify intricate patterns and relationships in data that conventional techniques can miss. supervised learning, unsupervised learning, and reinforcement learning are three of the main paradigms in machine learning.

(1) Supervised Learning is the most widely used ML technique, wherein algorithms are trained on a labelled dataset with a predefined target outcome. It is within this paradigm that algorithms such as linear regression, decision trees, and support vector machines learn to map input features to the corresponding output by minimizing the errors of their predictions. Such applications are especially valuable where historical data exists, and one needs to predict outcomes. The use of supervised learning, for instance, can prove very effective in seismic data analysis when attempting to predict aftershock probabilities against models trained against historical recordings of earthquakes. The model learns to recognize patterns that have been associated with seismic events and utilizes such knowledge in forecasting the likelihood of aftershocks, thus enhancing risk assessment and responding strategies. (2) Unsupervised Learning addresses data that has not explicitly been labelled or pre-specified outcomes. In this type of learning, the goal is to uncover the hidden structures or patterns in the data. The techniques used include clustering, which groups similar data together, and dimensionality reduction, a reduction in the number of variables that characterize the dataset. In seismic data, unsupervised learning can significantly help find patterns or anomalies known unknowns that may suggest seismic activity or regions of potential aftershocks. This technique enables the discovery of new, latent understanding that is seemingly not present by monitoring techniques. (3) Reinforcement Learning: Reinforcement learning is unique from the paradigms above. Training algorithms make a sequence of choices by merely rewarding the right actions and penalizing the wrong ones. The training loop is analogous to human learning processes, like trial and error; though it is applied less in seismic prediction the application is promising in an adaptive monitoring system. For instance, optimization of seismic sensor placement or alteration of monitoring strategies may be adjusted in real time based on incoming data to enhance the overall effectiveness of seismic activity detection. Machine Learning will advance the capability of identification and prediction of seismic events through complex pattern recognition capabilities. More importantly, ML offers strong tools for enhancing accuracy and understanding within seismic forecasting under supervised, unsupervised, and reinforcement learning approaches versus traditional statistical approaches.

Training algorithms on labelled datasets—where input attributes are associated with known outcomes—requires supervised learning. This approach works especially well for tasks requiring prediction. Algorithms for seismic data analysis, including support vector machines, decision trees, and linear regression, can be trained on past earthquake data to forecast the likelihood of aftershocks. These models can reduce prediction errors by understanding the patterns connected to previous seismic events, improving risk assessment, and guiding response tactics. For example, a model may predict the likelihood of aftershocks based on data from past earthquakes, which helps authorities better prepare. Unsupervised learning looks for hidden structures or patterns in datasets that lack explicit labelling. Methods like dimensionality reduction and grouping are frequently used. Unsupervised learning in seismic analysis can recognize patterns or anomalies that point to possible seismic activity. Clustering, for instance, can be used to group seismic data that are similar and identify odd behavior in particular areas.

Complex datasets are made simpler through dimensionality reduction, which facilitates the visualization and analysis of seismic data. By revealing information that more conventional monitoring techniques would overlook, this strategy can improve our comprehension of seismic occurrences. A study shows aftershock spatial distribution by combining various features and machine learning methods. For an analysis of 62,811 aftershocks from 171 mainshocks in China, results indicate that features do matter a lot. The research on deep learning techniques for modeling the prediction of the spectral acceleration values of an aftershock because conventional ground motion prediction equations lack one. With a set of 503 recorded mainshock-aftershock pairs, the results for CGANs outperformed the DNNs over 83% and hold much promise for more accurate aftershock predictions(Ding et al., 2021). It can therefore be combined with first aftershocks analysis and paired with the self-organizing feature map algorithm. Aftershock patterns can effectively be identified and improve the prediction of aftershocks through advanced data classification and clustering techniques(Madahizadeh & Allamehzadeh, 2009). Figure 1 is dedicated to illustrating the different types of learning models in Machine Learning.

4 Artificial Intelligence in Aftershock Prediction

It is difficult to anticipate the exact moment, location, and magnitude of an earthquake since there are no clear patterns to follow, making predictions unreliable. Artificial intelligence (AI)-based methods are widely recognized for their ability to uncover hidden patterns in data. These models yield encouraging results in earthquake prediction as well. Using AI-based methods, this work methodically examines the advancements made in earthquake prediction thus far. Eighty-four scientific research publications detailing the application of AI-based methods for earthquake prediction were chosen from various university repositories (Omi et al., 2013). A variety of AI methodologies, such as rule-based approaches, shallow machine learning, and deep learning algorithms, are implemented.

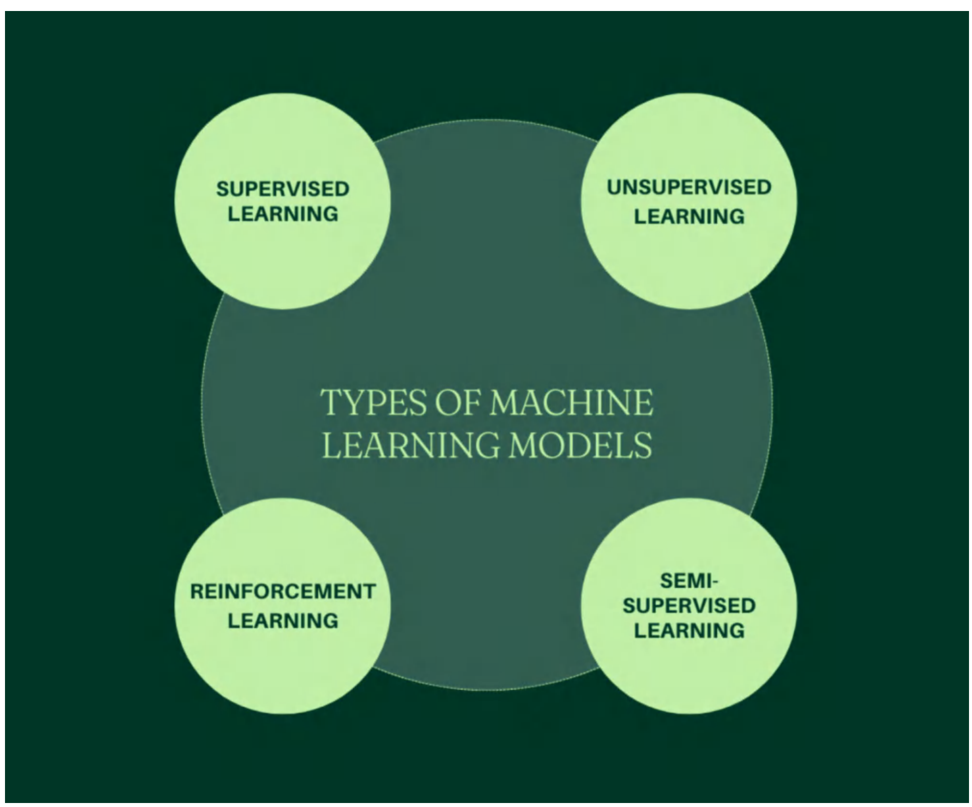

Fig. 1 Types of machine learning models

4.1 Integration with Seismic Systems

Earthquake prediction has made the most significant progress in terms of aftershock forecasting and earthquake risk management with the incorporation of Artificial Intelligence into seismic monitoring systems. AI's data processing capabilities can also be used to improve the timeliness and accuracy of later aftershock forecasts (Liu et al., 2023). Data processing, data collecting, forecast creation, and integration systems are a few of the essential elements of this integration. The initial stage of the seismic monitoring procedure is data collection. Numerous sensors capable of capturing various forms of seismic data are included in the majority of sophisticated seismic systems. Seismometers track the intensity of seismic waves and quantify ground motion. Ground motion acceleration is measured by accelerometers, and highly accurate surface displacement tracking is done using GPS stations. Together, the data from all of these sensors creates a comprehensive picture of the seismic activity (Karimzadeh et al., 2019). After collection, the data is sent to central processing units for aggregation and analysis preparation.

A paper discusses relative-intensity (RI)-based earthquake forecast models used in the Italian CSEP experiment. Translated into a framework that could be tested for earthquake numbers, by generalizing the RI algorithm into a smoothed seismicity model, the subject aims to establish the significance of RI in augmenting potential predictability of earthquakes in various time classes (Nanjo et al., 2010). At this stage, AI integration entails preparing sensor data for instantaneous analysis by AI models and laying in place effective data pipelines that guarantee real-time transmissions. AI has a significant impact on data processing, which raises the capabilities of seismic monitoring systems. In reality, with such massive volumes of data, traditional data processing techniques would not work well. Additionally, deep learning models, AI models, and other methods like CNNs and RNNs can easily analyse the nature of such massive volumes of data in order to handle seismic data accurately and quickly. These algorithms can be taught to identify complex correlations and patterns in the data that point to aftershock activity. CNNs, for instance, would examine the spatial characteristics of seismic waves, but RNNs would record temporal dependencies, improving the likelihood of detecting a certain aftershock sequence. The sophisticated computing power enables quick pattern recognition that could indicate the aftershocks earlier.

One of the main outcomes of integrating AI into seismic systems is prediction generation. After training, these models of AI can continuously analyse incoming data to estimate aftershock activity in real time. These projections are based on anomalies and patterns in the data that support probabilistic estimations of probable aftershock events and their magnitudes. Predictions can be updated in real time as new data becomes available, guaranteeing that the results are accurate and relevant for as long as they are needed. This continuous updating is essential for timely emergency response and effective risk management. In the management of aftershocks on impacted populations, for example, the AI-based now casting will influence decision- and action-making processes about evacuation plans, resource. System integration is the process of integrating AI models into the current seismic monitoring infrastructure both technically and operationally. Creating robust interfaces that provide seamless communication between AI algorithms and sensor networks is essential for the integration of AI and sensor networks. Integration activities include setting up data communication protocols, implementing real-time data pipelines, and ensuring interoperability between data management systems and AI models. All of these need to be combined with efficient system integration, as well as solving issues with data security, model deployment, and other scalability-related issues.

In order to provide seismic monitoring platforms with more desirable functionality and responsiveness, integration improves the interface between AI models and seismic systems. The next generation of aftershock prediction technology involves integrating AI with seismic monitoring. Aftershock prediction becomes more accurate and timely when data collection and processing sensitivity are improved along with prediction production. The effective deployment of these cutting-edge capabilities to the current seismic system infrastructure is ensured via system integration, which offers practical insights for risk management and emergency response. In fact, as seismic systems advance, artificial intelligence (AI) will play a bigger role in enhancing earthquake preparedness and prediction as well as creating new opportunities for reducing the effects of seismic activity on populations worldwide. Figure 2 illustrates the flow of the execution in the process of prediction model making.

4.2 The Role of AI in Time Monitoring: Real-Time Analysis

The confluence of artificial intelligence and the Internet of Things is revolutionizing industry operations monitoring and optimization in the modern era. In this study, we offer a system that integrates artificial intelligence-based predictive analytics with real-time monitoring from Internet of Things sensors. This technology allows for proactive interventions to enhance efficiency and save operational costs by detecting anomalies in real time and anticipating potential breakdowns. Our results demonstrate a notable enhancement in the early identification of anomalous patterns since the system reliably detects possible issues well in advance of them turning into

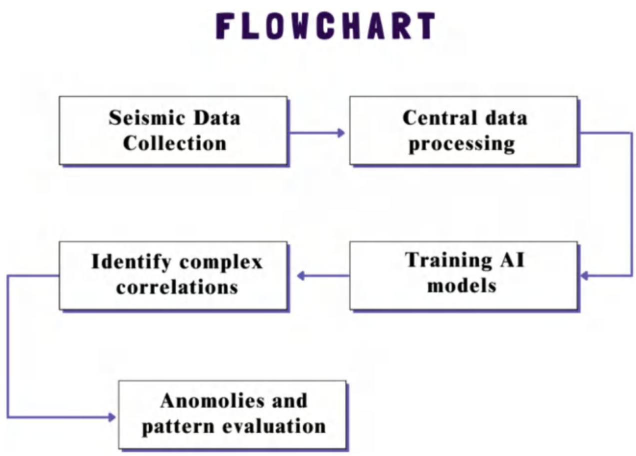

Fig. 2 The Integration of AI with seismic infrastructure

serious malfunctions. More than a million records from regulated and industrial production environments were used in our study. These records included crucial variables including temperature, humidity, and pressure. The outcomes show a notable improvement.

5 The Role of AI in Real-Time Analysis

Since forecasting aftershock probability is going to be very helpful in mitigating hazards following a main earthquake, the first issue was always how to foretell aftershocks in the first 24 h post-main shock. That was difficult because the data was incomplete for seismic activity, and so an important proportion of the early aftershocks went unrecorded. We present here a real-time technique that takes advantage of systematically incomplete observations available shortly after the main shock (Pwavodi et al., 2024). This combines a statistical model of incompletely detected aftershocks with an established model by Reasenberg and Jones. We apply this approach to retrospectively forecast the activity of aftershocks following the 2011 Tohoku-Oki Earthquake (M9.0) in Japan. Here, we show with analyses of catalogs from the National Earthquake Information Center/Preliminary Determination of Epicenters (NEIC/PDE) that the suggested method is able to make reliable aftershock forecasts within 24 h after a main shock. The model's performance is also tested with real-time data from Hi-net subsequent to a M6.3 event in Nikko, Japan (Shcherbakov et al., 2004). Our results indicate that this approach does indeed significantly improve the estimation of aftershocks during the most critical early hours following an earthquake and therefore enhances preparedness and response efforts in disaster-affected areas. A framework that relies on some type of machine learning for automated identification of seismic P-phase arrivals in noisy aftershock waveforms. Comprising Trigger, Classifier, and Refiner modules, EL-Picker uses ensemble learning to enhance the accuracy of its results, identifying up to 120% more arrivals than older techniques, proving itself efficient and versatile (Shen et al., 2019).

5.1 Data Quality

In the field of real-time aftershock prediction, AI plays a very crucial role. The quality of the data processed by AI is the most important factor in deciding whether its models can make reliable and effective aftershock predictions. High accuracy, consistency, and completeness are necessary for generating accurate, reliable predictions and actionable insights. For analysing the critically significant role of data quality in AI-driven seismic monitoring, one needs to study some key areas namely: sensor calibration, data pre-processing, and completeness.

Sensor Calibration: Sensor calibration is one of the key foundational elements in ensuring that seismic data is collected with proper precision. Seismic monitoring systems employ various sensors like seismometers, accelerometers, and GPS units to capture information on how the ground moves. Eventually, the sensors may drift or degrade over time due to many reasons like the environment, mechanical wear, and exposure to harsh conditions. Without proper calibration, the sensor measurements may become unreliable, resulting in bad predictions by AI models as well. The calibration of these sensors would ensure precise and reliable signals received from the environment. Calibration is the process whereby the readings from the sensor are compared to a known standard or reference point and deviations are corrected. For instance, a seismometer might be calibrated against a known source of vibration so it would read ground movements accurately. Accelerometers too may be calibrated against standardized acceleration references. Calibration tends to minimize error and ensures that the data acquired is as accurate as possible. Without proper calibration, the AI models relying on these data sets may not read the wrong information and, hence, might make unreliable forecasts regarding aftershocks. Therefore, a strict schedule for calibration and quality control measures will become essential practices to ensure that seismic data will remain accurate and useful for predictive modelling.

Pre-processing Data: Another is that the data pre-processing would be an important part of maintaining quality seismic data for AI analysis. Raw seismic data is usually noisy, and artifacts might just mask the actual signals of seismic activity. Noising sources include interference from other machinery, environment disturbances, and data transmission errors. These issues are resolved by applying pre-processing techniques to clean and refine the data before feeding into the AI models.

Filtering is one of the primary pre-processing techniques used to remove unwanted frequencies present in the data. For example, band-pass filters are applied to extract only the seismic signals of interest while suppressing noise coming from other frequency bands. This helps narrow down the analysis of the relevant seismic signals. Yet another type of pre-processing technique that scales the data is normalization. Normalization converts the data into a common range so it will be easier to process by the AI model. This is helpful when aggregating data from various sensors or sources, making input standardized and less prone to biases.

Another very important part of data pre-processing includes error correction. This is essentially the detection and correction of anomalies or outliers which can skew results. Outliers are recognized and corrected to make lesser interference upon the conclusion drawn from the data. Techniques for outlier detection and correction algorithms can be put in place to mitigate such interference. For example, an unusually high reading by a sensor deviating from surrounding data could be adjusted or excluded as such to ensure overall accuracy in the dataset. This improves the forecasting capability of AI in identifying patterns and making accurate predictions. Unless appropriately preprocessed, AI models might be misled by noise, causing reduced predictability rates of aftershocks.

Data Sufficiency: Completeness of the data is crucial in the quality of the seismic data to be implemented in AI analysis. Missing or incomplete data badly affects the predictions mainly in terms of aftershocks. For learning past patterns and making responsible predictions, AI models require good data sets. Gaps related to the understanding of the model can easily be formed when the data is missing. Predictions may not be properly made due to less accuracy in such situations.

Issues of incompleteness of data are therefore handled through imputation and interpolation techniques. Data imputation tries to fill in the missing values with a set of estimates based on what is known. This can be done through statistical methods, mean imputation, as well as the more complex forms of multiple imputation, which will take into account the uncertainty surrounding missing data and generate several plausible imputations. Interpolation is another method used to fill in missing gaps within data. This method will estimate the missing values because between two different values data can continue a trend or follow a pattern set up by the surrounding data points. For example, if a sensor fails to record data for a short period, interpolation methods might estimate missing values based on analysis of data before and after the gap. This helps in creating a continuous dataset from which AI can make relatively more precise predictions.

Data completeness is ensured not only by filling in missing values but also by verifying the integrity of the data that has been received. This includes checking up on the performance of sensors and systems used in data transmission to avoid losing any data and making sure all information available is garnered. In total, the quality of data is one of the critical factors for effective AI models in real-time aftershock prediction. Calibration of the sensor ensures measurements are accurate, and removing noise and artifacts by pre-processed data cleans the data. Techniques for data completeness actually fill gaps for a comprehensive dataset. All these qualities will help seismic monitoring systems leverage the power of AI and give their best shot toward more accurate and timely aftershock predictions that could significantly improve earthquake preparedness and response efforts. This new development in seismic monitoring represents an integration of high-quality data and advanced AI techniques which may bring something unprecedented on the new horizon for public safety improvement and decreased seismic event impact.

Seismic Monitoring: AI models have made a difference in allowing for the real-time analysis and prediction of aftershocks. The generation and updating of aftershock forecasts by means of using real-time data are considered one of the advanced tools in earthquake preparedness and response. Several key components comprise this process: real-time data ingestion, dynamic update of predictions, and integration of emergency response. Real-Time Data Ingestion: First, there must be the ingestion of real-time seismic data for the execution or updating of aftershock predictions. Contemporarily, modern seismic monitoring systems have a network of sensors that comprise seismometers and accelerometers, GPS units collecting ground movement data at all times, which they forward in real time to central processing units for aggregation and preparation for analysis.

Data Collection and Transmission: Sensors in a seismic monitoring network capture various kinds of seismic signals, such as ground vibration and acceleration. Such signals are communicated with very high-speed communication channels to central processing systems. Real-time data stream is highly important for AI models so that analysis can be done instantly; hence, updates in predictions could be done accordingly. Data aggregation: Once it arrives at the processing unit, the collected seismic data undergoes aggregation from various sources. It aggregates the information coming from sensors and locations for a complete dataset. This is necessary so the AI models can see an integrated and coherent view of the seismic activity in the area.

Data Pre-processing: Data must be fed into the model to be analysed by AI models. The pre-processing here involves cleaning of data and its preparation. This includes filtering out noise, normalization of the data, and rectification of errors and anomalies. Effective pre-processing here depends on the fact that it is ensured that the data fed into the AI models is accurate and relevant. Feature Extraction: From the pre-processed data, features that may be of interest to the AI models are extracted. Some of the representative aspects of the seismic signal related to aftershock activity and which are part of the features extraction process include amplitude, duration, and frequency. These features are then fed to the AI models. Dynamic Prediction Updates are how AI models are constructed so that the predictions generated based on the real-time data they receive. There is one major merit of AI use in seismic monitoring, which is the continuous updating of predictions based on new incoming data. This ensures that the forecasts are relevant and accurate for changing conditions. Initial Forecasting Generation: The initial data that an AI model receives is "fed" into its algorithms to produce predictions based on the patterns and relationships learned from historical data. For instance, the model may show the chances or likelihood of aftershocks being experienced in a particular timeframe and region depending on the current seismic activity. Continuous Monitoring and Refining: In case of new seismic data, the model continuously monitors and updates the incoming information and its predictions. This includes reassessment of the new patterns that evolved in the new data and revising forecasts based on new developments or changes. For instance, if there is increased seismic activity or a change in the pattern of ground movement, the model immediately updates the probability of aftershocks in real time and adjusts the forecasts with the new development.

Adaptive Learning: Many of the AI models applied to seismic monitoring have been based on adaptive learning in the sense that they enhance their performance through time. The more real-time data processed by this model, the better the sense of patterns it establishes regarding seismicity and accuracy in aftershock prediction. Preservation of the effectiveness of the aftershock prediction models is primarily brought about by this adaptive process in dynamic and evolving seismic environments. The system must make it possible for there to be real-time feedback from AI models on aftershock predictions. Such a feedback loop would be fundamental in allowing emergency response teams and decision-makers to be able to have the best up-to-date information about risks associated with aftershocks so as to adjust their strategies accordingly. Emergency Response Integration. Actually, an important integration in applying AI for earthquake preparation is into real-time aftershock predictions within emergency response systems to ensure that the information created by AI models adds value to the optimization of resource allocation and response strategies.

Delivery Time: AI models send real-time aftershock predictions to emergency response systems and decision structures. Delivered in a timely manner, there is the assessing potential impacts of aftershocks in fairly quick time, which helps responders make appropriate decisions. Resource Allocation: Good predictions, in real time, can be helpful in making efficient resource allocation. For instance, if AI models show a high probability of aftershocks occurring in a region, the emergency responders may aim their efforts and resources at that specific location. This may include sending more personnel, equipment, and supplies to the higher-risk areas, thereby increasing the efficiency of the response as a whole. But by integrating real-time predictions with a response strategy, decision-makers could then develop the most effective plan and implement it in their efforts. For instance, if such predictions indicate that aftershocks hit such critical infrastructures as bridges or hospitals, then one could adjust one's response strategy, pointing out specific areas that require more intervention to ensure reduction in damage and successful use of emergency response. Automatic aftershock forecasting system for China, utilizing a parameter-free historical analogy method. Capable of generating short-term forecasts within minutes of a major earthquake, the system achieved 83.5% precision in sequence type classification and effectively aids post-earthquake consultations, enhancing efficiency for scientists and government agencies Public Information: AI Predictions can be utilized to educate the public about aftershock risks. Because timely and appropriate information is essential in alerting the communities about the potential occurrence of an aftershock and avoiding impact, public information can include educating the public through these means: issuance of safety recommendations, information through social media, television, newspapers, newsletters, and community notice boards. Collaboration and Coordination: In many instances, good emergency response hinges on collaboration between several agencies and organizations. Real-time predictions will be useful since these will bring together a common information framework that users may apply with regard to the different activities of stakeholders.

This collaborative approach, in turn, means that any effort made to respond to an emergency is well-coordinated, and all resources available are put to optimum use. Post-Event Analysis: After an earthquake and their after-shocks, AI models can be helpful in post-event analysis to identify where aspects of the response could have been different or improved. Post-event analysis directly translates to better predictive models and response designs for future earthquakes, which are in turn couched in increased overall preparedness and response for earthquakes. In a nutshell, the process of execution and updating of aftershock predictions via the interface of real-time data is quite complex and includes data ingestion, dynamic updating, and integration into an emergency response system. AI models offer timely and accurate forecasts, which are important in effective emergency response and resource management, through continuous analysis of incoming seismic data. These predictions, when integrated into emergency response systems, enhance the ability to provide proactive and effective response to seismic events and, therefore, public safety in case of aftershocks. AI advancements and their application for seismic monitoring represent crucial steps forward in earthquake preparedness and response while opening new avenues for community protection and resilience improvement against seismic events.

5.2 Execute and Update Predictions Using Real-Time Data

The introduction of artificial intelligence (AI) has revolutionized the area of seismology and made it possible for scientists and emergency personnel to significantly increase the accuracy of their aftershock predictions in a clear and efficient manner. AI models, which utilize real-time data, offer not just a preliminary prediction but also dynamic updates in response to new data. This chapter covers a number of topics related to the implementation and real-time updating of seismic data-based aftershock prediction. Notable among them are the requirements for real-time data intake, dynamic updates, and emergency response system connectivity. Many papers were published between the years 2010 and 2020 and dealt with different models, such as rule-based, fuzzy, and approaches based on machine learning algorithms, with discussions around data sets (Tehseen et al., 2020).

Filtering in Real-Time Information: The ongoing gathering and subsequent analysis of seismic data provides a solid foundation for efficient aftershock prediction. A network of seismic sensors positioned along fault lines and in earthquake-prone areas is needed for real-time data intake. Sources of Data: Several technologies can be used to obtain seismic data, including: these tools detect ground motion and offer accurate information about the size and location of any occurrence (Voronov et al., 2021). GPS stations: By tracking even the smallest changes in the crust, technology from the Global Positioning System can provide information about tectonic movements. Satellite imagery: Over time, geological phenomena such as land deformation can be monitored using remote sensing technology. Data Transference: The collected data is immediately relayed in real-time to the central processing units using high-speed internet and advanced communication protocols. This is what has made it pivotal in keeping latency at its bare minimum; this is why AI models can process in a twinkling of an eye. Advanced algorithms analyse incoming data for potential signs of aftershocks, which may be recognized in patterns of seismic waves, energy releases, and spatial distribution of earthquakes. Data Processing: AI models use machine learning techniques to process the seismic data. They take historical data and real-time inputs into account, which can detect some correlations as well as patterns that might suggest an aftershock is imminent.

The models can be trained on vast datasets covering past occurrences of seismic activities so that they learn from previous experiences and hence make better predictions of future aftershocks. Continuously Refining: This refinement process must be continuous since after-shocks tend to manifest a chaining behavior, and will follow quite a diverse range of conditions such as the first shock magnitude, geological settings, and even the time passed after the occurrence of the event. AI models rely on algorithms that allow them to take up new data and reassess previous predictions, updating, in turn, their probability and timing of occurrence of the aftershocks. Feedback Loops: The addition of feedback loops extends the scope of predictive power for AI models. After passing through aftershocks, these operate on these events in real-time and recursively update their parameters so that it draws much closer to accuracy for later predictions. This recursive procedure will indeed provide a far better insight into the behavior of aftershocks and thus a much stronger framework of prediction. User-Friendly Interfaces: For researchers and emergency responders, friendly interfaces that ease the employment of these dynamic predictions are developed. An accessible format that could allow decision-makers to respond sensitively and promptly can be achieved through real-time data visualization, predictive analytics, and alerts. Emergency Response Integration: Therefore, real-time aftershock predictions must be incorporated into emergency response systems. Information provided by AI models in a timely manner can drastically improve the allocation of resources and response strategies such that emergency responders are better prepared for successive aftershocks. Influencing Decisions: Real-time and authentic information is required for emergency responders, as critical decisions made in evacuation, resource distribution, and measures in public safety should be based on that information.

Aftershock predictions generated by AI will provide the base for responders to concentrate their efforts in areas with high risks. For example, if a model gives a prediction that aftershocks are expected to happen in an area, then resources should be put into such an area to strengthen the present structures and help affected populations.

Resource Optimization: Resource allocation is one of the core activities in any emergency. AI models can help pinpoint the possible regions with the highest likely aftershock activity; therefore, there is an increase in how and when emergency management teams deploy people and equipment. Shorter response times will translate to general effectiveness in conducting the emergency intervention. Public Communication: Other than assisting emergency personnel, AI-based predictions can also allow communication with the public. Real-time updates can be disseminated through various media like social media, mobile applications, and local news. This keeps the communities abreast of the situation so that people can take proper precautions and remain safe during aftershock events. Scope for the future: Although it promises to integrate AI in the prediction of aftershocks, it is still filled with a number of challenges. The complexity of seismic phenomena calls for further research and development to produce meaningful accuracy and reliability of AI models. Other issues comprise the privacy of data, making the model interpretable, and the broad validation against real-world events. Higher Accessibility: Real-time prediction systems will also be allowed wider access to local governments and communities worldwide, thereby allowing the communities to be better prepared and respond to aftershocks and other shocks.

More training for classes can further increase resilience by training those involved in AI predictions that lead to relevant and suitable safety measures. The creation and upgrade of aftershock prediction using real-time data marks a giant step in the world's earthquake preparedness and response. Seismic data-in-flow analysis using AI and fine-tuning subsequent predictions while strengthening those insights into emergency response systems can be used to build the ability of communities to withstand seismic events. A long-term relationship seismology and the research and collaboration that will ensure continued confrontation with challenges while maximizing the utility of AI, even as the technology continues to open its doors to further scope will be essential and should be available to support that pursuit.

5.3 Challenges and Solutions

Challenges and Solutions for AI-Powered Aftershock Forecasting Utilizing AI for aftershock prediction is a novel and cutting-edge method of enhancing seismic safety and readiness. However, there are issues with this undertaking that could prevent it from being fully effective. In order to optimize AI's potential for managing seismic risk, it might be imperative to address these issues. The difficulties of data quality, model interpretability, and computing demands are discussed in detail here, along with a number of possible solutions. The review of time series analysis to identify critical transitions in real-world non-autonomous systems with complex dynamic behavior. It is a wholesome process starting from data collection to the judgment of detection reliability and assigns strengths and weaknesses for each step (Lehnertz et al., 2024).

(1) Problems with Data Quality is that a predictive model's solid foundation is provided by high-quality data, particularly when it comes to aftershock predictions. The type of data that is provided to AI algorithms, along with its quality, completeness, and reliability, is what essentially makes them thrive. The following are some particular problems that may occur. (2) Sensor Accuracy and Reliability: Extremely accurate and dependable sensors are required to detect earthquakes. Even after calibration, though, they can experience a failure or fall victim to outside interference, sending out the wrong signals. (3) Completeness of Data: Aftershock patterns can occasionally be very erratic, and insufficient data in the datasets can change or skew the prediction. Because of the missing data on the designated regions, the model might not be able to generalize. (4) Temporal and Spatial Resolution: The sensitivity of the model to detect faint seismic signals that indicate aftershocks may depend on both the spatial density and the rate of data collection. The suggested resolutions are specified below but should be considered in other situations.

Data quality can be improved by using advanced sensors that are considerably more resistant to external influences and have the capacity to capture data at a much higher resolution. In sensor networks, redundancy may assist mitigate the impact of individual sensor failures. Create reliable data preprocessing methods: It is crucial to create reliable methods for pre-processing and data cleaning. This could involve statistical imputation for missing data, bias correction, and noise filtering. Crowdsourcing and Open Data Initiatives: In an effort to supplement an existing dataset, include local populations in data gathering, particularly in regions of under monitored domains. Through data sharing and improved dataset completeness, open data projects facilitate researcher collaboration. Interpretability of the Model Deep neural networks and other complex AI models are examples of "black boxes." In other words, they are frequently incomprehensible. Many key applications, like aftershock prediction, may require an explanation for the model's predictions in addition to the predictions themselves. Trust and Adoption: Without fully understanding the underlying logic, more reticent stakeholders—such as emergency response teams and legislators—will rely on AI predictions. Concerns about regulations and ethics: Whenever AI forecasts make judgments that have a major impact on humans, there are ethical and regulatory ramifications. Interpretability. Techniques for Explainable AI Methods like LIME or SHAP aid in elucidating how models come to anticipate particular outcomes. These techniques could reveal which characteristics have the biggest effects on the final product.

Tools for Visualizing Models: Easy-to-use tools for visualizing models can help stakeholders better understand the behaviors of the models. Visualization can help make judgments less mysterious, which will increase users' acceptance and faith in the technology. Applying Domain Knowledge: Interpretability of the AI model can be improved by including seismology-related insights. This can be further improved by connecting model elements to established seismic concepts, which will help to clarify the reasoning behind the forecasts. Calculation Expenses The biggest obstacle facing AI-based aftershock prediction systems in computationally evaluating massive datasets in real time will be the resource-intensive nature of computational processing. Extremely High Processing Power Requirements: Due to the inherent complexity of AI models, many of them call for sophisticated technology, which is not widely accessible in much of the world, particularly in developing nations. Handling Large Amounts of Data for Instant Predictions: When a major event happens, quick action is crucial. Therefore, handling big data quickly to offer fast forecasts is a major obstacle.

The Strategies used to tackle the complex computing needs various methods can be used:

Optimization Techniques: Creating algorithms that improve how fast computations are done can greatly reduce the workload needed for these tasks. Methods like model simplification, reducing data size, and simplifying models have been used to make complex models easier to work with while keeping their performance. Cloud Computing Platforms: This technology can be accessed as needed for the required computing power. It's essential but doesn't require upfront investment in either hardware or software by researchers and practitioners. Edge Computing: This approach can be used to process data at the point of origin, reducing the delay and bandwidth issues that come with transferring large data sets to main servers. Works well with other systems. A major challenge in implementing AI for aftershock prediction is ensuring compatibility with existing systems focused on seismic monitoring and emergency response. Issues with Compatibility: New AI systems often struggle to work together smoothly with older systems, leading to data fragmentation and inefficiencies in workflows. Lack of Skills: Staff may not have the necessary skills to efficiently operate advanced AI tools, which can become a hurdle to their implementation. Steps to Facilitate Integration: To ensure the new AI system is effectively used, steps such as standardizing data formats, establishing common data communication protocols, providing training to current staff, and offering appropriate education can be taken. Collaboration with Technology Partners: Working with technology companies can provide the expertise needed for integrating systems, enabling organizations to adopt AI solutions that are compatible with their existing frameworks. The integration of AI in aftershock prediction offers great potential for improving seismic risk management. However, there are significant challenges to overcome, including ensuring the quality of data, making models understandable, and managing the computational demands of the algorithms without overburdening the system. By adopting a strategy that includes technological advancements, methodological improvements, and involving all stakeholders, it's possible to develop more accurate and dependable systems for predicting aftershocks, thereby saving lives and building community resilience against seismic threats.

The Table 2 illustrates the problem stamen and the suggested solution for the problem described.

Table 2 Challenges and solutions

Problem	Solution suggested
Data Integrity: Inaccurate models can be produced by noisy or incomplete seismic data	Utilize pre-processing and data-cleaning methods
Variable Features of Earthquakes: Variations in the sorts of earthquakes and the patterns of their aftershocks	Create models that are flexible enough to respond to varying geological conditions
Computing Capabilities: high processing requirements for complicated model training	For scalability, employ cloud computing resources and optimize algorithms

5.4 Related to Data Constraints

Predicting aftershocks is a crucial task in disaster management, mitigation, and getting ready for earthquakes. Accurate predictions improve emergency readiness, the distribution of resources, and the strength of communities. However, AI models used for aftershock prediction often face challenges with data. Understanding these challenges can lead to better models and more reliable predictions. This document explores three main issues: missing data records, bias in data, and the lack of data, along with potential solutions. Mitigating Missing Data is used to counteract the effects of missing data, several approaches have been used which include data imputation, data augmentation, and others. Data Imputation involves replacing missing values with substitute values using statistical methods. For regression models, this can include mean and median imputations, as well as more advanced methods like multiple imputation or k-nearest neighbour. The choice of method depends on the type of data and the extent of missing data. Data Augmentation involves creating artificial data points to fill in the gaps. For seismic data, this could mean generating hypothetical aftershock events based on known patterns or using domain expertise to simulate realistic scenarios. For instance, by analysing patterns of aftershocks following large earthquakes, synthetic aftershocks can be added to the dataset. Sensitivity Analysis is used to understand how missing data affects the outputs of models.

By gradually introducing missing data and observations, researchers can identify key data gaps and prioritize data collection efforts accordingly. Understanding Bias in Data refers to the situation where specific groups or events are overrepresented or underrepresented in a dataset. In the case of predicting aftershocks, there are various types of bias, including the bias that arises when historical data comes from a particular geographic area or magnitude scale, making it challenging for the model to apply these findings to different situations. This can lead to skewed predictions that fail to capture the full range of seismic activity. To address bias we use the mentioned methodologies. Diversifying Data Sources is used to tackle bias, it's crucial to use a diverse range of data sources for model training. This includes a broad spectrum of seismic events, which can be achieved by including data from different geological settings and historical periods. Collaborating with global seismic networks can also enrich the diversity of the data. Detecting Bias Techniques Utilizing Statistical Methods: Detecting bias involves applying statistical techniques to identify and quantify bias within datasets. Various methods in exploratory data analysis, visualization, and statistical tests can highlight the presence of bias. Once identified, corrective measures such as adjusting the dataset through reweighting data points or removing biased entries can be implemented. Ensuring Fairness in Algorithms makes algorithms more robust to biased data and can improve their reliability. This can be achieved through techniques like adversarial de-biasing, where models are trained to predict with minimal bias. Additionally, fairness-aware learning algorithms ensure that model performance is equitable across different demographic groups and contexts.

The Challenges of Data Scarcity are very vast. The Issue of Limited Data Availability is the scarcity of data, particularly in areas with less seismic activity. The lack of historical records can hinder the accurate training of artificial intelligence models. For instance, if an area has recorded only a few earthquakes over a century, the available dataset may not provide enough information to accurately predict seismic events. This poses a significant challenge to the model's ability to generalize and be effective in real-world applications.

Addressing Data Scarcity Efforts is the expanding Collection Programs that efforts to mitigate data scarcity involve expanding the scope and impact of data collection initiatives. This could include setting up new seismic monitoring stations in under researched areas or strengthening partnerships with local institutions to gather historical records. Initiatives may also incorporate citizen science, engaging communities to report seismic events and contribute to data collection efforts.

Creating Synthetic Data is a Promising Solution for addressing data scarcity and also involves creating synthetic data. For example, Generative Adversarial Networks (GANs) can be utilized to generate synthetic datasets that closely resemble the statistical characteristics of real seismic data. By training models on a mix of real and synthetic data, researchers can develop more robust models that enhance predictability. Transfer learning's method involves adjusting a model that was initially trained on a large dataset for a specific task using a smaller, more focused dataset. This strategy is particularly effective in aftershock forecasting because the data for local events is often limited. By leveraging insights from models that were trained on abundant data, the performance of models in areas with less data can be enhanced. The ability of AI models to accurately predict aftershocks is influenced by the challenges posed by data sources, including missing data, bias, and a lack of data availability. To overcome these challenges, a comprehensive approach is necessary, which includes strategies like data imputation and augmentation, diversifying data sources, implementing bias detection methods, increasing data collection, and generating synthetic data. By actively working to overcome these data limitations, researchers can improve the reliability and precision of aftershock predictions. This, in turn, contributes to enhancing disaster readiness and risk management efforts (Beroza & Zoback et al., 1993). The way forward requires collaboration across different disciplines and regions, aiming for a more integrated view of seismic events that leads to more robust and resilient communities.

6 Future Considerations

Future directions for the model in the area of aftershock prediction include its development into an AI model. Data collection can be made better and more standardized across institutions while sharing datasets to make them richer sources of knowledge. Model transparency and explainability matter, therefore; as long as data privacy and consent frameworks can be established, this approach may become efficient. Local communities might not only be less misled in the misinformation game, but they can be better involved in designing technology that will have a greater impact on them positively when their predictions are improved. Preparedness can be improved upon. Real-time processing capability is faster and results in more accurate forecasts.

6.1 Future Advanced Skills Report

The role of AI in the prediction of aftershocks will change as our knowledge of earthquakes grows and technology advances. Predicting aftershocks will be crucial in reducing the impact of aftershocks on communities and building greater disaster preparedness. The future of AI will be characterized by new techniques, integration with new technologies, interdisciplinary research, and formation of corresponding ethical and regulatory frameworks (Zhao et al., 2022). It discusses, by far, the most important advancements underlining those new possibilities in the aftershock prediction.

AI Techniques

(1) Advanced ML Algorithms: The landscape of machine learning keeps changing with newly designed algorithms and architectures underway that promise to better predict systems (Avula et al., 2024). Advanced neural network architectures such as CNNs and RNNs have already proven their usability in several fields of application, for example, in image recognition and natural

language processing. These techniques can be applied in the analysis of rather intricate seismic data used to predict aftershocks by noticing patterns from the data that normal methods fail to capture. (2) Deep Learning Innovations: Development of next-generation transformer models and mechanisms that can create better awareness in the model about the evolution of time dependencies over the data, which enables one to enhance the model's ability to attend on relevant features of the seismic data. (3) Transfer Learning: Transfer learning would take advantage of well-trained models for high volumes of data, possibly from different geographic locations or for different seismic events, and fine-tune them on locally available data. It could improve predictive accuracy where little historical data is available and inform insights or predictions gained from one location as applicable in another. (4) New Training Methods: The more complex the models, the more novel methods of training become necessary. The techniques that have been proposed as addressing some of the issues related to the lack of labelled data are few-shot learning and semi-supervised learning. These techniques enable a model to generalize well from only a few examples, a good fit for the aftershock prediction, where the data would not be readily available.

Integration with New Technologies

(1) Satellite Imagery: One of the innovative ways it can support aftershock prediction is through integrating AI with satellite images. The high-resolution satellite image can capture and enable real-time ground deformation, land use changes, and other geological features possibly associated with increased seismicity. Researchers can recognize precursors to aftershocks through image processing using AI algorithms. (2) Change Detection: The applied machine learning may be used to enable change-detection algorithms to scrutinize time-series data extracted from satellites in order to identify changes within the landscape that may be associated with the seismic event. In this regard, this source of information may be critical in comprehending the patterns of aftershocks and making subsequent predictions. (3) Geospatial Analysis: The most likely occurring aftershock pattern can be estimated using AI-based geospatial data-the integration of geological features, historical seismic activity, and other environmental conditions. (4) Internet of Things (IoT) Sensors: The use of IoT sensors in seismic monitoring is likely to make a difference where AI differs from prevailing seismic monitoring methods. The parameters to be recorded by the sensors include continuous data on ground motion, temperature, and others during a seismic event. With this integrated data, the occurrence of aftershocks can be predicted more reliably and timely by AI.

Data Fusion: Merging of all data sources, including those coming from sensors in IoT, satellite images, and historical records of seismic activity, strengthens the predictive models. Advanced data fusion techniques, hence, allow extracting insights using different data sets that will bring more significant understanding about seismic activity, their statistic.

(1) Advanced Data Fusion Techniques: With advanced techniques in data fusion, integration of data sources from multiple sources is quite important in improving the accuracy of prediction (Kishor Kumar et al., 2024). There are examples, such as geological surveys, seismic recordings, and socio-economic information, AI can develop a more holistic view of aftershock risks.
(2) Multimodal Learning: This style permits models to learn from a set of different types of data simultaneously. For instance, one can use textual data as in the report, and numerical data on seismic events for creating more precise forecasts.
(3) Feature Engineering Next feature engineering techniques are going to be much advanced and will help in optimizing the performance of the model. The ability to extract appropriate features from raw data improves the model's capability to discern patterns associated with aftershocks.
(4) Interdisciplinary Research: Collaboration Across Fields like the Future AI in predicting events of aftershocks will be highly reliant on multidisciplinary approaches. A lot of innovation and new approaches toward prediction must arise from cooperation among seismologists, data scientists, engineers, and urban planners. Also, Seismology and Data Science-Seismologists can merge by approaching and understanding the data scientists who have rich domain knowledge that can be used in guiding the development of AI models. They could collaborate with data scientists to ensure that their realism in modelling seismic behavior gets together with advanced analytical techniques. Engineers and planners may be more likely to provide after-shock impact predictions regarding structural and human infrastructures. The interface of engineering and urban planning would then lead to more targeted prediction models that consider the social perspective of aftershocks, thus making such preparedness efforts more effective by integrating Education and training programs will need to change to accommodate interdisciplinary collaboration. Curriculum of seismology will need to include AI and data science so the new generation equipped with sufficient skills can operate some of the state-of-the-art technologies designed currently. The design of the training program tailored for seismic science data scientists in predicting aftershocks will also be quite helpful in designing useful support for those after-shock prediction endeavours. The

few considerations to be made are ethical and Regulatory opinions; the ethical frameworks needed seismic monitoring and aftershock prediction will be very important applications of AI, but the primary theme will be ethical issues related to AI technologies. The use of AI technologies raises questions on data privacy, transparency, and accountability.

1. Data Privacy: One of the key concerns is that all data collected from communities will need to be used responsibly and ethically. Data ownership, consent, and usage must be laid out clearly to protect individuals' privacy.
2. Transparency and Accountability: Models that inform public safety decisions should be transparent. Stakeholders, from community members to policymakers, should understand how predictions are made and the basis for decision-making processes. This will help build trust and ensure accountability among those developing and deploying AI technologies.
3. Setting Regulatory Frameworks: Regulatory frameworks will also need to be set in place to govern the ethical use of AI in aftershock prediction, bringing into the fold a variety of considerations.
4. Standards on Data Collection: Well-defined standards on data collection should be set regarding what is collected and how the seismic data are processed to make it representative and reliable.
5. Model Validation and Testing: The regulatory agency can ask that rigorous validation processes on the AI model be carried out to ensure the model works with a reasonable level of accuracy and reliability in real-world scenarios.
6. Public Engagement: There is a need to engage with communities that will be most affected by the seismic activity to understand their needs and concerns, and mechanisms of public participation should be there in the regulatory frameworks on matters relating to decisions about the deployment of AI in aftershock predictions. The future of AI in aftershock prediction is accurate and has been improving over time and will keep improving further, advanced by innovative techniques in the field, integration of AI into new technology, multilateral interdisciplinary research, and ethical considerations. The ability to predict aftershocks will be augmented with the sophistication of machine learning algorithms, real-time data from IoT sensors, and collaborative approaches within the respective fields. However, the next step will require frameworks of ethics and regulatory standards with regard to the responsible use of AI technology. However, by careful consideration of these factors, AI can be used to enhance community resilience and disaster preparedness in the face of seismic threats. Table 3 illustrates the integration of the cutting-edge technologies and their concerns on ethical and moral values.

Table 3 Integration of new technologies and their concerns

Integration of new technology	Respective concerns
Remote sensing: Satellite data on seismic activity and ground deformation	Possible data misinterpretation, exorbitant expenses, and reliance on meteorological factors
Large-scale seismic and geological data analysis	Problems with data management, the possibility of data overload, and security issues with sensitive data
Geographic Information Systems (GIS)	Needs qualified workers for efficient analysis and could have problems with data accuracy
Privacy and security	Location and live details of individuals are viable to potential risk

7 Conclusion

The application of AI to aftershock prediction is a groundbreaking development in seismic hazard assessment. Previously, these forecasts were made using historical data and basic statistical models, which inevitably failed to account for a number of intricate behaviors of seismic events. Artificial intelligence (AI) has the potential to greatly improve the precision and promptness of aftershock predictions through the utilization of cutting-edge machine learning technologies and appropriate real-time data processing. Artificial intelligence (AI) has the ability to analyse vast amounts of data in incredibly detailed ways, which is advantageous for aftershock prediction. Geological features, historical seismic records, and even real-time sensor data can all be filtered by machine learning algorithms to reveal information that would not be visible through traditional analysis. As it develops this ability, AI Artificial intelligence (AI) has the ability to analyse vast amounts of data in incredibly detailed ways (Villegas-Ch et al., 2024), which is advantageous for aftershock prediction. Geological features, historical seismic records, and even real-time sensor data can all be filtered by machine learning algorithms to reveal information that would not be visible through traditional analysis. By gaining a deeper comprehension of the elements that contribute to aftershocks—such as the magnitude of the parent earthquake, the geological setting, and the spatial distribution of seismic events—the AI models would be able to forecast aftershocks. Furthermore, deeper learning development architectures, like CNNs and RNNs, enable the modelling of more complex temporal and spatial relationships found in seismic data.

These models' evolutionary paths can produce even more precise forecasts while evaluating likelihood and possible severity intensity of the aftershocks. Enhanced Reaction to Emergencies Better emergency response capabilities are directly correlated with increased predictive capability. Emergency services will be even more equipped to handle possible aftershocks by allocating the necessary resources at the right moment with a more accurate forecast. For instance, prompt warnings will assist communities in taking the required precautions, such as evacuating from dangerous areas or strengthening buildings before aftershocks occur. A predictive system powered by AI can make decisions in real time during an earthquake. AI systems can generate information that first responders and government agencies require by analysing data updates and predictions in real time. Thus, by reducing the chaos that comes with emergencies, this time-sensitive analysis helps to save lives by facilitating coordinated responses.

Effective Resource Usage: AI not only facilitates quicker emergency response times but also enhances resource distribution following a seismic event. Strategies for allocating essential resources—like food, medical supplies, and shelter—to ensure equitable access to services in the most impoverished communities are informed by predictive models. When there are aftershocks, the authorities can better plan their response by identifying the precise areas that will experience the greatest changes based on the location and timing of the aftershock shake.

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Advancements in Ozone Monitoring: Leveraging AI and ML for Environmental Protection

Mehak Malhotra, Mukul Garg, Pooja Mahajan, and Gaganpreet Kaur

Abstract

Role of ozone in regulating climate and air quality, emphasizes the need for real-time monitoring of ozone levels. Ground layer ozone pollution is a major threat to the environment and human life. In this chapter, the importance of ozone analysis is presented to understand the dynamics of the atmosphere and reduce its damaging effects. Earlier, traditional methods like ground-based observations and satellite-based measurements were used. However, these methods required high installation costs and had low spatial resolution. These were the major limitations of traditional methods, which paved the way for Artificial Intelligence (AI) and Machine Learning (ML) models. Supervised machine learning models like regression, decision trees, and random forest models use historical data for ozone level predictions. Unsupervised models include clustering techniques to identify hidden patterns in larger datasets. ANFIS (Adaptive Neuro-Fuzzy Inference System) is a deep learning model that combines the principles of neural networks and fuzzy systems. Nowadays, ML techniques are also used for spatiotemporal analysis of ozone levels. Ozone analysis plays a crucial role in environmental policy making, as well as public health protection. This includes identification of ozone hotspots and areas at risk of exceeding regulatory thresholds. Besides, this chapter highlights challenges faced in ozone analysis like lack of monitoring infrastructure in some regions for leveraging AI and ML.

Keywords

Ozone analysis · Artificial intelligence · Environmental monitoring · Deep learning

1 Introduction to Ozone Monitoring

Rising air pollution poses a significant threat to human health, and the ecosystems. Among various air pollutants, ground level ozone has major harmful effects on human life. Ozone plays a dual role, in shielding us from harmful UV radiations, and acts as a pollutant too. Globally, scientists, researchers, and governments need to shift their focus on analysis and prevention of ozone pollution. Ozone analysis plays a major role in examining the effects of human activities on natural processes. Some of these pollutants include vehicle exhausts, volcanic fumes, and industrial emissions, which lead to serious health issues, and threats to the environment by drop in ozone levels (Zhang et al., 2021). However, if ozone level increases in the atmosphere, it causes serious respiratory problems and cardio-vascular problems. This urges the need for researchers to work on effective models for ozone prediction and management.

So far, many AI-based predictive models have been developed for environmental modelling. These models are effective in predicting the ozone levels, and its effects on the environment and human life (AlOmar et al., 2020). These models also help the researchers in understanding the composition of the gases in the atmosphere. AI-based ozone prediction models provide us with data to maintain a good air quality index (AQI) globally. The most efficient model reported for prediction of ozone concentration is based on Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Taylan, 2017). For

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these prediction models, data from many sources such as ground monitoring stations, and satellite observation centers is collected by the scientists and researchers. These AI-ML models examine the data provided and identify a pattern or trend in the ozone levels, over various parts of the globe (Sorenson et al., 2023). Ozone analysis acts as a tool to understand the complexity of the atmosphere, and deploy strategies to protect the environment (Li et al., 2009).

With rapid occurring atmospheric changes, these models serve a role in working toward a sustainable future for our future generations. Many remote sensing and Machine Learning (ML) models have been developed to tackle the increasing threat of ozone pollution (Gong & Ordieres-Meré, 2016). Still, interdisciplinary research needs to be conducted globally to control ozone pollution and protect the environment. The study aims to review the research reports published on improvement of ozone analysis methods by using AI techniques and discusses various challenges in using AI for ozone analysis.

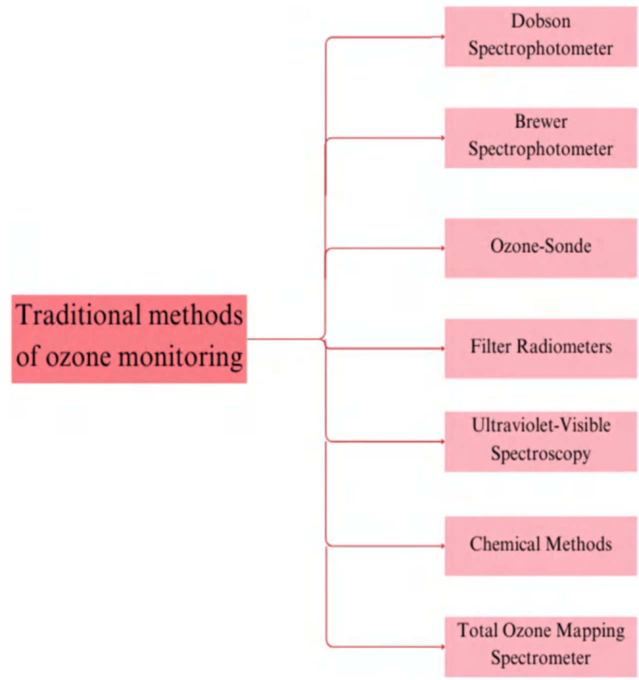

Fig. 1 Traditional methods of ozone monitoring

2 Traditional Methods of Ozone Monitoring

Earlier, traditional means of analyzing ozone had been extremely dependent on each other; the priority had been given to the comprehension of concentrations and effects of it on the environment and human health. During traditional times, people used to use manual monitoring and chemical analysis without any applications of AI techniques (Xu et al., 2021). There are various traditional methods of ozone monitoring as illustrated in Fig. 1. Traditional methods usually encompassed a network of ground-based observation stations equipped with instruments that measured ozone levels in air and collected air samples for laboratory analysis. Satellite observations as well as atmospheric modeling have also been employed in sampling distribution of ozone at this larger scale (Godin-Beekmann, 2010).

The primary traditional way to study different types of ozone is Brewer-Dobson circulation—transportation (Fu et al., 2019). In general, this model has given significant insight into both depletion and recovery dynamics of the ozone layer. Another instrument is the spectrophotometer Dobson which measures total amount of ozone within atmosphere layers. Ozone sondes are balloon-borne instruments that can be launched from a single location to carry out vertical profiles measuring ozone concentration across limited areas in this case (Thompson et al., 2023). Synoptically, the traditional techniques of understanding about ozone widely employed data assimilation and statistical methods in interpretive analysis of observational information and fallacious modeling.

Through these methods, however beneficial they may have been, there were immense challenges when it came to essential dynamic capture mechanisms entailed, inherent complexities of ozone distributions, and the interactive behavior among different atmospheric constituents. Finally, some traditional procedures applied to analyze the concentration of ozone gas have given us a starting point for knowing about ozone gas and why it is important. However, this has been a long journey that introduces artificial intelligence into ozone monitoring other than its traditional practices. This could be significant in enhancing the accuracy of programs developed to predict ozone while also explaining how it gets depleted.

Traditional methods of ozone monitoring have various limitations due to the above used methods make them inefficient. Figure 2 illustrates various limitations of the traditional methods of ozone analysis.

The disadvantage of limited spatial and temporal coverage of ozone analysis is due to inadequate data from remote regions, incomplete data integration, inefficient data processing, slow processing, lack of real time monitoring, no predictive capabilities, high costs and resource requirements for skilled personnel and maintenance, measurement errors due to instrument calibration issues and environmental and technical interference, limited public accessibility because of the data confined to researchers and agencies (Shabani, 2023). It is through combining traditional methodologies with new AI technologies that will accelerate research on understanding

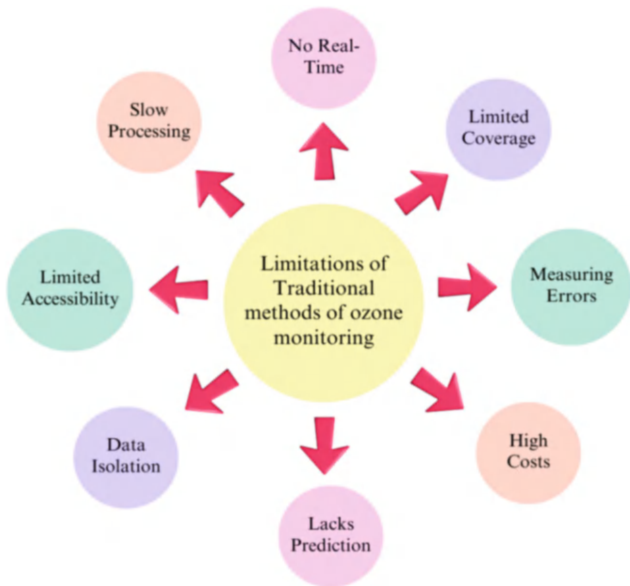

Fig. 2 Limitations of traditional methods of ozone monitoring

more about ozone and possible ways to deal with health issues related to air pollution caused by ozone depletion in future years ahead.

3 Role of AI and ML in Ozone Monitoring

Proper cleaning and verifying data is vital for the credibility and precision of ozone concentration data, big in terms of research on atmospheric science. The applications of AI and ML in ozone monitoring are shown in Fig. 3.

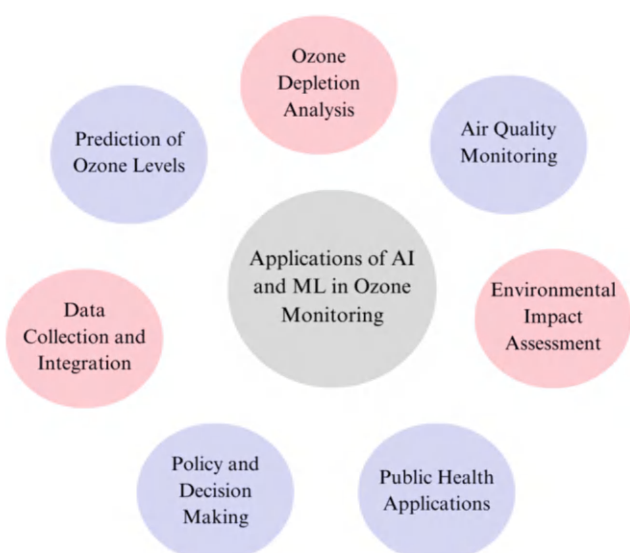

Fig. 3 Applications of AI and ML in ozone monitoring

AI and ML play a significant role in ozone monitoring by leveraging advanced techniques for analyzing and predicting levels of ozone concentration and their harmful impact leading to environmental damage (Yafouz et al., 2021).

3.1 Data Collection and Integration

Ozone monitoring needs a massive amount of data collected from different sources such as satellite imagery, weather sensors, air quality monitor, ground-based stations as shown in Fig. 4.

The process of integration of the datasets collected from the above sources is complex as each dataset differs in spatial and temporal resolution. AI and ML techniques such as data fusion algorithms and unsupervised learning are utilized to process these varying datasets (Himeur et al., 2022). These techniques help in reducing efficient and relevant patterns free from human errors. Advanced ML techniques such as clustering and dimensionality reduction help in preprocessing and integrating multi-dimensional datasets effectively. AI also plays a significant role in ensuring accurate and continuous ozone level monitoring by detecting the outliers in the dataset and providing real-time data acquisition. To analyze the data collected from image-based satellites, Convolutional neural networks (CNNs) are used and to enhance the predictive accuracy of these networks ensemble models are utilized by combining outputs from multiple ML algorithms (Cannizzaro et al., 2021).

An example is NASA's Earth Observing System (EOS). This NASA system includes the Aura satellite Satellite and the Sentinel-5P satellite. It has instruments called the TROPOspheric Monitoring Instrument (TROPOMI) and

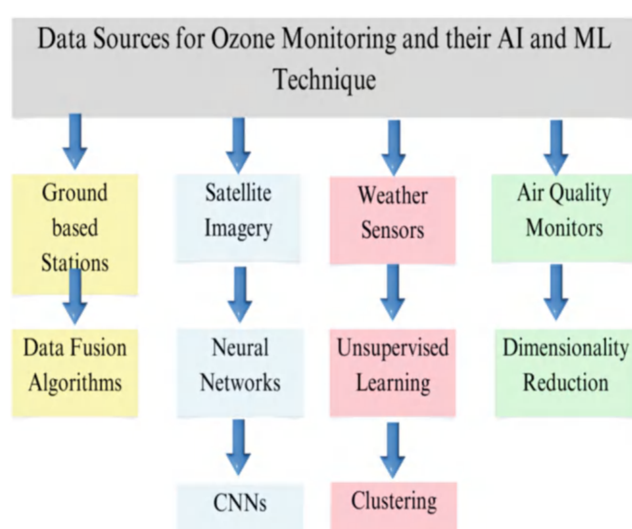

Fig. 4 Data collection and their AI and ML technique

the Ozone Monitoring Instrument (OMI) (Hossain, 2023). These devices collect comprehensive data on levels of ozone worldwide. AI models pre-process this data to locate trends and patterns. Google Earth Engine simplifies global ozone mapping by offering academics a cloud-based platform to integrate and analyze environmental data, such as ozone levels, from various satellite and ground-based sources (Al Saim, 2021).

3.2 Prediction of Ozone Levels

Historical as well as real-time data analysis is very necessary to predict the ozone levels and to forecast concentrations under varying environmental concentrations. Due to the high variability in the dataset collected for prediction of ozone levels traditional statistical methods fail and fall short in handling the non-relationship data (Wang et al., 2003). Thus, different ML models are employed for predicting ozone levels as shown in Fig. 5. Prediction models also take into consideration emissions of ozone precursors such as nitrogen oxide (NO) and volatile organic compounds (VOCs), as well as climatic factors including temperature, humidity, and UV radiation (Abdul-Wahab & Al-Alawi, 2002).

The European Copernicus Atmosphere Monitoring Service (CAMS) provides real-time ozone forecasts throughout Europe using machine learning (ML)-driven models (Peuch et al., 2022). These models forecast both short- and long-term ozone trends by combining pollution levels and meteorological data. CNN-based prediction models are used to estimate ozone levels in urban areas like Beijing (Wang et al., 2023), reducing health hazards by enabling proactive policy measures and sending out timely alerts.

3.3 Ozone Depletion Analysis

There is a need to monitor the ozone depletion in the stratosphere which requires analyzing spatial and temporal variations in ozone concentrations. AI models play a significant role in detecting anomalies, such as ozone holes, by processing large-scale satellite imagery and identifying the deviations from those of the historical data (AlOmar et al., 2020). Figure 6 shows the various AI and ML techniques for ozone depletion analysis. The integration of deep learning techniques like object detection algorithms and image segmentation helps to identify pinpoint thinning areas with high precision. Due to the current depletion of ozone layer ML models are integrated to simulate future scenarios under different policy measures helping in environmental governance. These ML models evaluate the harmful impact of ozone-depleting substances (ODS) like Chlorofluorocarbons (CFCs) on stratospheric ozone (Laube et al., 2023).

Sentinel-5P satellite data is used by the European Space Agency (ESA) to track the Antarctic ozone hole (Laat et al., 2024). The data is analyzed by AI-powered algorithms that provide insights into the success of the Montreal Protocol by quantifying the hole's size and depth. AI research initiatives assist policymakers design more effective responses by modeling the progressive phase-out of ODS and simulating the possible recovery of the ozone layer (Bell et al., 2023).

3.4 Air Quality Monitoring

The deteriorating air quality is causing harmful impacts to the complete ecosystem ranging from living things to nonliving things, human health to natural vegetation. There are various factors that are responsible for degrading air quality. One of

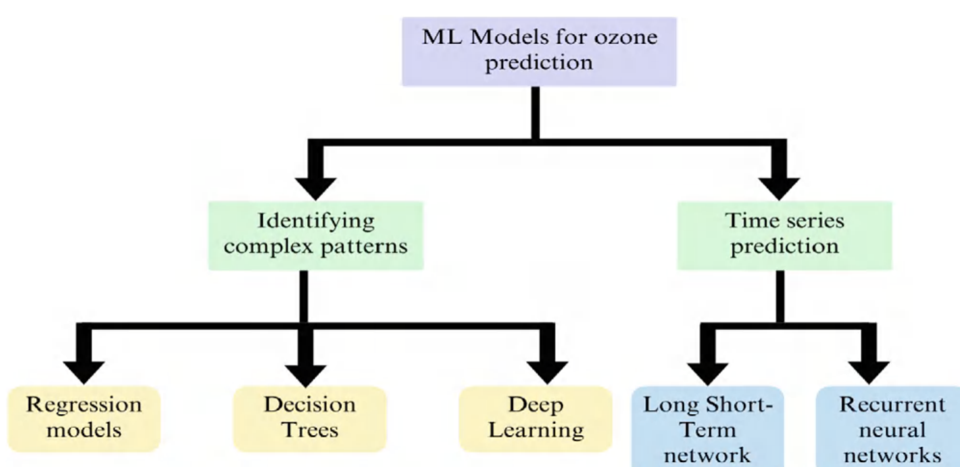

Fig. 5 Different ML models for predicting ozone levels

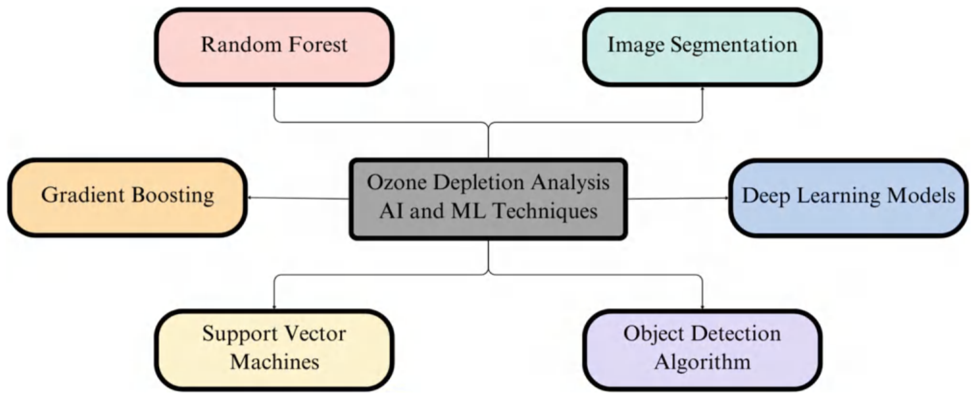

Fig. 6 Different AI and ML techniques for ozone depletion analysis

the major factors is tropospheric ozone that is a significant air pollutant and a major component of urban smog (Tang et al., 2011). It is necessary to take into consideration the intricate relationships between contaminants and weather when monitoring its levels. Ozone levels at local scales are predicted using AI and ML methods like gradient boosting and regression analysis (Montalban-Faet et al., 2024). Figure 7 depicts the various AI and ML techniques for monitoring the air quality due to tropospheric ozone.

There are real-time monitoring systems that are used to detect pollution spikes, identify hotspots, and forecast air quality leading to immediate corrective actions. These real-time monitoring systems use IoT sensors integrated with AI algorithms to process the streams of data.

The cities of Los Angeles, New Delhi and community projects use a variety of AI techniques and monitoring systems to assess the deteriorated quality of air. These cities use AI-enabled AQI systems that merge data from ozone monitoring with measurements of other pollutants for comprehensive air quality assessments (Zeng et al., 2024). Community projects using PurpleAir sensors are providing localized and low-cost monitoring solutions via ML techniques that analyze tropospheric ozone data (Heintzelman, 2022).

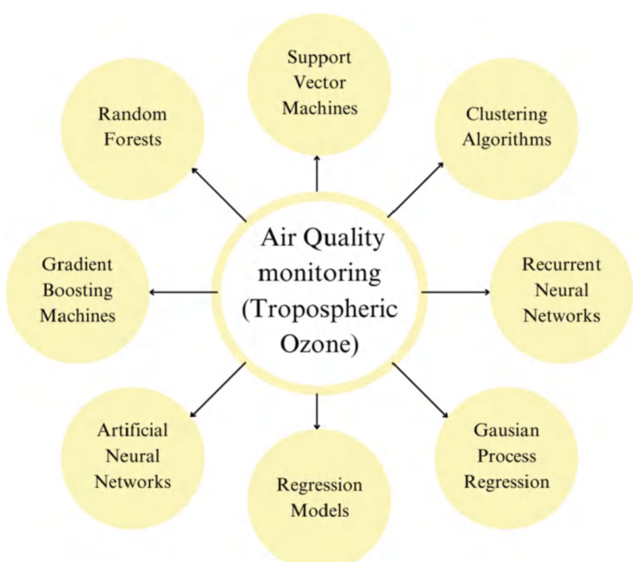

Fig. 7 Different AI/ML techniques for monitoring air quality (Tropospheric ozone)

3.5 Environmental Impact Assessment

Ozone helps in maintaining life and climate on planet Earth. GHGs increase global warming while the high levels of ozone can damage aquatic systems, forests, and agriculture. In order to replicate these interactions and provide insights into potential environmental impacts, AI models integrate ozone data into climate models (Szramowiat-Sala, 2023). Figure 8 shows various ML techniques like Deep Learning, Artificial Neural Networks, Gradient Boosting Machines, Support Vector Machines, etc., that explore the impact of ozone on specific ecosystems, such as crop loss from the high level of tropospheric ozone (Upadhyay et al., 2024). Farmers and agronomists can use new computer models to obtain information about potential crop yields in light of increasing ozone concentrations.

For instance, the Community Earth System Model (CESM) uses AI-enhanced simulations in environmental impact assessment in the Indo-Gangetic Plain. CESM examines how ozone interacts with climate systems and offers useful information for international climate policies (Zou et al., 2020). Research conducted in the Indo-Gangetic Plain supports the establishment of agricultural policies by using AI models to evaluate the effects of ozone pollution on rice and wheat yields (Dewan & Lakhani, 2024).

3.6 Public Health Applications

Exposure to ozone, especially in urban settings, can cause serious health problems, such as cardiovascular and respiratory disorders (Subramaniam et al., 2022). High-risk areas

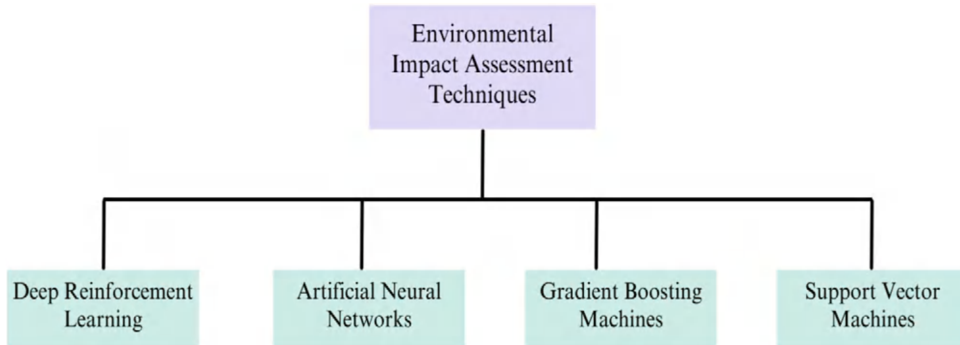

Fig. 8 Different AI/ML techniques for environmental impact assessment

and vulnerable populations are identified using methods like clustering and supervised learning. AI also makes it possible to create real-time health advice systems that combine ozone data from wearable health devices to deliver customized alerts (Wu et al., 2022). By advising people to take preventative measures during times of high ozone, these systems lower hospital stays and medical expenses.

Singapore integrates data from wearable health devices and environmental sensors to employ AI-driven smart city systems to forecast health hazards related to ozone exposure (Monitoring, xxxx). To educate communities about ozone-related hazards, especially during the summer when ozone levels are usually higher, the U.S. Environmental Protection Agency (EPA) uses ML models (Mirza & Shah, 2024).

3.7 Policy and Decision Making

Exposure to ozone, especially in urban settings, can cause serious health problems, such as cardiovascular and respiratory disorders. High-risk areas and vulnerable populations are identified using methods like clustering and supervised learning (Sharman & Holmes, 2010). With AI, it is possible to create a real-time health advice system that uses ozone data from wearable health devices to provide personalized alerts. These systems reduce the number of days people spend in hospitals and the costs of care by telling people to limit exposure to high ozone times.

AI tools are being leveraged to gauge the Montreal Protocol's success, using decades of data to quantify the reduction of ozone-depleting substances and their positive impact on the ozone layer (Chenier, 1997). Similarly, in India, AI models simulate the impact of reduction on vehicular emissions to reduce ozone levels in urban areas. This helps policymakers design traffic restrictions effectively (Dass et al., 2021).

4 Spatiotemporal Analysis of Ozone Levels

Spatiotemporal analysis refers to the examination of ozone concentration variations over both space (geographical locations) and time (hour, days, months, or years). To understand ozone behaviour, identifying patterns, and predicting future trends it is very crucial to do such type of analysis (Ma et al., 2020). The objectives of spatiotemporal analysis are to understand ozone distribution, monitor temporal needs, identifying different seasonal, diurnal, and geographical patterns in ozone behaviour, and assess the effect of anthropogenic activities, natural phenomena, and regulatory measures on ozone levels and use models to forecast ozone changes due to climate change or policy interventions (Christakos & Kolovos, 1999). There are various key factors involved in spatiotemporal ozone analysis and Fig. 9 illustrates the different factors of spatiotemporal analysis.

Statistical techniques, AI and ML models, Remote sensing and GIS, Ground-based monitoring are the different methods used for spatiotemporal analysis (Zang et al., 2021). Figure 10 shows a detailed overview of all the methods used for spatiotemporal analysis. There are various studies that have shown the implementation of all these methods leading to efficient temporal analysis (Ezimand & Kakroodi, 2019). Some studies are discussing some specific regions.

The study conducted in South Korea during the time period 1999–2010 (Seo et al., 2014) was to evaluate the spatiotemporal features of the surface ozone (O_3) variations with the help of meteorological factors. The researchers applied the Kolmogorov-Zurbenko (KZ) filter on O_3 time series to decompose them into short-term, seasonal, and long-term components using data collected from 124 monitoring sites in urban air quality and 72 weather stations. Authors also looked at the relationships between the O_3 and various meteoro-

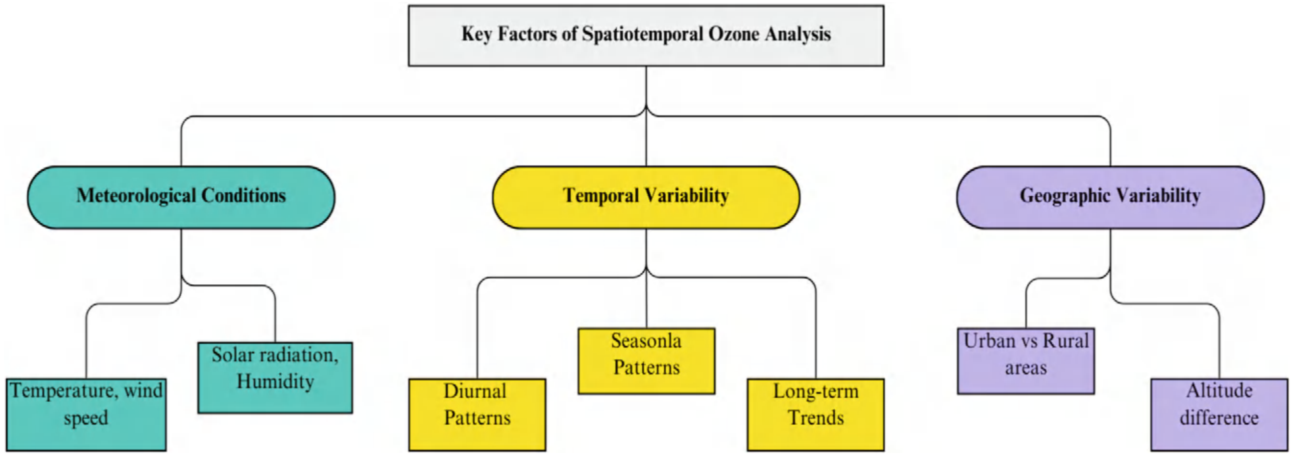

Fig. 9 Factors of spatiotemporal analysis

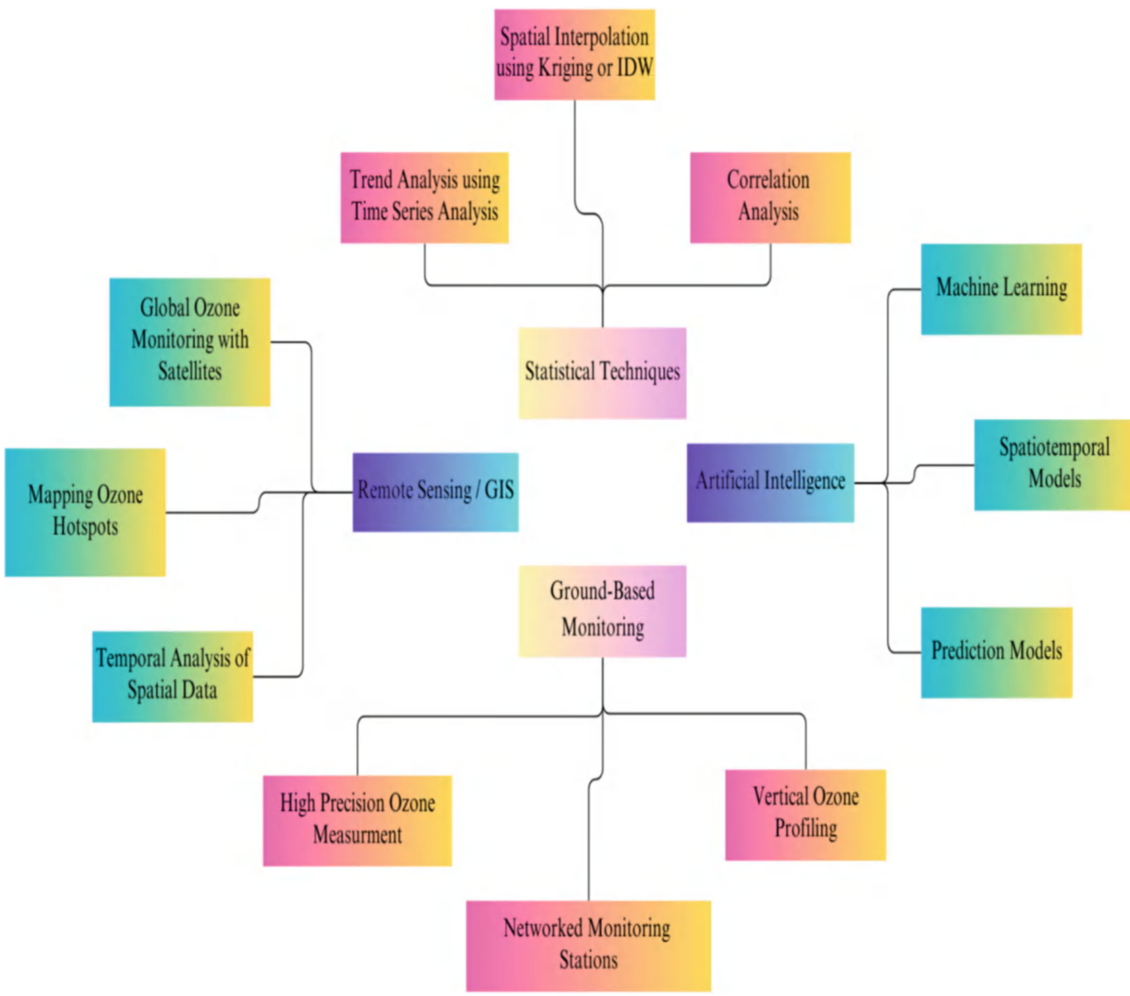

Fig. 10 Different methods of spatiotemporal analysis

logical components using multiple linear regression models. One important objective of the study in China between 2005 and 2017 was to analyze the spatiotemporal distributions of surface ozone, as well as long-term trending most impactful ozone pollution (Liu et al., 2020). To create a national prediction model based on the daily maximum 8-h average (MDA8) ozone observations, which are hyperspectral data satellite images used to establish patterns of ozone pollution, the researchers used the eXtreme Gradient Boosting (XGBoost) algorithm. To address heterogeneity of ozone concentration across regions and time, the technique was to create spatial and temporal terms. Results showed that the model has high prediction accuracy, R^2 values from 0.60 to 0.87 in the external test. This is the key conclusion drawn, that ozone pollution is a serious threat to public health in China. Actually, we can also see the increases in more and more areas. Also in other areas, especially in the Beijing-Tianjin Hebei area.

For spatio-temporal modelling of ozone, the research is conducted in Mexico City. This analysis will involve spatial–temporal interpolation and prediction of ozone (Huerta et al., 2004). The type of technique being used is a time-varying regression, which is defined to link observed ozone to air temperature and interpolated temperature at locations and times with data missing. The model reproduced the main periodicities of Ozone concentrations during the course of the day, supported by location-dependent harmonic components. The major conclusion arising is that the proposed model properly combines spatial covariance structures that improve understanding and forecasting of ozone levels in urban regions like Mexico City.

The monthly 8-h average O_3 concentrations across California were mapped in another study over span of 15 years (Bogaert et al., 2009). The spatiotemporal random field methodology employed was used in decomposition of seasonal O_3 patterns from stochastic fluctuations. Bayesian Maximum Entropy (BME) analysis was applied, and the resultant space time maps of seasonal O_3 patterns were detailed, and showed significant geographic variations in summer and winter months. These maps had clear and gradually changing geographical patterns, patterned by the physiographic and climatologically characteristics of California in the results. Based on the analysis, the main conclusion is that BME mapping exhibits superior accuracy than the established techniques, providing insights into the modes (spatiotemporal) of O_3 patterns and their physical mechanisms, as well as human exposure and risk assessment.

A second study also was carried out to characterise the spatial and temporal variability of daily 8-h maximum O_3 concentrations across the eastern United States during 1993 through 2002 (Lehman et al., 2004). The researchers reduced data complexity and interpreted spatial patterns of O_3 concentrations with a rotated principal component analysis (RPCA). This technique allowed for the identification of five homogeneous regions: Great Lakes, Mid Atlantic, Southwest, Florida, and Northeast. Results indicated largest O_3 concentrations were over the Mid-Atlantic region and Florida region exhibited considerable seasonal variability. Analyses show that regional characterization of O_3 concentrations can effectively discern seasonal and annual trends, and thus emphasize the significance of specifying spatial and temporal patterns in understanding air quality and its management.

5 Challenges and Limitations

AI and ML have revolutionized the ozone monitoring process in various applications and have the potential to revolutionize it to a greater extent but there are several challenges and limitations associated as shown in Fig. 11.

- **Data Quality and Availability**: ML models and AI techniques are solely based upon massive amounts of high quality data that give accurate results with high precision. In remote areas or areas at specific altitudes the collected data may be sparse or inappropriate leading to wrong predictions. This missing or false data can limit the performance of AI models. Due to unavailability of real-time and consistent data from ground-based stations, satellites, or balloon-based instruments, etc. AI models can make inaccurate predictions leading to less efficient models (Bhattacharyya et al., 2023).
- **Data Diversity and Integration**: The data used for ozone monitoring requires integrated data from various sources like satellites-imagery, ground-based stations, and balloon sensors, each with different spatial, temporal, and measurement characteristics. The efficient integration of the data from multiple sources does not take place due to varying data formats and varying measurement techniques (Chen & Zhang, 2014). This creates difficulty in training ML models on unified dataset.
- **Complexity of Atmospheric Processes**: Ozone behavior is challenging to model since the atmosphere is extremely dynamic and influenced by a number of variables,

Fig. 11 Limitations of using AI and ML models in ozone monitoring

including weather, pollution, and seasonal changes (Clifton et al., 2020). The intricate relationships between ozone and other atmospheric constituents may not always be taken into consideration by ML models. Because atmospheric chemistry is non-linear and frequently chaotic, AI models may not generalize well.

- **Model Interpretability**: The interpretation of many AI and ML models especially those of deep learning models is difficult and thus act as black boxes. Decision-making is very crucial in field of AI and ML especially in the scientific community where understanding the reasoning behind the predictions is very much crucial for validating the models and their results but this decision-making process is limited due to the lack of interpretability in AI models (Duan et al., 2019).
- **Model Overfitting**: When an AI model becomes too prone to a particular training dataset that when subjected to new or unseen data it results in poor generalization (Yaseen et al., 2015). This is called overfitting. When an ML model for determining ozone concentration level becomes too tailored to only one factor based data, when tested on new factor-based data it leads to wrong prediction of ozone concentration levels (Marvin et al., 2022). If there is variability in atmospheric conditions, a model trained on limited dataset will not generalize efficiently to different seasons, regions or other varying environmental factors, leading to inaccurate ozone concentration forecasts.
- **High Computational Cost**: ML models require significant computational resources for training and deployment purposes especially those involved in deep learning models (Patil et al., 2024). These resources require high computational cost and this high computational demand prevents the scalability of these models especially those models which require real-time ozone monitoring or large scale monitoring that involve use of sensors as well as remote sensing and GIS systems. This limitation becomes a hindrance in the path of efficient model and system building.
- **Ethical and Regulatory Issues**: The major concern taken into account in implementing any AI-based technique is the ethical and social considerations. Ethical concerns are like our data privacy, transparency in decision-making and algorithmic bias arising due to deployment of AI in environmental monitoring (Akinrinola et al., 2024). Public distrust, regulatory hurdles, and challenges in ensuring transparency and equality in environmental decision policy are the major problems that may arise due to misuse or lack of transparency in AI-based systems (Kuziemski & Misuraca, 2020).
- **Real-Time Processing**: For monitoring air quality and disaster response AI models made for ozone monitoring require real-time data processing (Kaginalkar et al., 2021). If this real-time data processing fails that means if AI systems do not respond to ozone data effectively due to latency issues and limited internet connectivity or computational infrastructure in small regions the dynamic applications of ozone monitoring are not fulfilled. Ensuring that the above situations do not take place is a challenging task.

6 Case Studies and Real-World Applications

The application of different forms of AI for measuring ozone has led to a completely new foundation, opening possibilities for high levels of precision analysis and improvement in predictive opportunities (Vázquez for Centre for Cities, 2020). This part highlights the practical application of the subject through case studies and examples based on ozone monitoring (Karatzas & Kaltsatos, 2007).

Various ML algorithms are reported to predict ozone levels particularly in urban areas (Pan et al., 2023) while ANN models successfully estimated ozone concentrations through comparison of past and present ozone data aligned with the diverse atmospheric conditions (Luna et al., 2014). Various ML algorithms are reported to predict ozone levels particularly in urban areas while ANN models successfully estimated ozone concentrations through comparison of past and present ozone data aligned with the diverse atmospheric conditions (Al Saim, 2021). Also, researchers used data from multiple monitoring stations to analyze ozone level (Yafouz et al., 2022). ANN models effectively forecast ozone levels across different locations by using various datasets of pollutant levels and atmospheric conditions.

Hence, ANN model can be applied in real-time monitoring and forecasting pollutant levels in air which helps the government in decision-making for issuing warnings and alerts. ML models combined with ANN models drastically approve the accuracy of analysis and also simplify the resource monitoring process (Mikalef & Gupta, 2021). Thus, ozone monitoring with AI and ML models contributes to the promotion of sustainable practices, addressing many environmental challenges (Brasseur, 2020).

Case Study 1: Predicting air quality standards using ANFIS

In Saudi Arabia, an ozone monitoring system was set up to accurately estimate ozone levels (Cha et al., 2024). This was identified as a necessity for good public health, to control increasing ozone pollution.

- **Ozone Monitoring Process**: The research started with collection of ozone concentration data from monitoring stations set up by the General Authority of Meteorology and Environment Protection in the Kingdom of Saudi

Arabia. This data was used to relate the variations in ozone concentrations with air quality standards.

- **AI and ML Techniques Used**: Adaptive Neuro-Fuzzy Inference System (ANFIS) was the major technique used in this study. This system is a model created by the combination of neural networks and fuzzy logics, designed exclusively to monitor complex ozone predictions. The fuzzy logic works on "if–then" rules to find relationships between quantities like nitrogen oxides (NOx), atmospheric pressure, temperature, and relative humidity.
- **Results indicating success**: The ANFIS model achieved a training error of 3.01% and testing error of 3.14%. The root mean square errors (RMSE) were calculated to be 0.84 for training data and 0.62 for checking data. This indicated high levels of accuracy in the prediction of ozone concentrations. Moreover, the model could accurately establish models between emissions and atmospheric conditions, which in turn contributed to air quality management.

The main intention of the research was to evaluate the influence of various meteorological parameters on ozone concentrations and present an effective estimation model for monitoring air quality. It clearly established the necessity of the application of AI methods to improve the air quality forecast accuracy, which is highly significant to human life and the environment.

Case Study 2: ANN for the prediction of tropospheric ozone concentration

This paper addresses the estimation and prediction of tropospheric ozone concentrations via artificial neural networks, a technique of artificial intelligence and machine learning (Abdul-Wahab & Al-Alawi, 2002).

Ozone Monitoring Process: Ozone concentration was monitored in an urban atmosphere with high traffic influence in a residential area through a monitoring process. These included hourly observations of nitrogen oxides and hydrocarbon species for an entire year. All the data collected within the entire year formed the basis of understanding the factors responsible for ozone concentration.

AI and ML Technique Used: The predominant technique used in this work was that of artificial neural networks (ANNs). These models were designed to capture complex, nonlinear relationships between ozone concentrations and a broad variety of input variables, from meteorological conditions to parameters of air quality. For this purpose, three different types of neural network models have been applied to analyze and predict ozone levels.

Successful Results: It was found that the results successfully predicted the ozone concentrations in the ANN models. Successive models showed better predictive accuracy of the models with R^2 values ranging from 0.7 for the first model to 0.91 for the third model. This indicates a highly correlated relationship between the actual observed and the predicted ozone concentrations. Further, it has been found that in the variation of ozone level, changing meteorological conditions could explain about 48% and other pollutants significantly also contributed.

The paper was designed to identify factors governing the levels of ozone, specifically during daylight hours when concentration is typically greater. It attempted to give a tool for rapid assessment for the decision-maker to use the minimum amount of data possible in assessing environmental situations. The research attempted to improve the models used to predict the concentration of ozone by trying to understand the contribution of the input variables.

Case Study 3: Surface ozone gas concentration prediction using ANN and WT

The main focus of the study is the prediction of surface ozone gas concentrations using a robust artificial intelligence approach (AlOmar et al., 2020).

Ozone Monitoring Process: In the study, ozone concentration levels were monitored at surface gas levels using data extracted from the London station in Ontario, Canada. This was the process of monitoring hourly measurements of ozone level levels over a year for full data collection and later analyzed. The goal is to understand and predict concentration levels of ozone well.

AI and ML Techniques Used: The artificial technique that was used most predominantly in this study was Artificial Neural Network (ANN). This was because the relationship that was to be modeled with this research was complex and the number of variables used as inputs. Other than that, wavelet transformation (WT) is also used as a preprocess. It is very much needed to remove noise for better quality input data. That improves the accuracy of the ANN model.

Successful Results: The results from the ANN model were very successful, as it predicted ozone concentration several hours ahead with accuracy, between 2 to 5 h ahead. The combination of ANN with wavelet transformation significantly improved the predictive accuracy of the model compared to traditional methods. It was important because many things like temperature, UV radiation, nitrogen oxides, and non-methane hydrocarbons levels also affect the ozone.

The purpose of this research is to create a strong model that is capable of giving warnings about ozone concentration levels. This is important in proper air quality control and safety of people's health. As global warming is resulting in rising levels of ozone, problems can arise both for agriculture and the economy. A study stressed that overcoming these problems lies in prediction accuracy and timeliness.

Case Study 4: Monitoring of Ground Level Ozone using Ensemble Model

The purpose of this study is to enhance the accuracy of O_3 monitoring at the ground level using low-cost sensors (LCS) and artificial intelligence (AI) techniques (Montalban-Faet et al., 2024).

- **Ozone Monitoring Process**: Implementation of sensors for monitoring air quality were calibrated from the module ZPHS01B ozone sensors. O3 concentration reference values were obtained from the official Air Quality (AQ) station in Valencia, Spain. The data for these gave $\mu g/m^3$ in 10 min intervals. Calibration is an attempt to increase low cost sensor performance with the addition of environmental data like temperature (T) and relative humidity (RH).
- **Techniques of AI and ML Utilized**: Raw ozone sensor reading would be used by Gradient Boosting and its equivalent ensemble machine learning methods for its conversion. This is chosen for the following reasons: its high capability to accomplish a large amount of error reduction in estimation.
- **Successful Outcomes**: With the Gradient Boosting algorithm the estimation error was shockingly small, about 94%. Although the performance in this case was much better than the previous similar work, it reflected the possibility that the air quality can be monitored using low cost sensors through an advanced AI technique.

In towns, this upgrade in spatial resolution is applied using the low cost sensor for ozonometric monitoring. In this regard, more stress is given to the need for increased accuracy levels in measuring ozone because it is a constitutive part of any air quality mechanism included within a smart city.

Case Study 5: Monitoring ozone levels using EEM-ML model

The paper examines the use of AI and ML technologies in preventing pollution and monitoring ozone levels. (Szramowiat-Sala, 2023).

Ozone Monitoring Process: The study emphasizes the need for atmospheric pollution monitoring, mainly to understand the origin of particulate matter (PM), generated mainly by combustion processes. The control process used more advanced instrumental analytical techniques by AI algorithms to improve the safety and accuracy of pollution detection.

AI and ML Techniques Used: A hybrid algorithm incorporating excitation-emission matrix (EEM) fluorescence spectroscopy with machine learning has been built. This EEM-ML approach is specifically tailored to determine and predict the sources of PM pollution like vegetative burning and mobile sources. The model was trained with the PMF source apportionment technique.

Successful Results: The EEM-ML model's predictions regarding the contributions of various sources to PM pollution were moderately successful. The system did particularly well in allocating emissions from gasoline and diesel, showing its utility in the field. The findings show that the model was able to predict PM emissions accurately and outperformed commonly used methods such as multilinear regression and principal component regression.

The research sought to use the features of AI and ML for improving the environmental monitoring system focusing on atmospheric pollution. By using these methods, the study will make the understanding of pollution more easily. Furthermore, it may develop more severe pollution prevention mechanisms.

7 Future Directions

The sustainability of AI models is currently dependent on how much and the quality of data that is used to train a model (Wang et al., 2024). The challenge we are facing is collecting coherent processed data which is available from different sources. Strong computers are essential in handling complex models (Gourdain et al., 2009). It's as if there was a requirement for an advanced calculator to solve some difficult math problems through computations. The study should also concentrate on improving hardware efficiency and algorithmic efficiency for such ozone analysis. There may occur unintentional biases in training datasets leading to biased AI models being created. An ethical framework must be considered when collecting data and training models with it (Schwartz et al., 2022).

Also, Explainable AI (XAI) could be improved upon in developing clear models of ozone analysis which are consistent with how the model arrived at its conclusions. As discovered in previous sections, AI can merge information gathered from satellite imagery, ground observatories, and atmospheric models (Young et al., 2018). Therefore, one way of enriching ozone forecasting techniques and policies is possibly by blending together environmental decision-making tools with AI-powered models for ozone analysis.

This serves as the reason why the need for ozone assessment came forward. There is a need to expand the current research on AI-based models through continuous learning, utilizing the existing data (Cooper et al., 2012). This needs collaboration between domain experts, data scientists and government officials in order to achieve global solutions. Even with all the advancements made in AI, research scientists are still an important part of the process of analyzing ozone because of their experience and specialized knowledge (Khullar et al., 2024).

Ozone analysis is a relatively new area for application of AI; hence there are many undiscovered aspects of ozone analysis that need further research. Thus, there are many expectations for ozone analysis's future prospects (Singh et al., 2022).

8 Conclusion

Concluding this book chapter, with the integration of AI techniques and ozone monitoring techniques, it is possible to extract distinct features from the atmosphere. Various AI techniques used here are Enhanced Data preprocessing, Quality control, and predictive modeling, which forecast ozone concentrations with more accuracy and lesser efforts. The alignment of AI with traditional techniques, such as soil monitoring stations and remote sensing by satellites, doubles up the ability to track ozone sources, lumps, and variations not only through the layers of the atmosphere but also distinct areas on the earth.

Apart from this, AI-inspired ozone monitoring systems produce data considering public health which provides real-time insights and allows preventive decision making. Though there are undeniable achievements, the challenges still remain; infrastructure of the hardware, speed of algorithms as well as ethical concerns of data gathering and model training, which need to be minimized to prevent unintentional biases. In order to solve these problems, there is a need for interdisciplinary collaboration that entails integrating scientists, data experts, and decision-makers in the creation and monitoring of implementable and equitable solutions.

Peeping into the future, the future possibility of AI-enabled processing of ozone data holds good, which can be accomplished through bettering models, associating them with decision-making instruments and development in explainable AI to amplify transparency and truth. Through embracing AI as the main instrument in our environmental stewardship initiatives, we would have better understanding about ozone dynamics and would lay services for the implementation of successful strategies to tackle the ozone pollution problem and to ensure the good health status for both current and future generations.

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Quantum Computing in the Field of Earth Sciences

Neetu Rani and Shweta Agarwal

Abstract

The principles of quantum mechanics will enable quantum computing to tackle complex computational problems that can revolutionize earth sciences. It will discuss the prospect of quantum algorithms for major areas such as climate modeling, geophysics, environmental monitoring, and remote sensing in those areas where classical computing could not cope with large complex datasets at the level of precision or speed required. Section 1 illustrates qualitative introduction to quantum computing—the causes of computational bottlenecks in the prevailing earth sciences methods. Another area that goes further into quantum computing's real-world applications is greater precision in climate simulation, forecasting subsurface exploration, and pollution modelling. This could eventually be reduced to more complex patterns that recognize the structures in data allowing quantum machine learning to develop insight for detecting patterns in greater datasets for more accurate predictions. Using several case studies quantum-enhanced earthquake prediction and climate modeling this chapter is applied towards real-world applications and discusses the current trends in this research area. The topic thereby illustrates the promises and challenges such as the limitations of quantum hardware, integration with classical systems, and scalability for large-scale applications in earth sciences.

Keywords

Quantum algorithms · Geophysical modelling · Climate simulation quantum · Geosciences · Resource exploration · Environmental computing

1 Overview of Earth Sciences

Quantum computing has immense potential in the enhancement of analysis on large geospatial datasets for more predictions and decisions in environmental management and disaster mitigation. Earth sciences are the scientific disciplines that study earth's structure, changes, and its various ongoing processes. These include geology, oceanography, climatology, environmental science, and meteorology. All of these discuss various aspects of dynamic systems involving the earth. Earth scientists try to explain natural phenomena related to climate patterns, geological formations, seismic activities, and interactions between Earth's atmosphere, hydrosphere, and biosphere. The complex relationships within the interconnected systems cry out for accurate gathering, analysis, and model predictive inputs to help solve problems for climate change, natural disasters, and resource management. Most of earth science relies on computational techniques to handle the vastness of the datasets being generated from satellite imaging, geophysical measurements, and climate models (Vance et al., 2024).

2 Quantum Computing Definition and Scope

Quantum computing relies on quantum mechanics, that theory of nature at the smallest scales for computations impossible for a classical computer. The quantum computer uses qubits which can be in states either 0 and 1 at the same time. Advanced computational power is facilitated by quantum entanglement and quantum interference. The scope

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of quantum computing ranges from solving optimization problems and simulating complex quantum systems to the processing of large-sized data efficiently (Otgonbaatar & Kranzlmüller, 2023b). Its applications are vast, ranging from cryptography, material science, artificial intelligence, and earth sciences, where it may guide new approaches to solving problems involving extreme precision and high speed.

2.1 Relevance of Quantum Computing to Earth Sciences

Quantum computing is specifically relevant to earth sciences because data set sizes are just too big and complex for studying earth systems. Traditional computing usually gets bogged down by the number of processes that need to be run when handling datasets of such a scale: climate models, seismic readings, geospatial information, and many more. Quantum computers can provide solutions to such problems since they allow for faster simulation, more accurate prediction, and multiple variables in the same data to be processed as a whole. For instance, it is where quantum computers enhance the accuracy of climate change and weather pattern models for climatology. Quantum algorithms can support geophysics in refining the analysis of seismic data for further advancement of possible earthquake prediction as well as access to natural resources. In summary, it provides a very advanced set of tools to answer intrinsic complexity in earth sciences (Virapongse et al., 2022).

Chapter Objectives: The primary purpose of this chapter is to determine where quantum computing and earth sciences meet in order to discuss how quantum technologies can transform the way computing is done in that field. Section 2 highlights computational challenges pertinent to earth sciences, like dealing with large datasets, complex system simulations, high accuracy predictions. Section 3 describes the application examples where quantum computing will or could benefit research in earth sciences heavily in the sphere of climate modelling, geophysics, and environmental monitoring. Section 4 illustrates the Quantum Environmental Modelling. Quantum Remote Sensing defined in Sect. 5. Concept of Quantum Machine Learning for Earth Sciences is defined in Sect. 6. Various case studies are demonstrated in Sect. 7. Section 8 demonstrates the current research trends and future directions to solve earth-related problems.

3 Challenges in Earth Sciences

- **Complex Data**: Earth sciences study massive and complex datasets, which provide the information needed to understand the natural processes on earth. The sources of data vary in temporal and spatial dimensions thus dealing with complex data is a challenge requiring sophisticated tools and techniques for analysis and interpretation (Voldoire, 2022).
- **Climate Models**: Climate models are very complex simulations of future climatic conditions. These models involve many variables such as temperature, humidity, wind patterns, solar radiation, and greenhouse gas concentrations. The models are also multidimensional, spanning over different time frames ranging from days to decades and geographic scales ranging from local to global. Such voluminous data from satellite observations, weather stations, and historical records may make climate modelling a computationally intensive exercise. Indeed, with the advent of quantum computing, it may be feasible to process large datasets consisting of hundreds of thousands of variables within a very short period of time and yield much more accurate predictions of future climate conditions (Bianconi, 2024).
- **Geospatial Data**: Geospatial data plays a very important role in geography, geology, environmental science, and urban planning. Owing to their inherent large-scale high resolution and multidimensionality, geospatial data are very demanding on computational analysis. The traditional approaches suffer from difficulties in processing the huge volume of data, particularly in a real-time application scenario. Quantum computing can bring a considerable speedup in geospatial analysis, thus promoting faster rates of processing for applications such as land-use planning, disaster management, and environmental monitoring (Havskov & Ottemoller, 2010).
- **Seismology Data**: It is a study of earthquakes and propagation of elastic waves in the earth. Seismologists analyze tremendous data coming from seismometers that record the intensity, duration, and frequency of seismic events. Seismology data is complex because it has temporal and spatial variability, and it is high dimensional. Generally, conventional methods are slow in processing and interpreting large-scale seismic datasets, mainly for predicting an earthquake and making a real-time assessment of hazard. Quantum processing can therefore revolutionize the processing of seismic data speeds and identify patterns of seismic activities with advanced forecasting models concerning earthquakes (Moradi et al., 2018).

3.1 Computational Limitations of Classical Methods

The enormous sizes and complexities of data sets characteristic of the earth sciences pose severe limitations to classical methods on classical computers. The main limitations are illustrated in the following section:

- Classical computers take much time to process a large number of data variables, say climate models or seismic simulations, potentially having billions of variables.
- Classical systems often cannot handle the storage demands of huge datasets, such as for geospatial and environmental monitoring data.
- A large number of most earth science models-the ones used in climate simulations, for example-require solving highly nonlinear equations. Such problems do not solve efficiently in the classical sense.
- The more complex the datasets are, classical methods may fail to produce highly accurate predictions, where multiple interacting variables contribute in unpredictable ways (Degen et al., 2020).

Quantum computing resolves these problems by providing some computational paradigms that enable parallel data processing and more rapid algorithm execution as well as handle complex, nonlinear problems more efficiently.

3.2 Importance of High-Precision Simulations

Earth sciences require high-precision simulations to predict accurately related to climate change, natural disasters, and environment changes. Such massive data-intensive simulation requires models sensitive to the small changes in input variables. Small errors in a model can make considerable errors in predictions, so high precision is extremely required for policy making and disaster preparedness (Lynch, 2008).

- **Climate Change Predictions**: Accurate models for climate change are needed for predicting future weather patterns, increasing sea level and extreme phenomena such as hurricanes and droughts. Quantum computing promises to give enough precision that would be achieved to refine these models to greater accuracy.
- **Earthquake Prediction**: Advanced simulation of seismic activity is likely to be utilized for the improvement of earthquake predictions, thereby providing a means of assisting in the reduction of the inherent risks associated with natural catastrophes.
- **Resource Management**: It is in the environmental science discipline that high-precision models are applied in resource management so that water, soil, and biodiversity can be managed efficiently.

With its capability to process immense quantities of information and solve even more compound equations with far better precision, quantum computing might indeed be the ultimate transformative tool for changing the quality and reliability of simulation results in Earth sciences. Perhaps quantum computers will indeed give much more accurate simulations that would then lead to the best possible insights and decision-making if and when more data can be processed and even more variables can be considered simultaneously.

4 Quantum Computing Applications in Earth Sciences

Quantum computing offers an innovative method to confronting the challenges of modeling climate via potentially handling the enormous complexity of climate systems with greater efficiency than classical computers.

4.1 Climate Simulations and Predictive Models

Climate simulations often require the explanation of long-term changes in earth's climate, such as changes in temperatures, interannual fluctuations of rainfall, and the frequency of extreme weather occurrences. Solutions of these differential equations with a manageable level of complexity are very essential in climate simulations. The resolution of models leads to an enhancement in the complexity of the equation by increasing the number of variables and data points. Quantum computers, with their capability for parallel computation and a relatively better ability to calculate non-linear dynamics, can really speed up such simulations. Further, the high accuracy of predictive models can be ensured by considering the simultaneous interactions of more variables, thus better predicting climate change and its impacts (Kumar, 2022).

4.2 Enhancement of Weather Forecasting Accuracy

That this data is to be processed in real time relies entirely on good predictive models of atmospheric dynamics hence it is substantially challenging for classical computers to analyze the data at an acceptable rate and with enough accuracy, especially as a factor in the chaotic nature of the atmosphere.

Quantum computing can dramatically speed up and improve the accuracy at which weather models are solved, even when solving relatively simple equations and with greater precision. This would lead to more reliable short-term and long-term forecasts, thereby improving disaster preparedness, agricultural planning, and water management (Katole et al., 2024).

4.3 Quantum Geophysics

Geophysics could well be the next area where quantum computing can make a sea change. At much bigger scales, this involves studying the physical properties of the Earth and subsurfaces. Seismic data analysis is concerned with the processing of huge and complex data sets to detect and interpret seismic wave-induced vibrations. The data so used is for mapping subsurface earth and for forecasting earthquake activity. Classical methods of seismic data analysis often suffer from the heavy volume of data and the computational complexity in solving inverse problems, namely the reconstruction of subsurface structures from seismic readings. Quantum algorithms, such as QFT and QAOA, may soon prove to be essential in solving complex problems in an efficient manner, and this may lead to accurate analysis of seismic data with the potential for better real-time monitoring of activity and improved seismic hazard assessments (Pathania et al., 2022).

4.4 Earthquake Prediction

The complexities and uncertainties that are inherently associated with seismic activity also make earthquake prediction one of the toughest challenges. Quantum computing could help in the enhancement of earthquake predictions by making in-depth simulations of tectonic movement as well as stress accumulation within a fault line possible. Quantum algorithms might expedite the early detection of warning signs for possible earthquakes by processing large-scale datasets that may emerge in real time, taking into consideration a much larger variety of variables all at one time. This would cause disaster preparedness and mitigation strategies as a whole to change, saving lives and limiting further economic damage (Zhai et al., 2024).

4.5 Subsurface Exploration (Oil and Gas)

Quantum computing can potentially be utilized in subsurface exploration, especially in oil and gas manufacturing. As part of this, seismic data analyses and solving inverse problems reveal the subterranean structure of the Earth. Quantum computers may expedite these processes because such vast amounts of data can be handled that would help explore energy sources much better, faster, and more accurately. In addition to that, quantum algorithms may allow optimal drilling paths and resource extraction methods with lesser environmental degradation yet maximizing output (Rezaei & Javadi, 2024).

5 Quantum Environmental Modeling

This includes extensive applications in attacking the universal problems of pollution, deforestation, and loss of biodiversity worldwide. Quantum computing can be applied towards modeling complex environmental systems with much more accuracy and efficiency.

5.1 Pollution and Carbon Emission Modeling

It requires the monitoring and modeling of pollution levels with carbon emissions. These things would most likely help in assessing environmental health and in developing policies implemented to combat climate change. Traditional models typically suffer because of the processing of real-time data from diversified sources such as industrial emissions, vehicle pollutants, and atmospheric chemistry. The best aspect of quantum computing is it will be able to enhance the precision and possibly speed of such models as it can take on larger datasets, thus it may permit accurate real-time monitoring of pollution levels and sophisticated predictions about carbon emission trends. This would help devise better strategies for pollution reduction and meeting the global targets on emissions (Otgonbaatar & Kranzlmüller, 2023a).

5.2 Ocean and Atmospheric Modeling

There is an interlink between oceans and atmosphere, and the impacts of changes in one are substantial in the other. For this reason, modeling ocean currents, air circulation, heat transfer requires accurate interactions between the above. Quantum computers can definitely improve modeling of oceans and atmosphere by solving more complex fluid dynamics and heat exchanging equations at greater speed and with accuracy. This may also enable forecasting with improved accuracies regarding sea-level rise, storm intensification, and other major events due to climate-related disruptions, which are crucial to environmental management and coastal planning (Zaidenberg et al., 2021).

6 Quantum Remote Sensing

Remote sensing is the acquisition and analysis of data about the Earth's surface and atmosphere acquired through satellites, drones, and other sensing technologies. Quantum computing may play an important role in enhancing remote sensing data processing as it will slowly penetrate the growth happening exponentially with respect to data volume.

6.1 Quantum Computing for Analysis of Satellite Data

For instance, a large amount of data is produced daily by satellites regarding the Earth's land, oceans, and atmosphere. Substantial computation is required to analyze this data, especially when it relates to high-resolution imagery or multispectral data. Quantum computing is able to accelerate satellite data analysis by significantly faster processing of large data and optimizing the algorithms applied to classify patterns and anomalies in the data. This may improve applications such as land-use monitoring, disaster response, and climate research (Gupta et al., 2023).

6.2 Effective Processing of Geospatial Data

Geospatial data can be obtained from satellites, sensors, and drones then data can be used in earth sciences for tasks like creating ecosystem maps, monitoring environmental changes, assessing natural resource usage. Quantum computers might be very efficient in processing complex geospatial data to achieve faster image recognition, pattern analysis, and fusion of data from different sources. This would permit even more precise and accurate mapping of natural resources, new urban development, and environmental changes in a bid to overcome the most daunting problems, such as deforestation and habitat reduction, sustainability of resource use (Rane et al., 2024).

7 Quantum Machine Learning for Earth Sciences

Quantum Machine Learning is still an emerging area that attempts to merge the principles of quantum computing with machine learning techniques in solving complex data and computational challenges. This approach finds prominent scope in earth sciences, where large datasets and predictive models are mandatory for understanding natural systems and could require large datasets and predictive models to understand natural systems. Here's an exploration of its key applications in earth sciences (Ho et al., 2024).

Quantum machine learning is the mixture of features offered by quantum algorithms and classical machine learning models; it enables faster computation, greater efficiency, and results accuracy. In classical machine learning, large data sets with computing power are used in model training; it is growing extremely difficult with the sizes and complexity of the datasets. Quantum computers base their processing on the quantum principles of superposition and entanglement, which enables them to process big amounts of data and complex computations effortlessly, against traditional systems (Turlapaty et al., 2010). Key algorithms in quantum computing comprise QSVM and QNN that accelerate training and inference time in machine learning models. These techniques offer the capability to conduct more efficient analysis of high-dimensional data. They are, therefore, of utmost importance in Earth sciences, which involve huge datasets derived from climate models, geospatial data, and environmental sensors that require speedy and accurate processing.

7.1 Applications in Climate Prediction Models

Climate prediction models are one form of simulating the Earth's climate for long periods to predict temperature and precipitation changes along with extreme weather events. Such models are based on complex differential equations coupled to many variables, including greenhouse gas concentrations, ocean currents, and atmospheric dynamics. Traditional machine learning methods have been applied in addition to forcing climate models, but they cannot easily cope with the heavy computational requirements of high-resolution simulations (Behrman et al., 2000).

Quantum Machine Learning can enhance climate prediction models by:

Handling Big, High-Dimensional Data in a Highly Efficient Way: Quantum computers can perform calculations involving many variables simultaneously. This facilitates the analysis of large high-dimensional datasets in the Earth sciences far more rapidly and efficiently than is currently possible with the most powerful supercomputers. For example, this could enable the detection of climate patterns, tracking of deforestation, or estimation of biodiversity.

Optimizing the Data Classification with QML: It is possible to modify the data point classification algorithms based on the discovery of patterns to better determine different climate zones or areas prone to hazards. This is due to the fact that quantum computers search large databases more efficiently, meaning they find better patterns in the data clustering.

Real-Time Monitoring of the Environment: With geospatial data processed quickly, QML can play a very important role in real-time monitoring of ecosystems, weather patterns, and climate changes to provide scientists and policy-makers with the needed information on time.

For example, it may empower QML to identify better early warning signals about natural calamities like hurricanes or earthquakes using subtle patterns within seismic or atmospheric data.

7.2 Quantum Neural Networks in Earth Sciences

Quantum Neural Networks, QNNs are the next step to take artificial intelligence forward with the use of quantum computers. QNNs are designed as an imitation of the classical neural network but utilize the aspects of quantum properties such as superposition and entanglement in the processing of information. In earth sciences, QNNs can be used to really model highly complex tasks like prediction of climate, monitoring of environmental change, and geospatial data analysis (Zhu et al., 2021).

Some of the applications of QNNs for Earth Sciences include:

- **Weather and climate better models**: The QNNs can be used to develop more precise and efficient predictive models. Therefore, more complex variable relationships can be processed by QNNs, for instance, concerning weather or climate change where finer predictions in extreme conditions or even long-term climate change are involved (Huang et al., 2022).
- **Geospatial data analysis**: QNNs can easily process large volumes of high-resolution geospatial data from satellite imagery or remote sensors. This may lead to better land-use classification, resource mapping, and deforestation or expansion monitoring (Streltsov et al., 2020).
- **Interpretation of seismic data**: QNNs aid in improving the interpretation of seismic data, hence helping in earthquake prediction and hazard evaluation as they can identify patterns that the traditional methods usually cannot (Bauer et al., 2021).
- **Environmental monitoring**: QNNs can take large quantities of environmental data, for example, pollutant levels or water quality measurements, and classify patterns that may reveal pollution or environmental degradation (Benedetti et al., 2019).

Quantum neural networks are likely to be a significantly powerful model as compared to classic neural networks for the modeling of complex Earth systems, and with higher accuracy, and superior performance in dealing with huge and dynamic datasets.

8 Case Studies and Research Trends

8.1 Case Study 1: Quantum Computing for Enhanced Weather Forecasting

Weather prediction is a complex and computationally expensive task due to the chaotic nature of the atmosphere and the number of variables involved. Large classical supercomputers are nowadays used in running numerical weather models requiring tremendous processing and enormous amounts of data, yet even with their modern enhancements, their predictions remain limited by computational power and accuracy. Quantum computing offers this solution by allowing faster processing and better resolution of complex weather systems.

The current case study focuses on researching the quantum computing potential for the improvement of models used in weather predictions. Quantum algorithms, like QAOA, appear to optimize the parameters of these weather models much better compared to classical algorithms. Such computers allow the simulation to become more accurate and take lesser time, and it accommodates a much larger parameter space with multiple variables as well.

For example, new studies indicate that quantum computers can more effectively model atmospheric conditions, providing higher resolution to real-time weather forecasts. Thus, this would mean greater early lead time into predicting extreme events—whether hurricanes, typhoons or floods, and even improved disaster preparedness through enhanced early warnings that require fewer human and economic losses. Besides, quantum-enhanced models will be contribution to long-term climate models wherein researchers understand how weather patterns evolve as a result of climate change (Lloyd et al., 2010; Rebentrost et al., 2014).

8.2 Case Study 2: Earthquake Prediction Using Quantum Algorithms

Earthquake prediction is still one of the most difficult problems in geophysical research, as the behavior of subsurface Earth and seismicity is highly complicated. In the traditional approach to earthquake prediction, established methods work on seismic data combined with pattern recognition of signs referring to the tectonic shift. Large volumes of seismograph data combined with nonlinear behavior of the tectonic movements prove an enormous barrier for the predictions under the paradigm of classical computing techniques.

Quantum computing will offer a new window of opportunities in seismic data analysis and earthquake prediction, where colossal datasets are highly computationally efficient and complex optimization problems in seismic models are handled. The subtleties and possible relationships within the data that even the most advanced classical method fails to obtain can be deduced using Grover's algorithm and QFT for seismic data processing.

Quantum computing has actually been put into applications to enhance the prediction of risks due to earthquakes. Researchers have, in fact simulated stress buildup along fault lines and modeled waves in finer detail using quantum-enhanced data analysis techniques. This simulation leads to better prospects to predict the probabilities in specific regions to prepare for earthquakes and take better preparedness and risk mitigation measures. Early works look quite promising in the direct application of quantum computing on simulating complex interactions among tectonic plates, and will eventually add to more dependable early-warning systems on earthquake occurrence.

9 Challenges and Future Directions

As promising quantum computing is, especially for Earth sciences, still much needs to be overcome before this truly promising area achieves full-fledged scope. Technological, computational, and practical hurdles need to be overrun before a widespread application can occur. Here are some of the major challenges and potential future guidelines for quantum computing in earth sciences.

9.1 Limitations of Quantum Computing Hardware

The current quantum hardware also has a very limiting factor-the landscape of quantum computing. A large part of today's quantum computers falls into the "noisy intermediate-scale quantum" (NISQ) era. These pre-existing quantum processors are mostly error-prone due to quantum noise and have limited qubits and processing powers compared to their classical counterparts.

Extreme stability environment is required in order to ensure quantum coherence for a little period and minimize error rates in the quantum operations performed by quantum computers. External disturbances of various types, such as temperature fluctuations and electromagnetic interference, make the quantum systems highly sensitive. Quantum error correction thus remains an active field of research, but still in the developing stages and with quite high computational overhead. Therefore, until quite more efficient quantum error correction methods appear, quantum computations will remain limited by their accuracy and reliability.

Moreover, the number of qubits that are available in today's quantum processors is not large enough to solve most Earth science problems, which depend on many computations involving very large data sets. Increasingly larger, fault-tolerant quantum systems will be important for long-term applications in climate modeling, geophysics, remote sensing.

9.2 Integration of Quantum and Classical Computing Models

The integration model of quantum and classical computing poses another challenge. The challenge is how to combine the capabilities of quantum computers with the best result obtained from the use of methods of classical computing. Hybrid quantum–classical algorithms seem to be the most promising approach toward practical application in Earth sciences. Here, a quantum computer is applied for parts of a computation with others off-loaded onto classical computers. For example, complex optimization or pattern recognition can be carried out by a quantum computer, while data preprocessing and visualization can take place on classical computers.

The challenge with this approach however is coming up with algorithms that can flip between quantum and classical computation as efficiently and seamlessly as possible. Protocols for data transfer and hybrid frameworks that will facilitate seamless communication between quantum and classical systems are also highly essential. Other research studies are looking at developing quantum co-processors that may be integrated with classical supercomputers to make the computations more efficient for earth science models.

9.3 Scalability of Quantum Applications in Earth Sciences

The ultimate limiting factor is the scalable application of quantum applications in Earth sciences. Even though quantum computation holds promise in small-scale simulations and theoretical models, scaling up the applications for realistic Earth science problems remains challenging. Earth sciences are analyzed on large amounts of data coming from sources such as satellite images, climate sensors, and seismographs, which require large-scale computational resources for processing and analysis.

Indeed, one of the challenges of scaling quantum applications will be to adapt quantum algorithms so as to handle the huge size and complexity of Earth science datasets. Many of the quantum algorithms will, for instance, work very well on small-scale simulations but not scale well for larger problems in terms of dealing with data and memory management and computational time. Quantum hardware must also evolve to support larger qubit counts and higher levels of parallelism so as to deal with the fact that Earth sciences are typically data-intensive. The second is that problems addressed by Earth science often require computations over large amounts of data in real-time streams and feeds, such as weather forecasting or environmental monitoring. Quantum computers have to be able to serve these needs and scale up well to create meaningful influence in the field.

9.4 Future Quantum Algorithms Tailored for Earth Sciences

To fully exploit the potential offered by quantum computing in this domain, developing future quantum algorithms tailored to the Earth sciences will be of vital importance. While general-purpose algorithms including Quantum Approximate Optimization Algorithm and Quantum Machine Learning have given great promises, they are not always optimized for the kind of computing challenge that data about the Earth poses. Future quantum algorithms should be engineered with deep perception of the physical and environmental systems that they claim to represent. For instance:

- Algorithm development that captures climate systems' nonlinearity and chaos. Algorithms must become those that even in computing climate models faster, they might do it in a way that makes them better at computing the probability of extreme events or how fast sea levels might rise or global temperature could shift.
- Algorithms in Seismic Data Processing. High-volume, real-time algorithms to process seismic data that identify subtle patterns in waveforms and solve associated inverse problems that underlie subsurface imaging.
- Quantum Environmental Monitoring Algorithms: Algorithms designed for the future should assist in enhancing the processing of environmental data, including carbon emissions, pollution levels, biodiversity patterns, through the fusion of fast-speed data and anomaly detection.

Additionally, algorithms that are designed to fully exploit the power of quantum parallelism and entanglement will be needed to accommodate high-dimensional data typical in Earth sciences. Other researchers continue to develop quantum-inspired algorithms, including those that can be run on classical computers, to serve as a bridge until full-scale quantum computing is more widely available.

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Machine Learning Approaches for Yield Prediction and Crop Management Optimization: A SLR

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Abstract

Climate change, resource scarcity, and population expansion pose serious difficulties to agriculture. By using sophisticated yield prediction and crop management techniques, machine learning (ML) presents viable answers to these problems. Through the use of genetic data, past crop yields, weather patterns, soil characteristics, and farming methods, this systematic literature review (SLR) investigates how ML might improve agricultural efficiency, resilience, and sustainability. Although both ML and deep learning (DL) techniques have been used extensively, DL models—which are distinguished by their neural network architectures—are becoming more and more popular because of their higher predictive accuracy. According to this review, temperature is the most commonly used variable that affects agricultural productivity estimates, followed by rainfall and soil quality. The main evaluation parameter for evaluating model performance turned out to be Root Mean Square Error (RMSE). However, given that many researchers emphasize limited access to public data, the scarcity of comprehensive and varied datasets continues to be a significant concern. The results highlight how crucial it is to create reliable datasets that cover a range of meteorological conditions, crop kinds, and yield records throughout time in order to improve machine learning-based agricultural production models. Addressing these problems would allow ML to reach its full potential in changing agriculture.

Keywords

Crop · Yield · Machine learning · Deep learning · Agriculture · Precision

1 Introduction

It is becoming more difficult for the agricultural industry to satisfy its requirements for fuel, fertilizer, food, and fibre as a result of climate change, population growth, and limited resources. The challenges that we are facing are quite trying. Pressure is caused by the causes listed above. Existing technologies, such as machine learning (ML) (Jogin et al., 2018; Obaid et al., 2020), are being acknowledged by an increasing number of persons who are involved in the problem. These technologies have the potential to improve crop management and agricultural output predictions. This is done in order to remedy the problems that have been discovered. This action is being performed in order to successfully remedy the concerns that have been discovered. Farmers can limit market volatility, environmental circumstances, and other effects on crop productivity (Bonkra et al., 2024). This is achievable because agricultural planning and yield projections are closely related. Statistical models, expert opinions, and historical data have projected agricultural yields throughout economic history. Machine learning algorithms employ many inputs to create accurate and timely predictions (Sarker, 2021). The databases may include genetic data,

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historical crop yields, weather trends, soil attributes, and agricultural practices. Machine learning algorithms may find complex patterns and relationships in this data, which traditional methods cannot. Agriculture experts can make educated decisions about resource allocation, production scheduling, and risk management that are effective and efficient. People who can execute these things have this skill. Improving crop management aims to boost yield projections (Kalimuthu et al., 2020). This may be done by boosting harvests, lowering input prices, and decreasing environmental effect. To achieve this, efficient resource administration and distribution systems are needed. This task may be completed using several crop management methods. The latest environmental data is used to decide fertilizer application rates, irrigation schedules, and machine learning algorithms (Bonkra et al., 2022) for adaptive pest management tactics. This facilitates adaptive adjustments. The collection includes crop status, weather, soil moisture, and disease and parasite risk. Predictive analytics, farm sensor data, and precision agriculture equipment may help farmers optimize inputs and field management. Technology may help farmers improve their procedures. This comprehensive method preserves the environment, boosts agricultural productivity, and optimizes resources. This method yields all results. One of the most enticing elements of ML (Kocher & Kumar, 2021) systems is their capacity to learn and adapt to inputs. This simplifies model upgrades. Data and expertise may increase machine learning algorithm accuracy and suggestions. You may aid them by providing more information. Farmers might adjust better and make better choices with more information. Feedback cycles may enhance agricultural machine learning models by learning from mistakes. Agriculture research and development is increasingly using machine learning. These technologies might transform agriculture, according to research in several sectors. Agricultural data trends and anomalies may be found using unsupervised learning approaches like clustering and anomaly detection. Tangible implementations demonstrate this. Agricultural output has long been predicted using supervised learning methods like classification and regression (Mourtzinis et al., 2021). The research found that advanced deep learning models like CNNs and RNNs (Dhruv & Naskar, 2020) can discover and evaluate temporal and geographical correlations in agricultural data. The models also predict accurately. This feature should improve prediction accuracy. Machine learning might transform agriculture, but it must overcome numerous obstacles before it can be completely incorporated. In locations with poor infrastructure and technology, data accessibility and dependability may be problematic. Algorithmic bias, model interpretability, and scalability must be examined to employ machine learning in agriculture properly. Lawmakers, farmers, data scientists, and agronomists from different sectors must collaborate to overcome these difficulties and maximize machine learning's promise in agriculture. Machine learning may improve food security, resilience, and sustainable agricultural growth with innovative ideas and collaboration (Parisineni & Pal, 2023). When considering continual cooperation, this is true. Data-driven analytics, predictive modelling, and adaptive decision-making may help agricultural specialists enhance operational efficiency, productivity, and food security in the face of fast global change. To ensure that farmer, consumers, and the environment all benefit from the integration of agriculture and technology, policies should be prioritized wherever possible. Agriculture companies make use of a wide range of machine learning techniques in order to enhance crop management and forecast output. Researchers and practitioners may choose the most effective technique by taking into account the requirements and constraints of an agricultural application. There are the following objectives of our study.

- To investigate the role of ML in optimizing crop management and improving yield predictions.
- To analyze how ML algorithms utilize datasets like genetic data, weather patterns, soil properties, and farming practices to enhance agricultural efficiency and sustainability.
- To explore ML-driven strategies for real-time decision-making in irrigation, fertilization, and pest control.
- To identify challenges in applying ML to agriculture, including issues of data accessibility, algorithmic bias, interpretability, and scalability.
- To highlight the need for interdisciplinary collaboration among agronomists, data scientists, policymakers, and farmers for successful ML implementation.
- To emphasize the potential of ML to address global agricultural challenges, ensuring food security, sustainability, and resilience against climate change.

The further sections of this paper are outlined below: Sect. 2 presents the fundamental background material, while Sect. 3 outlines the technique. In Sect. 4, we provide a more comprehensive analysis of the SLR's results. The last part, Part 5, offers concluding remarks.

2 Related Work

The literature review covers several machine learning research initiatives for crop management optimization and yield prediction (Al-Hamadani et al., 2024; Klompenburg et al., 2020). Comprehensively assess supervised learning. While focusing on agricultural output estimates, the authors demonstrate how these methodologies might be utilized and understood. This study examines how effectively classification and regression algorithms can use annotated historical data to predict future agricultural harvests. The authors also explore the advantages of organized data management that affects these tactics. We can build simple models that reveal the underlying elements that affect agricultural productivity using this knowledge. The authors studied clustering and anomaly detection in unsupervised learning for agricultural management in 2019 (Sheth et al., 2022), (Dhiman et al., 2023). This will enhance crop management tactics. This study assesses these techniques' capacity to find anomalies in agricultural datasets and reveal hidden patterns and relationships in unmarked data for exploratory research. Unsupervised learning may aid with crop management, resource allocation, and decision-making. This is because unsupervised learning cannot utilize labeled training data. This explains this scenario. Deep learning models like CNNs and RNNs helped the authors anticipate agricultural production. Deep learning methods are extensively tested to extract hierarchical properties from complex agricultural datasets. Models that account for geographical and temporal factors may incorporate the information needed for exact yield estimations (Bonkra et al., 2022; Joshi et al., 2014). The authors propose using deep learning to evaluate multi-dimensional data sets like satellite photos and time-series data. This research shows how varied strategies may increase agricultural production estimates using openly available data and improved processing. In their lengthy research, authors demonstrated how ensemble learning methodologies that include model results may improve prediction accuracy and robustness. This article examines ensemble techniques in agricultural data processing. These approaches include bagging, boosting, and stacking. Ensemble learning reduces bias and overfitting by using several models. Farmers and other agricultural professionals need reliable forecast information (Reel et al., 2021; Suganya, 2020). The authors investigate if reinforcement learning might enhance crop management methods. This research examines how reinforcement learning systems interact with their environment to find the best methods. Models that account for spatial and temporal relationships might incorporate yield estimates. The authors recommend deep learning for analyzing multi-dimensional data sets like satellite pictures and time-series data. This research shows how open data and processing advancements might influence agricultural production estimations. The study extensively examined how ensemble learning, which combines model results, might increase prediction accuracy and robustness. This research evaluates ensemble approaches for agricultural data processing. These methods include bagging, boosting, and stacking. Ensemble learning avoids bias and overfitting by using several models (Elavarasan et al., 2018; Gautron et al., 2022). Because they have critical information, agricultural professionals like farmers can create more accurate forecasts. The manuscript investigates if reinforcement learning improves crop management. This study seeks to understand how reinforcement learning systems may learn the best strategies from their environment. The authors focused on precision agriculture and predictive analytics. These methods enable successful crop management programs, giving them an edge over competition. This project investigates how to effectively evaluate large amounts of sensor data, satellite photographs, and weather predictions to provide farmers and other stakeholders with current insights and suggestions. Precision agriculture may improve food security by boosting crop yields, decreasing environmental impact, and optimizing resource allocation via predictive analytics. The study explores smart agriculture system productivity assessment using big data analytics. They prioritize combining machine learning algorithms with sensor data for fast decision support. Their research examines how farmers may produce meaningful ideas from streaming data from sensors, drones, and other Internet of Things devices using machine learning algorithms (Al-Hamadani et al., 2024; Haque et al., 2020). Data from various devices is analyzed to attain this goal. Big data analytics-based smart agricultural systems optimize irrigation, fertilization, pest management, and other operations to boost crop yields and resource efficiency. The study examined aggregate plant identification and management. Many surveys overlap. They support the idea that this technology might detect diseases. Convolutional neural networks (CNNs) (Balakrishnan & Muthukumarasamy, 2016; Dhiman et al., 2023) and other deep learning approaches can identify disease patterns in crop damage photographs, the researchers show. Authors conclude with a comprehensive evaluation of agricultural output forecast machine learning methods. They discuss this area's issues and solutions. This paper examines novel machine learning applications in agriculture and reviews related literature. Kumar and Jain examine data availability, model interpretability, and system scalability in their informative review of agricultural machine learning research and development. The literature suggests various agricultural machine learning applications. These include crop management optimization (Bonkra et al., 2022; Vaishnnave & Manivannan, 2022), disease and weed detection, and yield prediction. These in-depth studies attempt to illuminate agricultural machine learning's current condition, future potential, and new possibilities. Synthesizing data from multiple study articles yielded these results. Table 1 provides a concise summary of the fundamental traits, advantages, and disadvantages of each approach.

Table 1 Summary of different techniques used in crop yield prediction

Technique	Description	Advantages	Disadvantages
Supervised learning (Klompenburg et al., 2020; Suganya, 2020)	Uses labeled historical data to train models that can predict future outcomes based on input features. Common algorithms include regression and classification	— Well-established techniques-can handle structured data with known outcomes-provides interpretable models	— Requires labeled data for training-may struggle with high-dimensional or non-linear data
Unsupervised learning (Elavarasan et al., 2018; Sheth et al., 2022)	Learns patterns and relationships from unlabeled data, enabling clustering, anomaly detection, and dimensionality reduction. Common algorithms include k-means clustering	—Does not require labeled data-can uncover hidden patterns in data-useful for exploratory analysis	— Interpretability can be challenging-may not provide clear actionable insights
Deep Learning (Haque et al,. 2020; Joshi et al., 2014)	Utilizes neural networks with multiple layers to learn complex representations from data. Architectures like CNNs and RNNs are commonly used for image and time-series data	— Capable of learning hierarchical features-Effective for handling high-dimensional data-can capture spatial and temporal dependencies	- Requires large amounts of data and computational resources-Prone to overfitting with complex architectures
Ensemble Learning (Balakrishnan & Muthukumarasamy, 2016; Reel et al., 2021)	Combines predictions from multiple models to improve performance and robustness. Techniques include bagging, boosting, and stacking	— Reduces variance and bias-improves predictive accuracy-robust to noise and outliers	— Increased computational complexity-may be challenging to interpret ensemble models
Reinforcement Learning (Gautron et al., 2022; Vaishnnave & Manivannan, 2022)	Learns optimal decision-making strategies through trial-and-error interactions with the environment. Can be used to optimize crop management practices	—Can adapt to changing conditions-learns from feedback and experience-provides dynamic decision-making	— Requires careful design of reward functions-may suffer from exploration–exploitation trade-offs

3 Methodology

A pre-existing review mechanism preceded the systematic review. The widely accepted (Keele, 2007) criteria were used to build this technique. The research questions have to come first. After developing research questions, Google Scholar, Science Direct, Scopus, Web of Science, Springer Link, and Wiley were used to find relevant material. After selection, the research was screened and evaluated using quality and exclusion criteria. All pre-selected study data was then retrieved. Data was analyzed and synthesized to address research questions. Review preparation, execution, and reporting comprise this process.

During the early phases of the review's development, we generated research questions, defined a methodology, and evaluated the practicality of the strategy. In addition, we defined certain standards for choosing publishing sites, created initial search terms, and determined the method for selecting publications, all while developing research goals. The approach was altered to verify its suitability. During the evaluation process, publications were chosen from several databases. Relevant information such as author biographies, publication year, publishing style, and details about the study's aims was retrieved. After carefully gathering all the required data, a comprehensive summary of the available literature was created via a process of synthesis. During the Reporting the Review step, a thorough record of the results was created, successfully answering the research questions. Figure 1 depicts the methodology of our study will be carried out.

3.1 Research Questions

Understanding the current literature on machine learning (ML) and agricultural production prediction is the primary objective of this systematic literature review (SLR). This goal is accomplished by examining papers from various perspectives throughout the review. The approach of the SLR is guided by four research questions (RQs), which function as its framework.

RQ1 What kinds of machine learning methods were applied in previous research in order to make predictions about crop yields?

RQ2 For the purpose of predicting agricultural yields using machine learning techniques, which particular characteristics have been used in older research?

RQ3 For the purpose of determining the efficacy of crop production prediction models that are based on machine learning, what assessment criteria and procedures were applied in past studies?

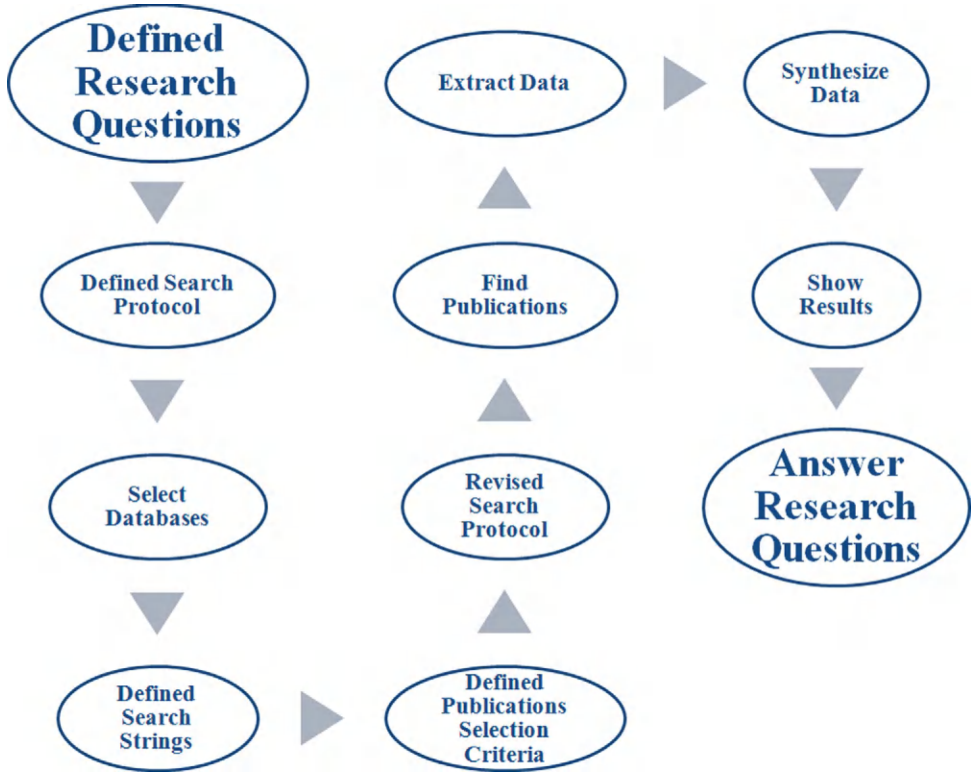


Fig. 1 Flow chart for work plan

RQ4 When applying machine learning algorithms to the field of agricultural production prediction, what are the most significant challenges that are anticipated to be encountered?

3.2 Search String

A comprehensive search was run across six different databases using the keywords "machine learning" and "yield prediction" to cover a wide range of relevant literature. Following the application of exclusion criteria and processing of results, a refined search string was created to improve the relevancy of the search: ("yield estimation," "yield prediction," or "yield forecasting") AND "data mining" "machine learning" OR "artificial intelligence" After doing this last investigation, a total of 625 studies were found. The search parameters used in each database were precise and customized to the functions of that unique database. The collection included altered copies of the original query and the optimized search string. These modifications were made to include more search fields and functions. It is important to note that the extended search query did not produce any publications when Web of Science and Wiley were used.

After applying some exclusion criteria 50 papers have been selected for final study and further analysis. The parameters for exclusion criteria are like field relevancy, language priority, year of publication; type of publication, publication is full length or not. The figure Multiple data sources show a wide range of papers for the review. Google Scholar had the most papers 303 of which 24 fulfilled review criteria. Springer's numerous publications validated the review's findings. Springer submitted 137 articles, but only 10 were accepted. Scopus found 88 publications, 11 of which were selected, indicating its importance in machine learning and yield prediction. However, the Web of Science database could not find any papers that met the study's requirements, suggesting a coverage gap in this field. Wiley submitted 25 papers, but only one qualified. The articles' content appears unimportant to the review. Though Science Direct had fewer publications, 20 were discovered and 4 were selected, indicating a subset of relevant research. Our findings suggest using several databases to ensure complete and robust systematic literature evaluations. The below Fig. 2 illustrates the comparison of retrieved and selected studies.

4 Results and Discussion

To provide the answer to research question 1 below Table 2 will illustrate the algorithm used with title, different sources.

RQ2 summarized the articles' machine learning algorithm characteristics. Figure 3 shows extracted characteristics.

RQ3 determined investigation assessment criteria. Figure 4 shows evaluation parameters and frequencies. The most common study parameter is RMSE.

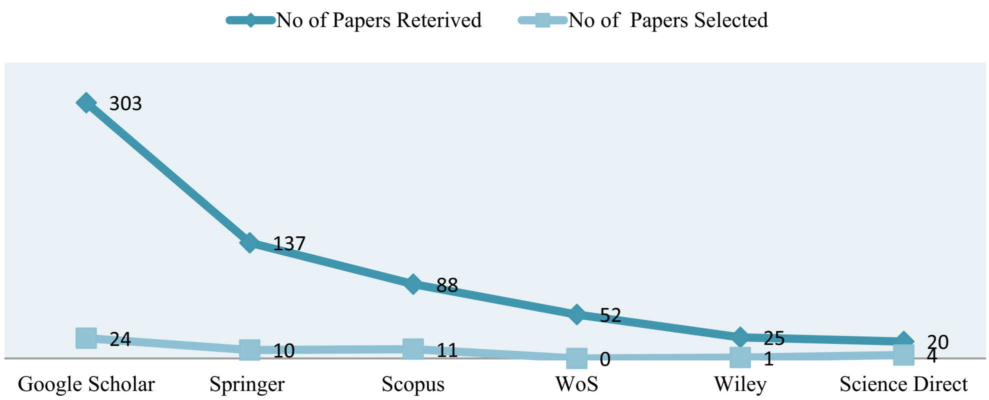
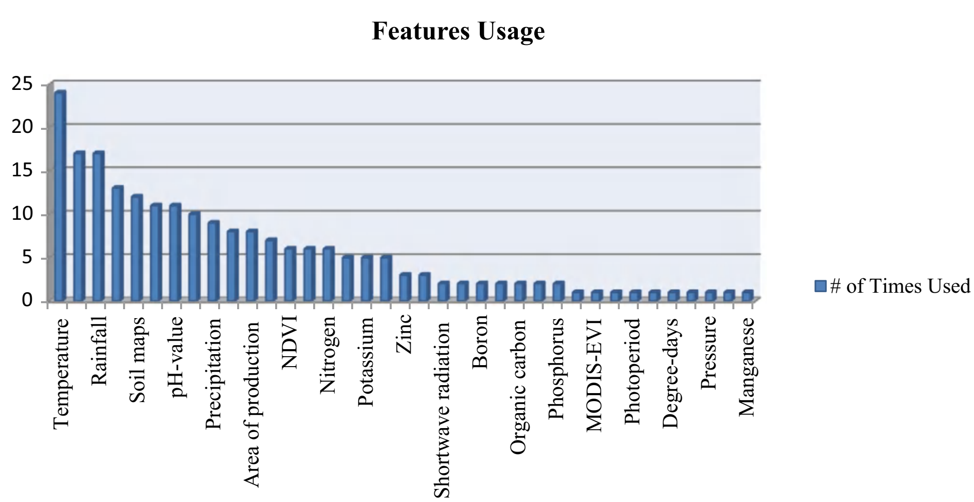


Fig. 2 Comparison of retrieved and selected papers

Table 2 Summary of different algorithms used in crop prediction

Source	References	Algorithm used
Scopus	(Shekoofa et al., 2014)	Clustering and decision tree
Scopus	(González Sánchez et al., 2014)	M5-prime regression tree and k-nearest neighbor, support vector machine
Scopus	(Pantazi, 2014)	Neural networks
Google scholar	(Çakır et al., 2014)	Neural networks and multivariate polynomial regression
Google scholar	(Rahman et al., 2014)	Decision tree, neural networks, and linear regression
Scopus	(Kunapuli et al., 2015)	Polynomial regression, logistic regression
Google scholar	(Matsumara et al., 2015)	Neural networks, multiple linear regression
Google scholar	(Ahamed et al., 2015)	Linear regression, neural networks, clustering, and k-nearest neighbour
Science direct	(Pantazi et al., 2016)	Neural networks
Scopus	(Jeong et al., 2016)	Random forest, linear regression
Wiley	(Mola-Yudego et al., 2016)	Gradient boosting tree
Google scholar	(Everingham et al., 2016)	Random forest
Scopus	(Gandhi et al., 2016)	Support vector machine
Google scholar	(Bose et al., 2016)	Neural networks

Fig. 3 Comparison of extracted characters



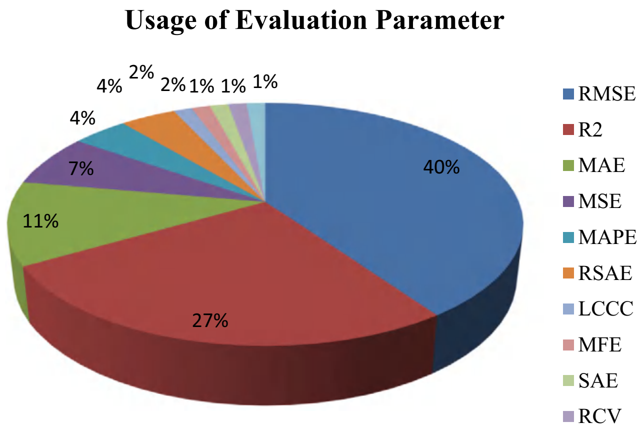


Fig. 4 Comparison of evaluation parameters

As part of our investigation into the papers and preparation for answering RQ4, we looked at any areas of concern that were brought to our attention or proposals for improving future models. The poor availability of data was a topic that was brought up in a number of studies and was widely explored. This indicates that the amount of datasets that were available to the public was restricted. In spite of the fact that the existing data demonstrated that the constructed systems operated well, it is recommended that future testing make use of datasets that include a wider range of products. This encompasses information that was gathered from a wide range of weather circumstances, different kinds of vegetation, and temporal records of agricultural yields.

5 Conclusion

This particular SLR is a good example of how the process of machine learning could revolutionize farming and the way in which crop is managed or the yields foreseen. Various types of machine learning such as reinforcement learning, supervised learning, deep learning, ensemble learning, and unsupervised learning open doors for improvement of agricultural methods and maintenance of food security. These opportunities may be realized through the application of machine learning in the discussed arenas. But to make machine learning for agriculture effective, problems related to the availability of data, the fairness of the model, and the explainability of the outcome must be addressed. In this context, it is mentioned that application of the ML can lead to better food security, optimization of the reduced effects of climate change on food systems globally, and encouraging the idea of collective innovation in agricultural system globally. Since a reasonable and exhaustive approach is necessary when predicting the outcomes of machine learning application in agriculture by presenting the benefits for the farmers, consumers, and the whole environment, the possible misleading effects should be examined as well.

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Resource Allocation in Agriculture and Water Management Fields

Harpreet Kaur, Tanisha Sharma, Shriya, Trishi Sharma, and Tisha

Abstract

The field of earth science is undergoing rapid advancements driven by emerging technologies. These technologies aid in understanding atmospheric and environmental systems while addressing global challenges, ultimately optimizing resources to improve agricultural productivity and sustainability. Artificial Intelligence (AI)-driven computational approaches are becoming pivotal for resource allocation, data analysis, and prediction in agriculture. Machine Learning (ML) optimization models and predictive analytics enable the forecasting resource demands and yield outcomes based on weather patterns, soil conditions, and historical data. Additionally, agent-based modelling and multi-agent systems are employed to optimize land use, water resource distribution, and infrastructure management. Reinforcement learning algorithms further enhance the decision-making in irrigation schedules and fertilizer application strategies as per crop growth stages. Fuzzy logic systems also provide flexibility in decision making accounting for uncertain data such as crop conditions and soil moisture levels. AI is reshaping agriculture landscapes by offering simulation models to test different agriculture methods under varying climate scenarios and resource constraints. AI-powered Internet of Things (IoT) systems analyse the data collected from sensors, satellites, and drones to provide actionable insights, automating decisions in real time. These AI models, integrated with IoT sensors, are particularly beneficial for providing real-time monitoring of soil moisture, weather conditions, water stress, and crop health. The collected data is further processed and analysed using ML and deep learning algorithms to inform resource allocation decisions. Moreover, optimization algorithms are used to find the best solutions for resource distribution. While remote sensing and ML and big data analytics help to analyse market trends and predict crop demand, enabling farmers to make informed planting decisions and reduce food wastage. AI-driven strategies for crop rotation and diversity also contribute in improving soil health and crop yield. Beside this, AI-based blockchain and cloud computing systems enhance monitoring and real-time resource management across multiple farms. Overall, AI-driven approaches and machine learning algorithms are playing a significant role in transforming agriculture practices, facilitating data-driven and sustainable resource allocation over large agriculture areas.

Keywords

Agriculture · Water · Machine Learning · Artificial Intelligence · Soil · Resource Allocation

1 AI-Driven Computational Approach for Resource Allocation in Agriculture

In recent times, farmers have been using Artificial Intelligence, or AI, a lot. AI technologies help them pick the perfect seed for the weather. It also aids them in growing more crops but with less resources. There are global challenges like changing climates, a growing population, and limited

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resources that can make it really hard to keep having enough food for everyone (Bibi & Rahman, 2023). But, with AI, a lot of these problems can be resolved. By adopting modern technologies, many downsides of old-fashioned farming can be improvised (Javaid et al., 2023; Ramachandran et al., 2018).

Precision agriculture is based on the usage of modern technology, computer software, and smart devices to make better farming decisions. Modern agriculture industry is using smart technologies like Internet of Things and AI for enhancing the production of various organic products (Ramachandran et al., 2018). For climate analysis, AI is considered to support decisions, while ML helps in revealing climate system attributes and forecasting (Javaid et al., 2023). So, it is the adoption of both AI and ML concepts that helps farmers to optimize soil quality and associated resources.

1.1 Computational Analysis for Resource Allocation

The modern world is comprised of data. Organizations in the agricultural sector use a large amount of data to have outputs. This data provides detailed insights to each process or farming method for each acre of the field to study and monitor whole supply chain and to gain inputs on the yield generation process. AI-powered predictive analytics make a way into agriculture and agribusiness. Also, AI can sort and differentiate market demand, predict prices as well as predict the best time line for sowing and harvesting for better outcomes. Artificial intelligence can also help in studying soil health, monitor weather conditions, and helping the user with recommendations of pesticides and seeds accordingly. Farm management software can enhance production with at most profit, allowing the farmers to make better decisions at every step for better production.

Application of AI in agriculture gives farmers a further enhanced support system, helping them to understand properly which areas need irrigation, fertilization, or pesticide treatment. Creative farming practices for example vertical agriculture can also uplift food production with minimizing resource usage. Resulting in less usage of herbicides, with better and faster harvest quality, higher profit with a safe saving amount.

1.2 AI in Water and Resource Management

AI hereby provides a modern solution for good harvest throughout every season and no one's efforts should be waste. Through different types of applications, farmers can be provided with vast platform for resource management. Firstly, the data can be collected using the real-time monitoring (e.g. Checking soil Quality, checking temperature, seed health, etc.). Further, water management can be done through automated water sprinkler and many more AI-based computational approaches. Moreover, farmers can sort the harvest and discard the affected crop.

AI-driven computational approach can help the user (farmers) to have vast data for smart –agriculture practices. Using these approaches, farmers can predict many things like, soil quality, seed genetics, water quality, crop health, diseases, and pest and sorting. The following points illustrate the benefits of AI technologies in water, pesticide, and resource management.

- **Optimizing automated irrigation systems**

AI applications enable automatic crop management systems. When combined with IoT sensors such as monitor soil moisture levels and weather conditions, these can decide with real-time monitoring, how much water is needed for production. An automation system is designed to preserve water by promoting sustainable agriculture and farming practices. AI algorithms such as smart greenhouses can optimize plant growth by automatically adjusting the temperature, light levels, and humidity with the help of real-time data. The data is stored in cloud service for monitoring and data storage. The real-time field data is transferred to the cloud using Wi-Fi modems and using Global System for Mobile communication (GSM) and cellular networks. Then an optimized model is used to compute the optimized irrigation rate which we can automatically use a solenoid valve controlled using an ARM controller (WEMOS D1) (Ramachandran et al., 2018). Field experiments can be utilized for observing plant canopy temperature and soil moisture status. Crop Water Stress Index (CWSI) of 0.35 is maximum level of water used for efficiency and optimum yield of wheat crop. CWSI approach is 10–15% water savings compared with soil moisture-based irrigation (Kumar et al., 2019).

- **Detecting leaks or damage to irrigation systems**

AI plays a crucial role in detecting leaks in irrigation systems. ML models can be trained to recognize specific signatures of leaks, such as changes in water flow or pressure. Real-time monitoring and analysis enable early detection, preventing water waste together with potential crop damage. AI also incorporates weather data alongside crop water requirements to identify areas with excessive water usage. By automating leak detection and providing alerts, AI technology enhances water efficiency helping farmers conserve resources. The data from the camera and thermal sensor can be collected and transferred to the server computer via Wireless Fidelity (Wi-Fi) technology and processed for analysis. By analysing captured data, algorithms and server software can identify patterns and anomalies that indicate potential leaks. Thus, the use of thermal, hyper-spectral cameras instead of traditional humidity sensors is useful in detecting water leaks in the agriculture irrigation system (Türkler et al., 2023). The water flow rate for different plants in irrigating agriculture land can also be controlled using AI-based computational approaches.

- **Automated pesticide spraying**

Applying pesticides manually offers increased precision in targeting specific areas, though it can be slow and difficult to work. Automated pesticide spraying can be quicker and less labour-intensive, but often lacks accuracy, leading to environmental contamination. AI-powered drones offer the best of both worlds by avoiding these drawbacks. These drones use computer vision to determine the precise amount of pesticide to spray in each area. Although this technology is still in its infancy, it is rapidly becoming more precise.

The solar sprayer is primarily used for spraying liquefied pesticides. This developed system can also be used for spraying fertilizers and fungicides, as well as functioning as an automatic spray-painting robot. The same technique and technology can be extended to all types of power sprayers. Additionally, this model can be used as mosquito repellent. The solar-powered sprayer reduces fuel consumption and lowers running costs. It not only minimizes the effort required for spraying but is also more effective than conventional sprayers. It protects operators from exposure to harmful chemicals and pesticides, making it a great alternative to engine sprayers. This sprayer will be highly valued when fuel resources are depleted (Poudel et al., 2017). It operates noiselessly, is eco-friendly, and produces no vibration. Its construction is simple and less complex compared to other sprayers, making this easy to use and manufacture (Luojia et al., 2022).

- **Yield mapping and predictive analytics**

Yield mapping employs machine learning algorithms to analyse large datasets in real time, aiding farmers in understanding crop patterns and characteristics for improved planning. By integrating techniques such as 3D mapping and data from sensors and drones, farmers can predict soil yields for specific crops. Data collected from multiple drone flights allows for increasingly precise analysis through algorithms. These methods enable accurate predictions of future yields, guiding farmers on optimal seed sowing times and resource allocation for the best return on investment.

Predictive analysis is a machine learning technique that forecasts future outcomes based on historical data (Chandraprabha & Dhanaraj, 2021). In agriculture, predictive analytics helps to determine the soil nutrients level required for the crops such as Paddy, Raagi, and Cumbu (Kesavan et al., 2018).

- **Sorting harvested produce**

AI is not only valuable for identifying potential issues with crops during their growth but also plays a crucial role post-harvest. Computer vision can detect pests and diseases in harvested crops and grade yield based on shape, size, and colour. This allows farmers to efficiently categorize produce, enabling them to sell harvested crops to different customers at varied prices. In contrast, traditional manual harvest sorting methods are often labour-intensive and time-consuming (Xiao et al., 2012).

- **Dynamic resource allocation**

Cloud computing enables business to adjust their resource usage dynamically according to their needs. A significant portion of the benefits associated with the cloud model stems where resource multiplexing achieved through virtualization technology. A system utilizing virtualization technology dynamically allocates data centre resources based on application demands, supporting green computing by optimizing the number of servers in use. To measure the unevenness in the multidimensional resource utilization of a server, different types of workloads are combined effectively, enhancing overall server resource utilization. A large set of heuristics has been developed to prevent system overload while saving energy (Khan et al., 2022).

- **Predictive analysis of water management**

Recent statistics reveal that approximately 30% of country's population lives in their life in cities expected to be two times more in size by the year 2050. Rapid urbanization has been connected with economic growth as well as changing lifestyles, is increasing pressure on already drained water resources and water bodies. The demand of water is increasing day by day across domestic, industrial, and Agri-sector is giving a lot of lack of water in river basins. Compounding this issue is the uneven distribution of water demand throughout the country (Sharma & Shekhar, 2021).

The predictive analytics model is divided into two key parts. The first part is Opinion Mining which is utilized to categorize public sentiment regarding water management and initiatives such as Namami Gange into three polarity classes: positive, negative, and neutral. Natural Language Processing (NLP) techniques are used to analyse the data from real-time monitoring like social media and surveys. Machine learning algorithms are utilized to train models on labeled datasets for accurate sentiment classification. Second part is Textual Analysis that is utilized to further analyse the classified data and identify specific factors and objectives related to water management and the Namami Gange initiative.

By combining opinion mining and textual analysis, this model focuses to provide a holistic understanding of the challenges and opportunities in managing water resources in India. This approach can significantly contribute to informed decision-making and targeted interventions through AI and Machine learning for future enforcement.

- **Genetic resource allocation**

AI came as a field creating a great opportunity for modern crop breeding, and is mostly used indoor study for plant science. AI brought huge computational power and many more new tools and techniques for future breeding. The present review will hold within how applications of AI technology can be used to utilized the current breeding practices. These approaches also help to solve the problem in high-throughput phenotyping and gene functional analysis, and to bring new opportunities for future breeding, Envirotyping data can be widely use in breeding and to explore the developing approaches and challenges for multiomics big computing data integration (Khan et al., 2022).

AI can bring us a renewed method that can predict soil quality and sorting seeds through sensors and analysis the real-time data. Productive data provided by the AI tool helps in selecting type and quality of seeds based on season. Seed that have some genetic defect can be discarded. These resource allocation approaches enhance productivity, sustainability, and economic viability in agricultural practices.

1.3 Limitations

There are numerous limitations and barriers that hinder the successful implementation of AI in farming. These challenges span economic, technological, skills, social, environmental, and policy dimensions. Multiple stakeholder approaches involving researchers, governments, private companies, and farmers are required to address these barriers.

2 AI-Driven Computational Approach in Water Management Field

This section of the chapter will discuss how AI-driven computational approaches help in water management to address challenges associated with water scarcity and distribution. Advancements in recent technologies like AI and ML have changed the way we live and work. Farmers can take advantage of technological advancements to improve the functioning of irrigation systems. AI can help them to make right decisions which can help in managing water supply, waste water treatment, distribution, and disposal. AI in water management can help solve various problems like water leakage, theft, or inaccurate measurements. Notable advances have been made by AI in water resource management and hydrology in recent decades (Doorn, 2021).

For example, monitoring water quality, drought prediction, using smart water grids, and agriculture precision. AI algorithms help in analysing historical data related to seasonal patterns for predicting future water demands. The drought prediction system in AI can provide predictions of weather and help in proactive planning and the smart water grid helps in enhancing the water networks to minimize loss in water and enhance the efficiency of system (Review & of Science & Technology, xxxx).

2.1 Advantages of AI in Monitoring Water Quality and Predictions

Water quality is worsening day by day due to urbanization and rapid economic growth. Clean water is important for living however, there are still many people who lack access to safe and clean drinking water. AI can help provide systems to monitor the water quality and check the contamination and pollution level in water to ensure whether it is drinkable or not.

AI is a powerful and helpful tool for water management and treatment of water to help it meet quality standards for safe drinking and preventing water pollution.

- AI uses models like Artificial Neural Networks (ANNs), fuzzy logic systems, Convolutional Neural Network (CNNs), and Long Short-Term Memory (LSTMs) for monitoring water quality and prediction of pollution levels (Doorn, 2021).
- AI uses advanced techniques like Artificial Neuro-Fuzzy Inference System (ANFIS) Feed-Forward Neural Network (FFNN) and K-Nearest Neighbours (KNN) to analyse drinking water and ensure it's clean, safe, and environment friendly. ANFIS predicts water quality index which helps calculate how clean or polluted water is. FFNN and KNN predict quality of the water (it tells if the water is of high, medium or low quality) (Review & of Science & Technology, xxxx).
- There is an essential requirement to measure, control, and monitor the water quality. The main and primary contaminant that is present in water is known as TDS (Total Dissolved Solids). It is hard to filter out TDS substances. Various other substances are also present that aren't mere solids for e.g., potassium, sodium, chlorides, lead, nitrate, cadmium, arsenic, etc.

- ML models like Logistic Regression, Support Vector Machine (SVM), Gaussian Naive Bayes, Decision Tree (DT), and Random Forest (RF) are used to classify if the water is drinkable or not.
- Representation by Explainable Artificial Intelligence (XAI) for e.g., force plot, test patch, summary plot, dependency plot, and decision plot which are generated in SHAPELY explainer explains the features, prediction score, and justification behind the evaluation of water quality.

AI models and systems for water management are better than traditional systems as they are cost-effective and take less time (Hmoud Al-Adhaileh & Waselallah Alsaade, 2021; Nallakaruppan et al., 2024).

2.2 Application of AI in Water Resource Planning and Allocation

AI has a wide range of applications in water resource planning and allocation. Information Technology helps in enhancing management and allocation of water.

Some applications of AI in water resource planning and allocation are:

- **Demand forecasting**: demand forecasting predicts the demand of water in future.
  - AI uses historical data for this prediction like climate patterns, land use patterns, and growth in population. Based on the data, AI helps in the allocation of water to various sectors like industry, household, and agriculture. This ensures the authorities that there will be no over use or shortage of water, the future demand is fulfilled and there is no wastage of water.
  - Models like neural networks and support vector machines help in predicting water consumption patterns.
- **Drought and flood management**: AI uses models to predict weather and soil quality
  - AI analyses the intensity of floods and droughts which can help take various decisions and measures.
  - AI analyses the data using sources like weather patterns, river flow rates, soil moisture levels, and satellite images to help predict drought and flood.
  - These predictions and study can help take prior decisions and give early warnings which helps to control and reduce the impact.
- **Monitoring water quality**:
  - AI can help measure water quality and check the level of contamination in soil and measure soil pollution.
  - AI uses various models and systems to help check the impurities in water. Models like ANN, fuzzy logic systems, CNNs, and LSTMs are used to check the water quality.
  - Advanced AI techniques like ANFIS, FFNN, and KNN for monitoring drinking water and make sure if it's clean, safe, and environment friendly.
- **Leak Detection and Infrastructure Maintenance**: AI can help monitor water distribution networks for leaks and pipe failures.
  - AI uses real-time monitoring for early leak detection and predictive maintenance.
  - AI detects anomalies in water flow and helps in the prediction of early leak detection which helps in reducing cost and control water loss.
  - AI helps predict future failures, optimize maintenance schedules and increasing the lifespan of the infrastructure.
- **Real-Time decision making**:
  - AI can help provide real-time decision idea for water management (Srivastava, 2023).
  - AI-powered planning and decision making can help optimize planning efforts.
- **Climate change impact**:
  - AI gives various benefits in providing the impacts of climate change by using various tools and methods to analyse data and help in decision-making.
  - It helps in prediction of extreme weather events, rise in sea levels etc. with great accuracy.
  - AI can help analyse the results of change in climate on water resources and find preventive measures in managing it.
  - AI helps in providing measures to combat climate change by analysing this information.
- **Optimizing irrigation in agriculture**:
  - AI can help optimize irrigation system by using various sensors and models
  - AI helps in irrigation and agriculture by providing methods and analysing soil moisture levels, weather conditions, and crop characteristics.
  - These methods help to control wastage of water.
  - Irrigation system made by AI for e.g. smart sprinklers can help to adjust the water supply to the needs of the crops (Doorn, 2021; Lin et al., 2024).

2.3 Water Resource Management Using IoT

Efficient water resource management using IoT is required to address current challenges. Few conventional challenges are mentioned below.

- **Current challenges**:
  - Monitoring and detection: Most water utilities lack real-time monitoring and detection because of which it is difficult to detect leaks, pipe bursts, and conditions. Traditional methods are often costly and time consuming (Lalle et al., 2021).
  - Communication issues: Wired connections are difficult to work with especially in harsh or underwater environment. It makes it difficult to detect and sense the condition because of which wireless technologies are preferred (Lalle et al., 2021).
  - Energy efficiency and power back up: In Smart Water Grid (SWG), communication consumes most of the energy especially in harsh environments like underground. To solve these drawbacks, communication system must have low powered energy usage, better range, and signal penetration (Baanu & Babu, 2022).
- **IOT integration for water resource management**
  - The SWG helps in combining the technologies of information and communications. Its main function is to add an information layer to the tradition water distribution systems which includes smart water sensors, meters, and real-time data analysis which helps to manage valves, pumps and find out water leakage (Baanu & Babu, 2022).
  - Wireless communication technologies such as LoRa, Sigfox, NB-IoT, and others, are low-powered and provide large communication ranges.
  - Future directions: the future direction says that the SWG should have low-powered energy consumption, long communication range, and should be cost-effective. LPWANs (Low Power Wide Area Networks) can be used for leak detection, smart water metering, and quality monitoring (Baanu & Babu, 2022; Lalle et al., 2021).

2.4 Challenges and Limitations of AI in Water Management

Although various AI applications are being utilized in water resource planning and allocation. However, there are a few limitations associated when implementing AI in water management. The conventional limitations of AI in managing water in agriculture field are shown in Fig. 1. Let us have a look at these briefly:

- **Data issues**: AI models use high quality data which makes it complex and unsuitable to use in small water utilities which limits its effectiveness. The handing and processing of large amount of data is again a big challenge.

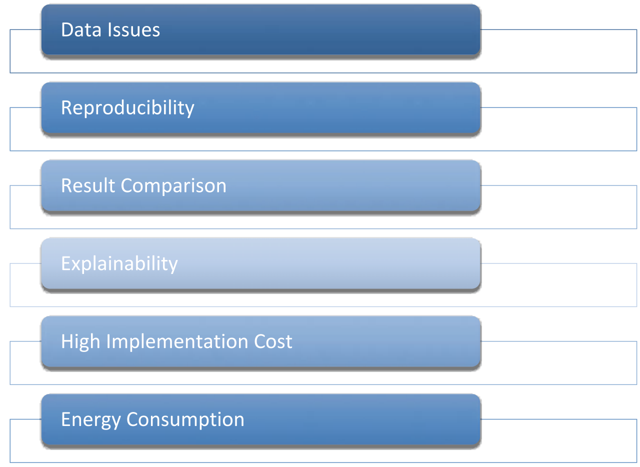


Fig. 1 Limitations of AI in water management

- **Reproducibility**: AI models lack reproducibility due to selection of random elements and custom methods.
- **Result Comparison**: Different evaluation metrices are used by researchers which makes it hard to compare various AI models.
- **Explainability**: Models made by AI are complex which leads to explainability issues and makes it hard to understand it's working especially in complex models.
- **High Implementation Cost**: Implementation of AI in water management can be costly as it requires investment in sensors, communication networks, and computing infrastructures which makes it difficult to work with smaller utilities or developing utilities.
- **Energy Consumption**: AI consumes a huge amount of energy especially in real-time applications like smart water grid which makes it difficult to use it in areas having less energy resources. Moreover, the power backup systems impose additional cost. The large-scale consumption of energy by AI can eradicate some environmental benefits like carbon footprints (Mahmoud et al., 2023).

3 Optimizing Soil Quality, Climate Condition Using AI and ML

India is projected to become the most populated country by 2050, and we are already struggling to meet current domestic food production needs. This rapid population growth will strain our resources, highlighting an urgent need to enhance productivity and strengthen resource distribution to ensure a safe future for us and the upcoming generations. Adoption of sustainable farming practices and modern information systems and software tools emerge as innovative technologies to combat current challenges in the agricultural sector (Lin et al., 2024; Sharma et al., 2020). AI, ML, Deep Learning, and Predictive Modelling are some of the technologies that allow computers to learn from current data and make smarter, beneficial decisions over time.

AI is a field of Computer Science, which mainly focuses on training a computer system to complete tasks that humans cannot do. Moreover, AI also involves decision making for developing intelligent systems. ML is a sub-area of AI where computer systems learn relationships from pre-existing training datasets (Huntingford et al., 2019). ML builds upon computational and analytical methods that enable computers to learn from datasets. Deep Learning is a specialized branch of ML that is based on neural networks with many layers in order to understand complex data patterns. Predictive modelling is a statistical process that analyses past data and patterns to predict future outcomes.

3.1 Optimizing Soil Quality Using AI and ML

The soil (i.e. Soul of Infinite Life), is responsible for sustaining life on earth (Huntingford et al., 2019). The importance of healthy soil can't really be overstated, as a lack of nutrients can greatly lower the crop yield (Oliveira & Silva, 2023). In many countries, farmers count on the old and traditional methods of farming, which are based on suggestions of the elderly. This practise leaves farmers with uncertainty and randomness which is only meant to increase with the rise of population and global warming. Soil testing is a helpful tool for analysing the available nutrient content in soil and determining the appropriate amount of nutrients to be added to a given soil based on its fertility and demands of the crop we want to grow (Huntingford et al., 2019). Soil testing is a key method for analysing soil health, which includes measuring various properties, including nutrient assessment, soil pH (potential of Hydrogen), organic matter content, and soil texture.

Technology-abled farm maintenance system acts as no less than a miraculous saviour for ensuring food security all over the world (Sharma et al., 2020). AI is one such major field in computer science that is advancing quickly and has various subfields (Lin et al., 2024; Sharma et al., 2020).

3.2 Effective Crop Management domains

Artificial intelligence is reforming the agricultural sector by boosting processes and resources (Lin et al., 2024). Agriculture is a sector where we cannot generalize situations and apply a common solution. AI techniques have equipped us to take into account the intricate details of each situation and provide a solution that is best fit for that particular problem. Development of various AI techniques is helping the agriculture sector in solving complex problems under various sub-domains of agriculture (Huntingford et al., 2019; Sharma et al., 2020). Figure 2 shows several domains associated with agriculture practices.

The optimization methods for different fields of agriculture are discussed as follows:

- **Crop prediction**

The prediction of crop yield is highly favourable for promotional strategies and estimation of crop expenses. Some of the specifications that play an important role in predicting crop yield include: pH values, soil type and quality, harvesting schedules, and weather patterns like sunshine hours, temperature, rainfall and humidity (Bannerjee et al., 2018; Sharma et al., 2020). An ANN model using the back propagation learning algorithm can predict yield from soil parameters. In 2014, researchers presented a neural model for projection of 7 different crop yields using inputs from the atmosphere and consumption of fertilizers (Bannerjee et al., 2018).

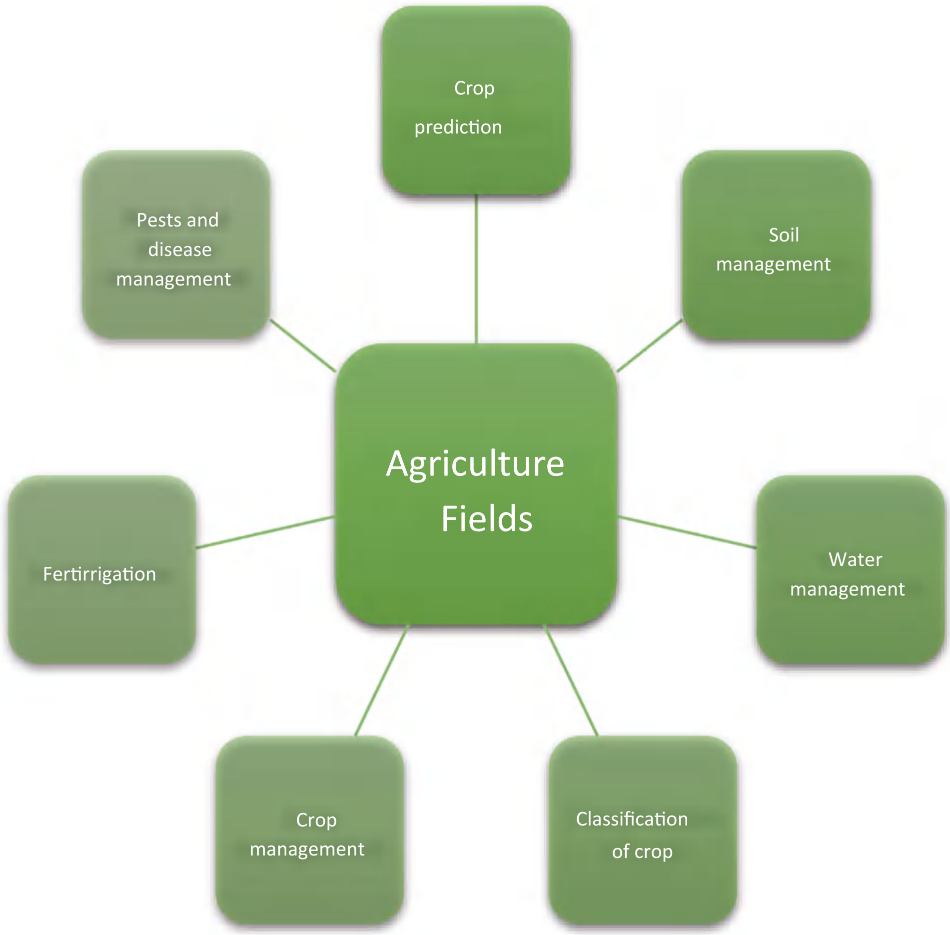
- **Soil management**

Soil Management assures plant nutritional sufficiency. The development of crops depends on the nutrients that are obtainable from a particular soil (Oliveira & Silva, 2023; Sharma et al., 2020). A scientific analysis of pH values, soil nutrients, and soil moisture are crucial for determining the properties of soil. Acar et al. implemented an Extreme Learning Machine (ELM) based regression model for predicting humidity of the soil surface (Sharma et al., 2020).

An improper combination of soil nutrients can massively affect the growth and development of crops. Identifying what these nutrients are and determining their impacts on crop yield with Artificial Intelligence enables farmers to easily make the necessary alterations. While human observation lacks full precision, machine vision models can observe soil conditions for gathering essential data in order to combat crop diseases. This data is then used to evaluate crop health and predict yields while notifying of any issues.

It is very challenging to figure out the impact the origin (source or type of soil, plant, or environmental conditions) has on crop yield and plant growth due to the involvement of complex factors. There are many variables involved in the relationship between soils and plants. Varying climate makes the management of these factors even more complicated. To estimate erosion's impact on productivity, a fundamental set of data is defined. Availability of Nutrients and Soil Organic Carbon (SOC) or Soil organic matter are heavily influenced by soil erosion (Bannerjee et al., 2018).

Fig. 2 Agriculture fields



- **Water management**

Improper irrigation leads to crop loss and degraded quality. It is quite beneficial to optimize water consumption with the use of AI in irrigation techniques. A fully self-automated drip irrigation system integrated with different kinds of sensors to monitor the pH and Nitrogen content of the soil has been discussed. It makes use of Artificial Neural Networks (a type of AI) in order to make intelligent decisions (Bannerjee et al., 2018; Oliveira & Silva, 2023).

- **Classification of crop**

Organizing different crops into categories provides understanding about where different crops are grown around the world. AI and ML can analyse large amounts of satellite and drone imagery to classify different types of crops. Using these images, ML algorithms can distinguish between crops based on patterns, colour, and other features (Sharma et al., 2020).

- **Crop management**

The wrong combination of nutrients in soil can seriously affect the health and growth of crops. The crop yield can significantly be enhanced by identifying nutrients for crop needs. Human observation has limited precision but a computer vision model can spot issues and obtain reliable data in order to control crop diseases This important plant science data helps farmers figure out a plant's health, how much crop they can expect, and any potential problems. This whole process starts with plants triggering AI systems through sensors that check their growing conditions. This then sets off any changes needed in the environment (Pierce & Lal, 2017). In general, crop management systems cover each aspect of farming, acting like a manager for the whole process (Oliveira & Silva, 2023). A multi-layered feed-forward artificial neural network-based system has been formulated on the Island of Italy to protect crops from damage due to frost (Bannerjee et al., 2018).

- **Fertirrigation**

Fertirrigation is the process of applying fertilizers through irrigation systems, allowing plants to receive water and nutrients simultaneously (Oliveira & Silva, 2023). IoT-based smart sensors placed in the soil measure parameters like moisture, pH, temperature, and nutrient levels. AI algorithms process this data to make decisions on when and how to irrigate and fertilize the crops (Sharma et al., 2020).

- **Disease and pest management**

Crop diseases are a matter of great importance to farmers. Computerized systems are being used globally to figure out diseases and tackle them. Computer vision can spot pests and diseases. This works by using AI to scan images for mold, rot, bugs, or other things that could hurt the crops. Along with alert systems, this helps farmers immensely by allowing them to act quickly and prevent the spread of disease (Zhang et al., 2019). Using a highly efficient AI system over the course of crop growth lowers the chance of diseases and lowers the financial consequences. DL methods have been employed in many farming zones, helping lots of farmers find crop sickness from images of plant leaves (Huntingford et al., 2019; Oliveira & Silva, 2023; Sharma et al., 2020).

The interactions between the infective agent and the infected organism can be studied to identify different plant diseases that cause harm to plants. However, the type of disease cannot be predicted due to unrecognizable traits. Various diseases start in the soil or the roots of the plant and affect the whole plant (Suchithra & Pai, 2020).

3.3 Involving ML to Optimize Soil Quality

Use of ML techniques offers the benefit of providing accurate data needed for precision agriculture (Folorunso et al., 2023). A study conducted in Calabar, capital city of Cross River State, Nigeria included five Machine Learning Algorithms to predict SOC (a significant indicator of Soil fertility) (John et al., 2020).

Let us understand these five Machine Learning Algorithms as specified in (Folorunso et al., 2023; John et al., 2020).

- **Random forest**: It is a widespread and influential ML method that is suitable for handling regression (predicting a numeric value) as well as classification (predicting a category) tasks. This algorithm works by creating multiple decision trees (sequence of questions) and combining their predictions to provide accurate results. Random Forest is also good at dealing with noisy/messy data.
- **Cubist regression**: It is a machine learning model that combines a decision tree (predicts outcomes based on input data with a flowchart-like structure consisting of nodes and branches) with multiple linear regression models (statistical method that assumes the relationship between the outcome which is to be predicted and the factors affecting that outcome to be linear) This means it makes predictions based on rules derived from the data.
- **Artificial neural networks**: ANN is a variant of machine learning model that is good at predicting outcomes in complex situations where relationships between data aren't straightforward. During training, the ANN adjusts its connections based on the known input data and known outputs. Once trained, it can then predict outputs for new, unseen data.
- **Support vector machine**: It is a smart and efficient tool for differentiating between different classes of data and can also predict continuous values. By transforming the data into a space with more dimensions, SVM can find relationships that aren't obvious in the original data.
- **Multiple linear regression (MLR)**: It is a way in machine learning used to predict a target variable (in this study, Soil Organic Carbon or SOC) based on several other related variables. By establishing a linear relationship via a specific mathematical equation, MLR helps in understanding how changes in these factors influence SOC.

The RF model proved to be the most effective model in the study because it can support large sets of data with multiple input parameters so it is highly compatible for predicting soil qualities dependent on several factors such as pH, nutritional and humidity levels, organic content. Utilization of organic manures and fertilizers is needed to raise SOC levels (Bochenek & Ustrnul, 2022; Pierce & Lal, 2017). Improper soil management techniques and overuse of chemical fertilizers is the central cause for heavy loss in soil quality. Machine Learning strategies contribute in the field of agriculture and enhance data analysis for prediction purposes (Suchithra & Pai, 2020).

Hence, by using Machine Learning algorithms, the condition of soil can be predicted beforehand, allowing us to take needful measures prior to the hard work. This serves as an example to demonstrate how useful ML algorithms are to farmers and the agriculture sector.

To sum it up, AI and ML have numerous advantages when used in the field of agriculture to optimize Soil Quality, which let us have a look at briefly:

- Accurate prediction–Using Machine Learning techniques for the estimation of parameters exhibits low error indices, which is extremely beneficial in the agriculture sector.

- Complex dataset–Forecasting crop yield involves huge datasets containing satellite and/or archived data. Utilizing AI techniques like regression algorithms (RF) and Neural networks (CNN) provides quicker and precise predictions. This provides relief as doing all this work accurately and quickly is not humanly possible (Sharma et al., 2020).
- Reliable prediction–The algorithms help predict the disease/weed even with images taken on smartphones, which are easily accessible to farmers. Detection of diseases in the early-stage leaves time for saving the crop before it is damaged beyond repair (Sharma et al., 2020).
- Crop protection–efficient irrigation practices cut back on water-related damage to the crops and thereby increasing crop yield and protecting the crop as well (Sharma et al., 2020).

3.4 Optimizing Climatic Conditions Using AI and ML

Climate change, induced by human behaviour, puts Earth at risk with rising temperatures and severe weather occurrences (Shanmugavel et al., 2023). In recent years, the influence of climate change on agriculture has become an alarming truth globally. The use of chemical fertilizers and pesticides leads to worsening and sudden changes in the climate (Zhang et al., 2019). The exploration of Artificial Intelligence and Machine Learning techniques is essential, especially for climate change adaptation in cities and sustainable development as AI-ML techniques offer unique and efficient advantages, as opposed to conventional methods (Shanmugavel et al., 2023).

In recent years, scientists have started using machine learning techniques to improve General Circulation Models (GCMs) and it is a kind of computer model that estimates long-term weather and climate trends). ML methods are (semi) automated practices to data interpretation that make minimal to no pre-existing assumptions. ML models such as Random Forest and 2D Convolutional Neural Networks can help GCMs make more accurate predictions, even for some atmospheric processes, like cloud formation or storm intensity which are too complex or small to be fully captured by GCMs. RF models can be trained to improve accuracy even in extreme weather cases and machine learning such as 2D CNNs can improve predictions of precipitation extremes (Bochenek & Ustrnul, 2022; Huntingford et al., 2019).

Dealing with climate change has gotten pretty tough for cities all over Africa, as mentioned in several research projects. The integration of AI–ML technologies can provide significant enhancement in this scenario (Pierce & Lal, 2017).

Thus, the implementation of machine learning techniques for analysing climate change helps us immensely. Energy is conserved and the understanding of long-term trends can be used to predict rainfall intensity and flood risks.

3.5 Limitations of AI and ML in Soil and Climate Optimization

- Choosing and refining dataset can be challenging for people with non-computing background. Not everyone is comfortable and ready for technology to take over as this shift could be overwhelming for someone who isn't familiar with computers and technology in general (Bannerjee et al., 2018).
- Incorrectly labelled data may lead to an ineffective forecasting system. Any error in labelling and uploading of data could alter the results significantly.
- Improper installation of sensors in the field alters the accuracy of the system. Hence, there is a need to be very mindful while dealing with datasets as many factors are dependent on how accurately data is dealt with (Bannerjee et al., 2018).
- Excessive training of the prediction model may result in a delicate and highly responsive prediction system so we need to be thoughtful about that too.

In order to overcome these limitations, we need to grant resources to collect information along with boosting education and training to enhance local knowledge. Making partnerships and working together with groups from other countries can be a good way to share information. In addition, frequent soil check and collective public facilities can solve these problems (Sharma et al., 2020).

4 Optimising Crop Production Using AI and ML

Agriculture in the twenty-first century faces several significant challenges. To feed our growing population. Farmers need to produce more food using less land while keeping down the effect of farming on natural world and biological diversity. AI and ML enhance creativity and efficiency across various applications by enabling data-driven decisions. AI-driven irrigation systems and crop management tools allow for precise monitoring and action based on real-time data, improving crop yields and sustainability. Farmers should also keep in their mind that it is very important to take care of land by ensuring that future generations can also continue farming successfully. Sustainable farming provides a method to deal with this problem through a framework about the right time, place, and source (Akintuyi, 2024).

4.1 Effective Crop Management

Management of crops plays an important role in the field of agriculture. Managing crop production is very important because many farmers just focus on growing crops. It provides a method that how the crop is to be grown by use of technology that can accessed easily and removable. Sustainable farming is only possible with smarter use of AI resources like the ones mentioned in Fig. 3.

Traditional farming methods can cop up as the use of harmful pesticides, which can damage the soil and make it less fertile over time has become very common. Farmers need to be proactive and responsive in order to achieve a healthy crop each time. Practising sustainable farming can contribute in safeguarding crops and enhancing overall productivity. Through these practises farmer will not only be able to obtain a successful crop but also preserve resources for the upcoming future generation (Mamai et al., 2020).

- **Healthy oil and smart fertilizer use**

Only AI and ML hold potential to make farming more efficiently. It helps with better resource tracking, smarter farming practices, and improved waste management. Therefore, with good resource management, better prediction about crop and land can be made. It also identifies problems in agriculture, such as crop diseases, poor storage, pesticide issues, weed control, and irrigation challenges.

Soil can be become healthy only if it is able to retain its nutrients back. Organic products should be preferred over chemicals and fertilizers. Farmers can analyse the data and add the right amount of fertilizer accordingly. For example: Adding lime or gypsum can help raise soil pH and improve calcium levels, which is crucial for plant health (Shanmugavel et al., 2023).

- **AI in water and resource management**

Water is crucial not just for direct use but also for food production, fisheries, and industry, it's important to study these interconnected systems. Implementing drip irrigation which helps in delivering water straight to the roots, can help in minimizing evaporation and storm water and storm water runoff.

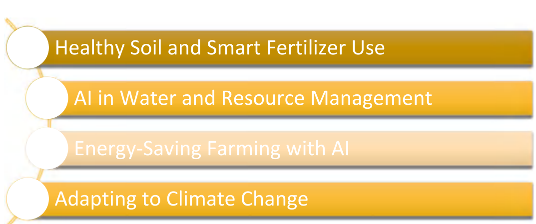


Fig. 3 AI resources necessary for effective crop management

Soil sensors and water channels can also provide a great help. This helps save water, especially in dry areas, where there is scarcity of water, we need to ensure that what is the requirement of the crop (Nova, 2023).

- **Energy-saving farming with AI**

The most efficient ways to use energy are cutting down on waste and lowering the farm's carbon footprint. Photosynthesis mainly depends on factors like sunlight, air, water, soil, and CO_2. In greenhouses, special equipment helps in maintaining these conditions within the right limits. Plant's yield comes from the energy it gets from specific light wavelengths. Therefore, LED lights help plants to absorb this energy more efficiently. For example: to grow potatoes we need to look for the best Spectrum of LED light (Mohammed et al., 2023).

- **Adapting to climate change**

Sustainable resource management helps AI learn from long-term data to predict climate challenges like droughts or floods. Understanding ocean–atmosphere interactions and improving climate models have made it possible to predict climate variations a few months ahead. With this info, AI helps farms adapt to changing climates, ensuring continued productivity. But still, these forecasts have a lot of uncertainty. This uncertainty can lead to cautious strategies that protect against bad years but may lower overall productivity and lead to inefficient resource use and environmental damage (Jain et al., 2023).

4.2 Steps to Protect Crop and Optimizing Its Production Using AI and ML

Once a crop grows it becomes very important to look after that crop. Each step plays a crucial role from planning to harvest and then marketing. Let us see how AI and ML contribute in steps of farming.

- **Planning and preparation**

The initial step involves selecting the relevant crops based on climatic conditions, type of soil, and demand in market. Farmers should assess local conditions and trends.

Example: A farmer in a tropical region may choose to grow rice or sugarcane due to favourable climate conditions, while a farmer in a temperate zone may opt for wheat or barley.

- **Soil testing**

Soil can be analysed on different parameters like pH level, nutrition, and fertilizers in it. Then accordingly, farmer will be adding that particular fertilizer to overcome the deficiency of that nutrient in the soil. On that basis, he will be selecting which type of crop is to be grown. For example: if there is lack of nitrogen in soil then farmer will grow leguminous crops i.e. beans, peas, etc.

- **Land preparation**

This step involves clearing the land, then ploughing the field to break up compacted soil. Then tilling the land and smoothing soil beds for plantation and applying right amount of manure and fertilizers in the soil. Practice reduced-till farming can be used to maintain soil structure and reduce erosion.

- **Choosing seeds**

It is very important to predict whether the seed is good or not for specific land and climate condition. AI helps in integrating seed quality and improve the test which measures seed germination time period and its growth rate.

- **Plantation**

AI technology can provide benefits of proper spacing while sowing seeds on agriculture land. Furthermore, it also helps in calculating the depth of soil while sowing seeds and recognizing different plants and fruits and their counting.

- **Irrigation**

Drip irrigation system can provide an aid to solve to problem of water wastage. The main focus should be on how to reduce the difference between the actual soil moisture and the desired moisture level at a specific time. This can be done by optimizing drip irrigation systems with buried water sources in dry soil. This will help in controlling soil moisture with accuracy (Khan et al., 2006).

- **Nutrition**

Plants need enough nutrients in the soil to grow well, especially key minerals like nitrogen, phosphorus, and potash. While copper and iron are also important, they are needed in smaller amounts. It's crucial to use these nutrients wisely to avoid pollution, particularly from excess nitrogen. This balance between what nutrients are added to the soil and what is to be removed. Example: if there is deficiency of sulphur, then add sulphur-rich fertilizers (Rengel, 1999).

- **Weed and pest control**

Many advanced tools and technologies are being used, such as camera-guided weeding, sensor-based spot spraying, robotic weeding, and drone mapping. Researchers are also developing new methods, like using sensors for electrical weed control and direct injection of herbicides for targeted treatment. Example: Use of neem oil to protect crops from weeding (Owen et al., 2015).

- **Crop monitoring and maintenance**

It is very important to identify signs of disease, pest, and nutrient deficiencies at the earliest stage. Different algorithms are to be followed to monitor these crops. Example: A farmer inspects plants weekly and notices yellowing leaves, indicating a nitrogen deficiency. So, immediate action can be taken to add an appreciate amount of fertilizer.

- **Harvesting**

Timing is very important when it comes to harvest a crop. To maximize crop yield, harvesting of the crop can be done when its maturity reaches at its peak.

- **Post-harvesting**

It plays a vital role by providing a method to clean a crop and store it, once it is harvested. Example: A farmer has cultivated rice in this field. Farmers can store the harvested crop in dry big air tight drums. Farmer can monitor grain moisture levels to prevent spoilage during storage.

- **Marketing**

AI and Machine Learning are changing many industries, so why not in the agricultural sector. Companies are creating technologies to help farmers monitor crop and soil health more easily. Two leading AI technologies, hyperspectral imaging and 3D laser scanning, gather detailed data on crop health for analysis. Direct sales can help farmers to maximize profits bypassing middlemen (Kohls & Uhl, 2002).

- **Record keeping and evaluation**

This involves keeping a record of cost, yield, and sales. Through this farmer can maintain the expenses of seed, labour, and resources against this income generated out of the crop.

4.3 Methods to Boost Productivity

Now, we will be studying briefly about some important terms that help in boosting productivity of crops.

- **Crop rotation and cover cropping**

Crop rotation has been practiced for a long time. In this method, we grow crops alternatively every year so that the soil can get sufficient time to retain back its nutrients. This improves soil health and reduces the need for chemical fertilizers. As chemical fertilizers result in the depletion of the fertility of the soil. But now, it is believed that synthetic fertilizers and pesticides could completely replace crop rotation system. Example: growing maize and soybeans (Francis & Clegg, 2020).

- **Integrated pest management (IPM)**

Farmers often make decisions about which crop varieties to plant and how to rotate them, but predicting how these changes will affect pest populations is tough. For biological control to be effective, farmers need to see clear and reliable benefits. Even though there is evidence that natural enemies can help control pests. The results can vary widely depending on factors like plant diversity, pest, and farming techniques. The use of these economic thresholds has helped bring together different stakeholders in IPM. Biological control methods—such as introducing beneficial insects, enhancing habitats, or managing natural enemies—are gradually being combined with other IPM strategies (Ehler, 2006).

- **Precision agriculture**

This involves gathering real-time data about soil, crop conditions, and weather through sensors placed in the fields using GPS and sensors. This helps minimize waste and also ensures resources are used efficiently which results in higher yield and lower environmental impact. For example: aeroponic technology to grow green leaves in mist without the use of soil.

- **Agroforestry**

This practise includes cropping along with growing trees. The aim is to integrate the benefits from both sides. Vegetative buffer strips (VBS) can reduce the runoff of agrochemical pollutants. Trees contribute large amounts of aboveground and belowground biomass, helping store carbon deeper in the soil. Trees improve soil productivity through processes like biological nitrogen fixation, efficient nutrient cycling, and capturing nutrients from deeper soil layers. Variations in carbon storage within different soil fractions suggest that studying microaggregates could be a useful indicator of a soil's carbon storage potential. The success rate to increase crop production becomes higher.

- **Carbon footprint reduction**

Healthy soils are stable, resilient, resistant to erosion, easily workable, provide good habitats for microorganisms, and act as significant carbon sinks, leading to lower carbon footprints. This practice involves reduction of greenhouse gas emissions, and focuses on renewable energy use on farms. Reducing machinery use can help prevent soil compaction. Reducing greenhouse gas (GHG) emissions is essential for tackling climate change, and understanding the carbon footprint is key to this effort (Fang et al., 2011).

4.4 Trends in Agriculture

A strong trend can be observed over a large scale in agriculture. Trend arises from change in environment. Land is measured on bases of agricultural performance through land and farm labour productivity, as well as the use of technological inputs. Farmers are using GPS and IoT sensors, through which they can stock the progress rate by focusing on saving environment. Vertical farming is opted in urban areas. Through this type of farming farmers are able to produce at minimum cost on less land. This is an efficient and sustainable way of producing crop. Transportation cost also lowers down as the crop produces is near the consumer.

With the development of technology in agriculture, many things have become easy. Today farmers are able to access using their weather stations and explore farming robots or drones (UAVs) (Saritas & Kuzminov, 2017).

- **Crop models**

Satellite observations enhance crop models to better predict regional crop yields. It briefly analyses the relationships between crop characteristics, which correspond to model state variables, and satellite data, along with the common types of crop models used. This helps us to understand how different crops grow. Observations show all the requirements of a crop like soil, water, and other nutrients. This can help farmers to predict and figure out the best ways to take care of their crops.

- **Agronomic guidelines**

Guidelines should be based on sound economic theory applied to agronomic data. While data should be based on the relationship between crop yields, inputs, soil characteristics, and weather they all are equally important. We argue that the rise of precision agriculture technology has made this information even more valuable. These guidelines include advice on things like soil care, when to plant seeds, how to water crops, how to control pests, and how to use fertilizers. They are based on research and local farming conditions, helping farmers make smart choices that increase their harvest while reducing harm to nature (Bullock & Bullock, 2000).

- **Algorithms for automated decision-making**

Algorithms for automated decision-making replace manual work. These programs can analyse information like weather forecasts, soil moisture, and images of crop health. For small areas of farmers' fields, researchers need a deeper understanding of how crop yields, input rates, soil characteristics, and weather interact. This technology makes farming easier, saves on labour costs, and helps farmers manage their crops better by allowing them to respond quickly to changes (Sharma & Borse, 2016).

4.5 Side Effects of Chemical Use on Land

All living organisms have been severely affected by the use of chemical fertilizers, especially nitrogen fertilizers (as depicted in Fig. 4).

Overusing chemical fertilizers can harm our environment. Soil, water, air, and land are interrelated to each other. When farmers frequently keep using these fertilizers, that creates an imbalance of nutrients in the soil. Not only that but other living organisms had to suffer from it. For example, overusing fertilizers high in nitrogen and phosphorus can lead to too much of those nutrients, while other important nutrients like potassium and certain micronutrients may run low. This imbalance can result in making soil harder and results in loosing fertility. Heavy use of fertilizers can increase soil erosion. This results in poor water absorption and bad plant roots. The plant has to struggle a lot to grow in that type of soil. The fertilizers wash away the nutrients by removing the top soil. This top is very essential otherwise productivity would decrease and land will not be able to produce food. The pH level of the crop gets changed which makes it more compact.

Overall, while chemical fertilizers can help crops grow in the short term, their long-term effects on soil health can be harmful. So, AI can click pictures on the spot to identify pests and diseases early. This can help in the reduction of utilization of the fertilizers. The farmer only has to spray insecticides and pesticides on limited crops only. It can also adjust watering schedules to reduce chemical runoff. These methods can be very helpful advice for smarter decisions and make farming easier and better for the environment (Bishnoi, 2018).

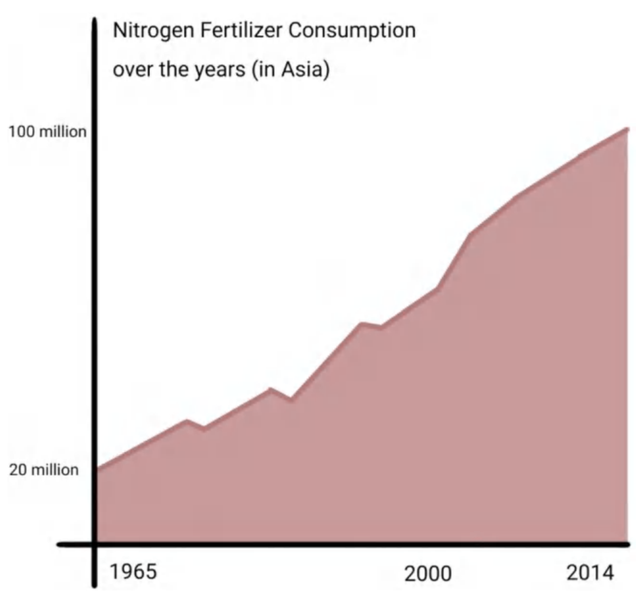


Fig. 4 Graph showing continued use of Nitrogen fertilizers in the agriculture system

4.6 Role of AI and ML in Gross Domestic Product

Agriculture is crucial for feeding the world, contributing 6.4% to global Gross Domestic Product (GDP) and providing jobs and income for millions. As the global population grows, food demand is expected to rise by 70% by 2050.

To meet this demand, farmers will need to produce more food using fewer resources, such as water and chemicals. This is where technology comes in. Machine learning is increasingly recognized as a powerful tool in agriculture, employing algorithms like decision trees, random forests, and support vector machines to enhance crop yields.

AI and machine learning can effectively evaluate how various factors—such as temperature changes, rainfall, and insecticide application—affect crop yields, significantly reducing the time required for yield predictions. Robots and automated machinery can perform all tasks like planting and harvesting, saving time and labour costs (Kumar et al., 2022).

5 Conclusion

This chapter explores how Artificial Intelligence and Machine Learning are changing farming for the better. AI and ML offer innovative solutions to global problems the agriculture sector faces like- changing climates, a growing population, and limited resources. Artificial intelligence can help farmers sort and differentiate market demand, study soil health, monitor weather conditions, and allow checking for appropriate areas to distribute pesticides and seeds. Real-time data can be taken from the sensors employed in the fields. This data can then be utilized to decide how much water is needed, thus preserving water. AI algorithms such as smart greenhouses can optimize plant growth by automatically adjusting the temperature, light levels, and humidity. AI-powered drones make automated pesticide spraying quicker and less labour-intensive, while being accurate and reliable as well. Real-time monitoring and analysis enable early detection, preventing water waste together along with potential crop damage. By integrating techniques such as 3D mapping and data from sensors and drones, farmers can analyse large datasets in real-time, offering understanding of crop patterns and characteristics for improved planning. AI in water management can help solve various problems like water leakage, theft, or inaccurate measurements. AI uses models like ANN, fuzzy logic systems, CNNs, and LSTMs, and advanced techniques like ANFIS, FFNN, and KNN to monitor water quality and predict pollution levels. AI algorithms help in analysing historical data related to seasonal patterns for predicting future water demands. The drought prediction system in AI can help provide predictions of weather and helps in proactive planning and the smart water grid helps in enhancing the water networks to minimize loss in water and enhance the efficiency of system. Soil testing is a key method for analysing soil health, which includes measuring various properties, including nutrient assessment, soil pH, organic matter content, and soil texture. AI and ML have numerous advantages when used in the field of agriculture to optimize soil quality, such as accurate and reliable prediction, crop protection, and many more. Algorithms for automated decision-making replace manual work. These programs can analyse information like weather forecasts, soil moisture, and images of crop health. AI and ML are helping make farming better. They let farmers make choices based on data and manage resources well. This cuts down on waste and helps the farm run smoothly. These technologies can process a lot of data, guess harvest sizes, and even run farming tasks on their own. By adding AI tips to usual farming ways, farmers can grow more crops. They can adjust to changes in the weather and aim for green farming goals. This makes sure we have enough food for the future. Despite all these glorious benefits, however, there are certain limitations that the use of AI and ML brings along; like lack of time and digital skills, high implementation cost, energy consumption, improper installation of sensors, etc.

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Optimizing Crop Yields with Machine Learning: Techniques and Applications

Hitkar, Keshav, Pooja Mahajan, and Gaganpreet Kaur

Abstract

Agriculture stands at the core of our ability to sustain a global population; however, it faces a host of challenges: environmental change due to climate, resource shortages, and a growing requirement for higher productivity. Machine learning (ML) has demonstrably appeared as a powerful possibility for raising crop yields and promoting sustainable farming strategies in response to these challenges. Concerning crop yield, determinants include temperature, precipitation, and humidity, which rely on climate and soil characteristics, for example, texture, moisture and fertility together with agricultural methods including fertilization, irrigation, and tillage, along with biological forces from pollinators, pests, and diseases Together with pollution, topography, and water quality, and more, affect crop yields, thereby making crop productivity management even more challenging. The following is therefore a generalizable of how use of various machine learning models can be used for yielding prediction in Agricultural production. Within the sphere of supervised learning models, the families of algorithms that matter are linear regression, random forest, and support vector machines. A handful of other studies choose the unsupervised learning methods and deep learning how these algorithms including the CNN and RNN for the yield predicting. As well, the case for using remote sensing technology combined with geographic information systems (GIS) for the monitoring of crops is examined. Such tools seem to have proven their usefulness in guiding agricultural decision-making, based on these examples. Further, by the application of overall machine learning perspectives; factors such as water and nutrient management in crops are boosted. Last of all, the study focuses on the new development of artificial intelligence and machine learning in the agricultural field. Modern technologies and the identified areas of scholarship to enhance food production and productivity include among them technology such as Artificial Intelligence to increase crop production.

Keywords

Machine Learning (ML) · Crop productivity · Artificial Intelligence (AI) · Geographic Information Systems (GIS) · Remote sensing technology

1 Introduction

Agriculture continues to be a key component of economic development, particularly where it is the economy's primary base of production and labour. While these critical sectors have many challenges from weeds, pests, and diseases, agricultural yield and quality are still at risk (Mukherjee, 2021). The facticity and productivity of the land, water availability, and climate also affect its agricultural potential or physical land features. The global population is expected to increase by 2.3 billion in the next half a century, furthering the pressure on already strained agricultural sectors as demand for food will double.

Machine learning (ML) and Artificial Intelligence (AI) are two big technologies that involve the study of processed data and the two have begun penetrating agriculture in terms of yield (Bal & Kayaalp, 2021). These technologies are more

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advanced and have causative data that could be climatic, like temperatures, level of rainfall, humidness of the soil, and the kind of soil in which the fruit greets the yield better. AI is also being used in Agriculture with the prediction of yields through ML algorithms, to reinforcement learning algorithms for irrigation use and fertilizer (Shaikh et al., 2022). The technologies in farming integrated with AI and ML methodologies used in supervised learning such as line regression, Random Forest, Deep learning methodology, especially Convolutional Neural Network CNN also enhance the decision-making power concerned with farming and produce by the farmers (El-Ghamry et al., 2023). These technologies enhance human interventions and management of agricultural systems resulting in improved yields and efficient future use of resources.

The book chapter is organized as follows: Sect. 2 explains the factors which affect crop yield production. ML models for crop yield production are explained briefly in Sect. 3. In Sect. 4, remote sensing and geographic information systems (GIS) data integration is explained. In Sect. 5, the techniques of optimization in crop management are presented. Section 6 discusses the challenges and limitations. The future directions and innovations for future development are presented in Sect. 7.

2 Factors Affecting Crop Yield Production

Many factors affect crop production including climatic factors, biological factors, quality of soil, methods used in farming, technology adopted in farming, and environmental conditions (Shah & Wu, 2019) (Fig. 1). Environmental factors consist of temperature, precipitation, and humidity influence plant growth. Genera that influence plant growth and health are referred to as biological factors.

Accessibility of nutrients and water is influenced by the quality of the soil needed for plant growth (El-Ramady et al., 2014). Promoting techniques of cultivation such as watering, feeding, and succession, in a given region can improve crop

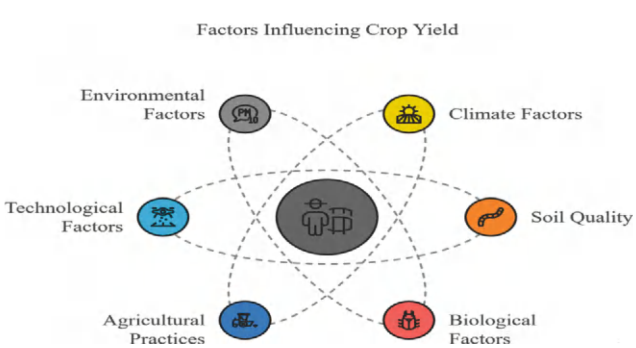

Fig. 1 Factors that affect crop yields

production. Technological factors such as the mechanical revolution, the use of high-yield inputs, and the inputs revolution in farming increase output efficiency. Finally, factors like climate, including air and water quality as well as terrain can either favour or hinder growth thus showing sustainable measures for higher yield since these are important factors to consider.

2.1 Climate

Various climatic factors such as temperature, rainfall, wind, humidity, etc., have major impact on crop production. Temperature is one of the most significant climate factors by which crop growth and advancement are most affected. Energy has a perfect temperature where plant seeds will grow and come to full production rates. High temperature causes heat stress, reduces the rate of photosynthesis, flowers early, and reduces grain-filling and thereby poor productivity. However, low temperatures might limit growth; germination might be limited, and the plants are most likely to be attacked by diseases (Wahid et al., 2007).

Irrigation is very sharply defined in crop production because it controls things like germination, growth, and even the uptake of nutrients (Li et al., 2009). As they are warm temperatures, a condition of low rainfall comes with drought stress in most plants due to the consumption status of water, and plant photosynthesis or transpiration efficiency. On the other hand, large amounts of rainwater in the soil and roots cannot get adequate oxygen that is needed and some root pests occur. In farming seasons, yields are elements whose levels are greatly affected by conditions such as; In the cropping seasons, yield is an element that has severe impacts on the levels that are caused by conditions including excessive rainfall and dry weather. The degree of the relative air humidity influences the transpiration activity and incidences of diseases (Bovi et al., 2016). High humidity conditions lead to disease formation in plants, which has negative impacts on crop production. On the other hand, low humidity greatly reduces rates of transpiration thus leading to loss of excessive water and more watering to maintain optimum water status. Wind influence, consequently, can be grouped into definite and indirect forces on the crop or directly on it (Gardiner et al., 2016). It is possible to cause yield loss by the storm's destructive force to the crops like stem bashing, and uprooting of immature fruits and leaves. It controls the evaporation and the transpiration at an interval level but raises the amount of water being let out of the soil and through the plants. But another factor that affects the pollination processes, and as a consequence significantly affects the plants like cereals and fruits is wind.

2.2 Soil Factors

Soil quality is dependent on how well it can hold water as well as nutrients and its ability to support plant roots. Sandy soils are those in which water is not retained and possess a low capillary set but while clayey soils are waterlogged, they can be compacted with poor pore status and root intrusion. Since it holds water but is not waterlogged it is suitable for soil that provides high crop yield which is loamy soil (Kaur et al., 2020). The nature of soil always calls for concerted policy efforts since knowing what to grow and how to cultivate requires a proper understanding of the nature of the ground.

Sustaining soil consists of chemically—available ingredients like nitrogen phosphorus and potassium which form a vital input in plant production. Sometimes the soil may lack the nutrients required for the crop to grow to maturity or any yield at all at the required time. The energy crops depend on the soil for their nutrition for instance any form of nutrient depletion will affect the vegetation of the crops. So, more comprehensiveness such as soil fertility, individual fertilization process, the amount and type of organic matter, and soil pH are significant for realizing high yield for crops (Lal, 2020). The nutrient concentration needed by the plant and microbial activity within the soil are all affected by soil pH. Slightly acidic to neutral soil pH (6–7) is favoured by all the crops (Agegnehu et al., 2021). If a plant is to be grown in solid soils that are highly acidic or alkaline, the above-mentioned nutrients may be available, but they can be difficult to absorb. Reduced plant health, reduced yields, and greater need for manipulating pH using lime applications to raise the pH, or sulfur and lower the pH are expressions of this.

2.3 Biological Factors

The leaves, stems, and fruits are nibbled by insects, rodents, and birds, which kill or reduce the size of the fruits or prevent the growth of the plants. Second, when these crops are already weakened by pests, pests spread diseases to them as well and it makes it worse for the plants (Strange & Scott, 2005). Pest control by pest predators, pesticides, and crop requests is vital as regards the gain gained by the crop to its health. Very fatal diseases to crops and may massively degrade the yield originating from fungi, bacteria, and viruses (Timmis & Ramos, 2021). Some diseases include blight, rust, and wilt which affect the various parts of the plant and cause slow growth, poor yield fruits when mature as well as destroy stalks. Reducing losses such as these is accomplished through regular identification and treatment, and also through the use of disease-resistant varieties. Weeds are known to compete with crops by competing with them for water, nutrients, sunlight, and space. They can also limit yields by denying main crop access to resources such as light, water, and nutrients. Weeds can also host pests and diseases that may infect crops and in the process affect crop production (Kumar et al., 2021). The presence of weeds is detested and ought to be eliminated through pull, spray or cover this aids in the realization of the highest yield.

2.4 Agricultural Practices

Irrigation should be well done to water crops appropriately and at the proper time to affect growth and yield. Several irrigation methods affect yield differently.

Distributes water precisely at the root zone of the plant, saving water that otherwise would have been uselessly evaporated. Especially in areas experiencing low rainfall; it has the benefits of increasing both water use efficiency and crop productivity.

Imitates rain and may reach multiple acres of the field at once. However, if applied excessively, water may be wasted and high humidity within crop canopy implies high disease risk. Irrigates fields with water, which is sometimes expensive, leads to erosion of the soil or waterlogging and thus a poor yield of crops (Manik et al., 2019). This utilizes sensors and artificial intelligence to control the distribution of water in the soil and make appropriate use of good water for better yields.

2.5 Fertilization Techniques

Fertilization is an action that restores the nutritive value of plants growing in the soil as needed. Fertilization using effective methods helps increase crop yield but any ineffective and wrong ones will put the environment and crop yield at stake. These are grown from natural raw materials which allow for the enriching of the soil structure and reciprocally supplementing of nutrients over a specified period to achieve sustainable yields (White & Brown, 2010). Nutrients which supply, immediately available, to the plant and require a shorter time to absorb: nitrogen, phosphorus, and potassium. Its use, however, can lead to nutrient leaching, and soil erosion that leads to nutrient loss in plants. It refers to automating the process of applying fertilizer by applying AI systems to obtain the type and amount of fertilizer application using the condition of the soil and the crop (Swaminathan et al., 2022). It cuts wastage and boosts the output of crops which have little or no impact on natural resources.

The ability to grow different kinds of crops in one area, in one season, is called crop rotation. It has positive impacts on the improvement of the soil structure and pests, diseases, and weeds, generally, leading to higher and sustainable yields. Each crop that then grows and harvests uses different nutrients from and replaces different nutrients in the ground. Beans and peas are legumes that can fix nitrogen in the soil making the ground amenable for farming by the subsequent crop (Ahmed et al., 2021). Variation in crops stops pests and diseases' ecological cycle, making infestations that can damage produce yields. Because the diverse growth characteristics of crop varieties don't adapt to the changing planting techniques, they can be used to control weeds.

2.6 Tillage Practices

Tillage is the act of ploughing some time before planting or cultivation is done (Triplett & Dick, 2008). Most plants benefit from either polite or frequent usage but overuse or improper use can hurt structure by losses from erosion, compaction, and nutrient leaching. Different tillage practices have varying impacts on yield. Typically allows deep ploughing that interrupts the soil matrix potentially enhancing erosion chances but offers a level seedbed. In the long run, it lowers soil productivity hence the yields derived from the soil. Reduces the what by doing shallow cultivation or leaving the cover crops in the field. This improves water retention by soils, diminishes cases of soil erosion and soil fertility, and thus improves yields. This also involves placing crops right into the soil with a natural structure and without inversion of soil layers, which retains moisture and nutrients. It is less likely to cause soil erosion and is suitable for soil health, Moreover, it is also one of the most effective methods of achieving sustainable yield gains in the long run.

2.7 Technological Factors

Farmers' adoption of HYVs has also played a big role in increased yield production among crops (Herath & Jayasuriya, 1996). These genetically originated seeds are produced and optimized to produce more yields within appropriate conditions, resistant to pests and diseases, and stable in stress. It has been previously applied to increase crop productivity and enhance sustainable agriculture's characteristics. Because of their flexibility to adopt climate change and their ability to incorporate low chemical input including fertilizers and pesticides, they allow farmers to produce more with less.

Mechanization in agriculture means using machines to perform farming activities such as planting, harvesting, and irrigation or ploughing without involving many men (Rasmussen, 1982). Mechanization helps due to enhanced speed in farming methods, secondly by reducing the usage of hands, and lastly, most importantly, bringing the work to the right time. For this reason, it also contributes to effective space management on the floor as well, even making it easy for the farmers to cover large areas of the countryside. This has been made possible through practising the use of tractors, harvesters, and irrigation systems as a pull factor towards improved yields since there will be little or no wastage.

Precision farming implants modern information technologies such as sensors, drones, GPS, and remote sensing to work with fields at the finest level (Khanal et al., 2020). These tools ensure the farmers can check on the soil, water, crop, and even nutrient deficiencies and then decide on the manner to irrigate, to add fertilizers among others. Precision farming successfully properly applies the resources, restores conditions necessary for plant growth, and thus increases yield. They also assist in reducing overuse of water, fertilizers, and pesticides on the farm hence making farming a little friendlier to the environment.

2.8 Environmental Factor

Irrigation is a critical factor in crop production and part of it depends on the quality of water used to irrigate crops. Disease-causing agents such as heavy metals, salts or toxic chemicals in water retards plant growth, reduce nutrient intake, and possibly become toxic to the plant (Nadeem et al., 2018). High salinity water negatively affects the soil quality, while polluted water brings pathogens that negatively affect plant health. Lack of clean quality water means that such availability is crucial in ensuring the fertility of our soil to feed our crops sufficiently.

High on this list as a factor that poses a threat to crop production is environmental pollution with emphasis being made on air pollution (Manisalidis et al., 2020). Among such compounds, it is necessary to mention sulphur dioxide (SO_2), nitrogen oxides (NO_x), ozone (O_3), and particulate matter deformation of plant tissues, inhibition of photosynthesis, and decrease of plants rate of growth. For instance, a review article finds out that ozone-induced oxidative damage in plants, which is evidenced by a reduced yield, especially on the affected crops. Same as with pollutants in the air it was discovered that it can change the properties of the soil and qualities of water which in turn impacts crop production. Quality air is quality for the crops and it means that better yield can be harvested thus the control of air quality is crucial in farming (Dingenen et al., 2009).

These factors include the relative steepness and level of the land, the degree of slope, altitude, and direction of exposure to light affect soil drainage, erosion, and cropping results. Slopes involve the hazards that slope land may cause soil erosion that lowers the fertility of the topsoil and its water retaining capacity. On the other hand, low areas being areas of poor internal drainage cause waterlogged soils which limit rooting depth and oxygen status. In farming, slopes or irregular surfaces are usually related to management practices for soil conservation such as terracing or contour farming, for example, proper use of water and increased production on such terrains (Chowdhury et al., 2016).

3 ML Models for Crop Yield Prediction

Crop yield prediction is an important task in agriculture and can potentially improve food security and farm efficiency. Several ML models can be used to process the enormous agricultural data to help us optimize crop yield. Below is an overview of models that are commonly used.

3.1 Supervised Learning Models

They are based on unlabelled data, wherein crop yield is predicted based on input features (weather, soil properties, crop management practices). Some common models include:

- **Linear Regression**: It's one of the simplest models for predicting continuous variables (Hara et al., 2021). It can also model a relationship between different features (e.g. rainfall, temperature, soil fertility) and yield of a given crop for prediction of crop yield.
  - **Advantages**: Simple and interpretable.
  - **Limitations**: Uncomfortable with non-linear relationships.
- **Random Forest**: This ensemble learning method works as it creates a bunch of decision trees, takes the output of all the trees, and combines it (Kulkarni et al., 2018). It works so well for finding complex relationships between features and yield since it helps reduce overfitting.
  - **Advantages**: It's about non-linearity and it's great for big sets of data.
  - **Limitations**: Time constraints allow us to tune needs and turn them into the least amount of score.
- **Support Vector Machines (SVM)**: SVM supports regression (SVR) to identify the plane that has the greatest disparity for predicting real values such as crop yield (Esfandiarpour-Boroujeni et al., 2019). It especially makes sense when the dependence between features is nonlinear.
  - **Advantages**: Well-suitable with higher dimensions and Kernels good for non-linear data representation.
  - **Limitations**: It takes too long to generate good solutions for large datasets, and hyper parameters require optimization.

3.2 Unsupervised Learning Models and Clustering Techniques

These techniques are used when the data that is available does not have a label or it is being searched whether crop data is related to a certain level of productivity or some other group of data.

- **K-Means Clustering**: It can group places or farms based on characteristics such as soil type, climate, and modes of farming so that verses that have similar yield characteristics can be identified (Yu et al., 2021).
  - **Advantages**: Easy to use and beneficial in seeking relationships between variables.
  - **Limitations**: Affected by the first selected clusters and outliers.
- **Hierarchical Clustering**: This method establishes clusters that are hierarchically formed (Murtagh & Contreras, 2012), which gives a possibility of inciting the identification of different crops or farming regions.
  - **Advantages**: Is not restricted to any given number of clusters in advance.
  - **Limitations**: Computational cost for large datasets may be a major issue.
- **Principal Component Analysis (PCA)**: Although not categorised under clustering, PCA can also be used for reducing the dimensionality of the dataset, which can in one way or the other ease the identification of key features that affect yield (Kurita, 2019).
  - **Advantages**: Sometimes diminishes the number of input variables for a model thus making it efficient.
  - **Limitations**: A disadvantage of using this technique is that some information may be lost during reduction.

3.3 Deep Learning Models

ML models of deep learning models are a subclass of those models that use neural networks with a drastically increased number of layers (deep architectures) to learn from data. For both large and complex datasets, these models are exceedingly effective.

- **Convolutional Neural Networks (CNNs)**: CNNs are used for image data, but can be applied to spatial data in agriculture, for instance, satellite imagery or drone data for assessing vegetation health, or predicting yields (Kattenborn et al., 2021).
  - **Advantages**: It's good for analysing spatial and image data.
  - **Limitations**: The need for large datasets, however, and its dependence on this large amount of computational power makes it nonsensical to perform without first having analysed all of the existing data.
- **Recurrent Neural Networks (RNNs)**: For many applications, the data we need to model is sequential (weather changes, soil moisture, and crop growth over time in agriculture are some examples) (Devi et al., 2024). For these, RNNs are designed to handle.
  - **Advantages**: Applicable for temporal data and sequence modelling.
  - **Limitations**: Tough to train, have vanishing gradients.

- **Long Short-Term Memory (LSTM)**: LSTM, a special type of RNN, is designed to overcome the vanishing gradient problem, which makes it much more viable for long sequences of data, like multi-season crop yield prediction from trends in the past.
  - **Advantages**: Also good when you want to build models with long-term dependencies in sequential data.
  - **Limitations**: It is relatively heavy in parameters and computationally expensive.

3.4 Applications and Techniques

- **Feature Selection**: Techniques like mutual information or recursive feature elimination (RFE) can then be used to select key crop yield driving features, like soil health, rainfall, and temperature (Elavarasan et al., 2020).
- **Model Ensemble Techniques**: If we have more than one model and we can combine the predictions (our Random Forests and SVMs for example) to handle the uncertainty in the data, we will get better accuracy.
- **Data Augmentation**: If you have image or satellite data then artificially enlarging the data set is good because deep learning data augmentation models rely on such techniques (Ghaffar et al., 2019).

4 Integration of Remote Sensing and GIS Data for Crop Yield Optimization

Agriculture has benefited a lot from Remote Sensing and Geographic Information Systems since they make it easier for large-scale monitoring of crops to be affected (Atzberger, 2013). These technologies offer important information about crop conditions, growth rates, soil properties, and climate, which applied to models developed using ML, can greatly improve yield estimates and optimization processes.

4.1 Remote Sensing

Satellites fitted with sensors measure several parameters influencing crop productivity, including moisture content of the ground, health of plant canopy, and differential infrared temperatures (Gerhards et al., 2019). This imagery enables real and near real-time evaluation of crops at various cycles of the cropping process. Some key uses include:

- **Monitoring Crop Health**: Concentrated biophysical variables for example the Normalized Difference Vegetation Index and Enhanced Vegetation Index can be derived from satellite data to evaluate the crop state and density. A higher value normally indicates a healthier crop.
- **Soil Moisture Detection**: Irrigation management to prevent drought stress is one of the functions of satellites such as Sentinel-1 to estimate the amount of soil moisture through radar.
- **Temperature Monitoring**: Data of the surface temperature saves time to monitor heat stress or frost hazards that might be a threat to crops. Thermal sensors in satellites such as Landsat 8 offer such information.
- **Disease and Pest Detection**: Remote sensing can sense that crops are stressed due to diseases and pests, through the ability to look at differences in the reflection spectrum. Screening allows for early diagnosis therefore early intercession is to be made.
- **Yield Estimation**: Remote sensing can help to approximate crop yields by connecting NDVI to previous yields. Using three data sets, ML yield estimates are almost exact, and satellite imagery can also be used for yield forecasting.

4.2 Geography Information Systems (GIS)

Satellite imagery is extensively used in the application of GIS technology to process and analyse spatial data. Key GIS functions in agriculture include (Ghosh & Kumpatla, 2022):

- **Mapping and Zoning**: GIS produces line and bar maps that categorize farmland into areas depending on features such as type of soil, altitude, and standing of crops. These maps also assist in the controlled application of inputs such as water and fertilizers through an area with more accuracy or precision farming.
- **Spatial Data Integration**: It is based on multisource data input (satellite images, soil data loggers, meteorological data) to give farm conditions a general picture.
- **Monitoring Environmental Factors**: The latter because the weather conditions, distance from water sources or even the terrain's features in certain GIs can be analyzed to enhance performance in crop business.
- **Decision Support**: Through GIS farmers can make decisions such as the right time to sow their crops, water the crops, and even the time to harvest depending on a GIS analysis of the weather patterns in the area. Figure 2 presents factors enhancing crop yield through fertilization.

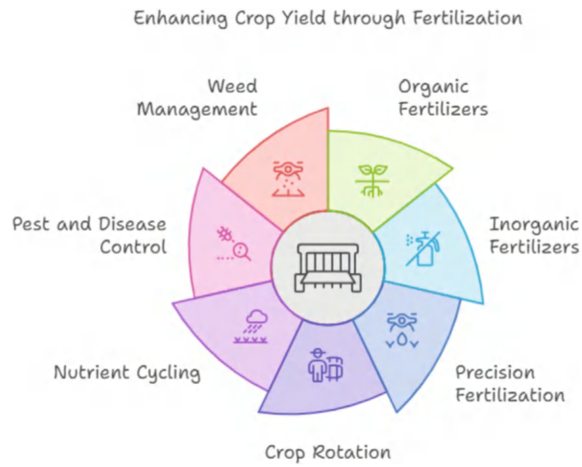

Fig. 2 Enhancing crop yield through fertilization

4.3 Case Studies on the Application of Remote Sensing Data

Case Study 1: The Use of Remote Sensing for Maize Yield Forecasting in Sub-Saharan Africa

In this study, the authors used Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data collected in tandem with ground observations to produce yield-predicting models for maize in SSA (Mayowa, 2019). They adopted the Normalized Difference Vegetation Index (NDVI) to study vegetation health information for the specific period of the growing season to result in ML models that associate NDVI information with output yield data.

- **Results**: All the models accurately forecast maize yield across the different regions, enabling farmers to provide the necessary input and increase yields.
- **Impact**: The yields were predicted early enough, helping the small-scale as well as the commercial farmers to plan their resources well and make better decisions.

Case Study 2: Surveying for Agriculture in the US

Those methods of precision agriculture are used by large farms in America. Satellite imagery adopted by farmers in conjunction with GIS helps to monitor huge acres of crops involving wheat, corn, and soya. Sentinel-2 satellite data is one good example of its functionality in monitoring wheat crop health (Rogus & Dimitri, 2015).

- **Technology**: Using GIS software, farmers worked against yield potential maps generated with the help of NDVI and LAI. Variable rate technology known as VRT was applied with a view of applying fertilizers only in the areas that the GIS map showed needed them.
- **Results**: This use of remote sensing together with GIS data lowered the costs of fertilizers, enhanced yields due to efficient use of inputs, and minimized the effects on the environment by avoiding cases of over-fertilizing.

Case Study 3: Monitoring of Rice Crop in Southeast Asia using Sentinel-1

Regarding applications of **Sentinel-1** satellite data within Southeast Asia, rice crops that are highly dependent on water conditionality were observed. Sentinel-1 makes use of radar-based technologies for monitoring and imaging even the rice paddies that are surrounded by cloud cover (Phung et al., 2020).

- **Water Management**: Analysing soil moisture content and Flood risk helped the farmers to regulate the irrigation regime that in turn controls water logging which is a Major threat to rice production.
- **Yield Estimation**: Scientists used artificial neural networks to predict how radar data can be linked to rice yields. It also showed calibration if the above-named techniques for getting the Remote sensing were used to forecast and better resource use across the region.
- **Results**: This analysis contributed to better ways of using water and enhanced rice production for smallholder farmers as well as commercial producers and millers.

4.4 Benefits of Integrating Remote Sensing and GIS with ML

When remote sensing and GIS data are integrated with ML models, the following benefits can be achieved:

- **Precision Agriculture**: Fertilizers, water, and pesticides therefore can be delivered at the farm or plant and made to reach the precise area it is needed thus saving a lot of it and increasing yields (Ayaz et al., 2019).
- **Early Warning Systems**: Remotely sensed information may give signs of drought, pests, and diseases, enabling farmers to act and prevent loss of yields.
- **Yield Prediction**: Another way that satellite imagery can help increase yield is through the use of ML that can be taught from past data on yield from satellites to plan better for future yields while monitoring risks.
- **Sustainability**: Thus, there is potential to minimise one's impact on the physical/natural environment and either maintain or enhance yields when resource use is properly managed.

5 Optimization Techniques in Crop Management

The efficient control of crop growth is an important factor in enhancing production alongside the restricted usage of items such as water and fertilizer (Shaviv & Mikkelsen, 1993). Given the current state-of-the-art in artificial intelligence, especially **RL** and **optimization techniques**, the means through which these essential inputs are controlled is evolving. Improved irrigation and fertilization methodology are explained below through the use of reinforcement learning techniques. Next we show real-life examples of optimization in agricultural practices.

5.1 Use of Reinforcement Learning (RL) for Optimizing Irrigation and Fertilization

Reinforcement Learning (RL) is defined as a learning technique founded on the paradigm of an agent, learner, or decision-maker interacting with an environment to assemble rewarding experiences that lead to maximizing some sort of total payoff (Gureckis & Love, 2009). In crop management, RL can hence be applied to determine which irrigation and fertilization schedule to adopt through the adaptation of lessons within the soil conditions, the climate, the growth of the crop, and resource utilization.

5.1.1 Irrigation Optimization Using RL

Another use is in supplementing rain to maintain effective soil moisture status for crop production. The idea of applying Reinforcement Learning is to successfully reach the minimum of water consumption whilst still managing appropriate plant health and maxing out plant production (Abioye et al., 2022).

- **How RL Works in Irrigation**:
  - The RL agent takes input which is the state like moisture in the ground, the likely weather, growth stages of crops, etc.
  - The agent then passes the input and chooses an action such as irrigating a given amount of water or, avoiding irrigation at given intervals.
  - The environment (the crop field) responds or gives feedback in the form of a reward, which could be crop health, water conservation or an increase in yield (Fischer & Connor, 2018).
  - In the process, the agent gains experience in which action results in the improved health of crops and the least wastage of water.
- **Challenges**:
  - Irrigation has to be based on real-time sensor data (for instance soil moisture sensors and weather stations) to feed the RL algorithm with the correct information (Qiang & Zhongli, 2011).
  - This means that in applying the RL model the immediate goal of Irrigation must be achieved in combination with long-term goals like combating drought stress or overwatering.

5.1.2 Fertilization Optimization Using RL

Likewise, RL can maximize fertilization by accruing the best practices of applying the right concentrations of fertilizers, at the right time (Vejan et al., 2021), so that plants complete their necessary nutrient requirements at the correct development stage without polluting the environment.

- **How RL Works in Fertilization**:
  - The RL agent observes information on nutrients present in the soil currently or in the past, the rates of growth of crops, and the current environmental factors.
  - After this, it calculates the right portion of the fertilizer for use at the different growth phases of the crop.
  - The reward function could be based on such elements as the state of the crops, the rate of growth and development, and the effectiveness of fertilizers (Vejan et al., 2021) (yield/rate of fertilizer used).
  - Eventually, the RL agent determines the appropriate amount of fertilizer by acting correctional to minimize the case costs and environmental impact of over-fertilization.
- **Challenges**:
  - Fertilization RL systems must capture crop type data and crop growth stage and also the external environment data to determine fertilizer application rates.
  - This has to be integrated into the reward function since one has to ensure the quick growth of crops as well as the sustainability of the soil for the long term.

5.1.3 Case Studies on the Application of Optimization Algorithms in Agriculture

Several real-world case studies have demonstrated the successful application of optimization algorithms, including reinforcement learning, in optimizing irrigation, fertilization, and other agricultural practices (Ding & Du, 2024).

Case Study 1: RL for Smart Irrigation Systems in Vineyards

In this case, researchers developed an RL-based irrigation system for vineyards in Spain, where water is a scarce resource. The system was designed to minimize water usage while maintaining optimal soil moisture for high grape yield and quality.

- **System Setup**:
  - Soil moisture sensors were installed across the vineyard, and weather forecasts were integrated into the RL system.
  - The RL agent learned from daily moisture readings and weather data to decide when and how much water to apply.
- **Results**:
  - The RL-based system reduced water usage by 30% compared to traditional irrigation methods.
  - Grape yield and quality were maintained or even improved, showing that efficient water use did not compromise productivity.
- **Impact**:
  - This case highlights how RL can be used in regions with limited water availability to optimize irrigation without sacrificing crop yield.

Case Study 2: Fertilizer Application Optimization in Wheat Fields Using RL

In the United States, an RL-based fertilization system was implemented in wheat fields to optimize nitrogen fertilizer application. The goal was to minimize fertilizer use while ensuring sufficient nutrients for optimal wheat growth (Wu et al., 2022).

- **System Setup**:
  - The RL agent was trained on data from past growing seasons, including soil nitrogen levels, wheat growth rates, and weather data.
  - The system monitored soil nitrogen levels in real-time and adjusted fertilizer applications accordingly.
- **Results**:
  - Nitrogen fertilizer use was reduced by 20%, and wheat yields remained consistent with previous years, demonstrating that optimal fertilizer timing and quantities were learned by the RL system.
- **Impact**:
  - This system reduced the environmental impact of nitrogen runoff while maintaining high yields, contributing to both economic and ecological sustainability.

Case Study 3: Genetic Algorithms for Multi-Objective Crop Management

A study conducted in Brazil explored the use of **Genetic Algorithms (GAs)** for multi-objective optimization in crop management. The goal was to optimize the use of both water and fertilizers in corn fields, balancing yield maximization with resource efficiency (Sarker & Ray, 2009).

- **System Setup**:
  - Genetic algorithms, inspired by natural evolution, were applied to search for the best irrigation and fertilization schedules. The algorithm generated various "solutions" (schedules), tested them through simulations, and selected the best ones based on performance.
  - The objectives were to maximize crop yield while minimizing water and fertilizer use.
- **Results**:
  - The GA found an optimal balance between yield and resource use, reducing water consumption by 25% and fertilizer use by 15% while maintaining high yields.
- **Impact**:
  - Genetic algorithms proved to be effective for solving complex, multi-objective optimization problems in agriculture, allowing for more sustainable crop management practices.

5.1.4 Other Optimization Algorithms in Crop Management

Apart from RL, other optimization algorithms have found application in crop management.

Particle Swarm Optimization (PSO)

PSO (Wu et al., 2022) is a population-based optimization technique inspired by the social behaviour of birds or fish. It has been applied in precision agriculture to optimize irrigation schedules and fertilizer application rates.

- **Case example**: In a rice farming project in China, PSO was used to optimize water distribution across multiple fields based on real-time sensor data, leading to a 20% improvement in water use efficiency.

Simulated Annealing (SA)

SA (Bertsimas & Tsitsiklis, 1993) is a probabilistic optimization technique used to find the global optimum of a given function. In agriculture, it has been used to optimize planting schedules and crop rotation patterns.

- **Case example**: Farmers in Argentina applied SA to optimize planting schedules for soybean and maize crops, balancing planting times, weather risks, and resource allocation. The algorithm improved overall yields by 12%.

6 Challenges and Limitations of Applying ML to Agriculture

Introducing ML in the agricultural sector has a high impact, but many factors, pros and cons must be considered for better results. More often these include data availability, data quality, complications in the models used, and variability characteristic of the agricultural systems.

6.1 Challenges in Applying ML to Agriculture

a. **Data Availability and Quality**

Getting high-quality labelled data for any ML is a daunting task, especially in agriculture. Information concerning soil, crop, and climate is scattered, limited by region, and challenging to gather in large amounts.

- **Heterogeneous Data Sources**: Information in agriculture originates from various sources; sensors, satellites, records of farm activity, and observations (Atzberger, 2013). The incorporation of these multiple streams of data into one data set poses certain difficulties.
- **Lack of Labeling**: Most of the ML use cases involve training data with labelled features that need to be improved in many applications (e.g. identifying diseases in plants).
- **Seasonal and Spatial Variability**: Agricultural data is not consistent with seasons, weather conditions, and region or crop differences and therefore it becomes very difficult to apply generalized solutions to different regions or crops.

b. **Model Interpretability**

Some of the practices and recommendations deal with the use by stakeholders likely to lack formal training in the business, such as farmers or agronomists (Bertolozzi-Caredio et al., 2021). Interpretation of black-box models for regular AI-power7 stakeholders to either believe or act on the advice provided by professional models such as deep learning is very problematic.

- Explain ability of AI Systems: Farmers should be able to ask and receive answers to questions concerning why a particular decision is arrived at by an AI model (for instance, why a specific schedule of irrigation is proposed to be adopted). This is because the interpretability of the models in use can be a major turn-off when it comes to adopting the new ML technologies.

c. **Climate and Environmental Uncertainty**

Weather factors such as storms, droughts, floods, diseases, pests, climate change, and improvements in the environment are major drivers of agricultural systems. Such dynamic and often extreme conditions make it difficult for ML models to explain the phenomena in question.

- **Difficulty in Prediction**: Heterogeneous meteorological conditions (droughts, floods, frosts, etc.) strongly affect crops and, in most cases, models fail to provide fairly precise prediction of these conditions.
- **Climate Change**: Since climate data determines the value of these models and new climates alter values models based on previous data prove faulty. Agricultural systems call for models that embody some flexibility and ability to alter their performance concerning the ever-shifting environmental conditions.

d. **Infrastructure and Technological Adoption**

Some of the common issues affecting the decision-making of many farmers especially those from developing regions are in the area of technological support including computers and internet, sensors, and effective machinery (Pivoto et al., 2018). This restricts the extent to which ML technology applications could scale up.

- **Resource Constraints**: This means smallholder farmers will also lack the sensors, drones, and computing capabilities needed to capture the data necessary for ML models.
- **Technology Gaps**: They observed that much of the time, even organisations and individuals in regions that have access to technology might not fully understand how to use it, which slows down the implementation of ML solutions.

e. **Cost and Scalability**

Introducing and implementing the multiple ways of artificial neural networks, possibly for large-scale plantations, might be costly for small farmers. All these solutions involve spending on sensors, data acquisition platforms, and frequent cloud services for model storage and updates.

- Cost of Data Collection: However, implementing the usage of IoT, drones, and satellite imagery subscriptions at large-scale farms may be very costly.
- Scalability Issues: In general, a model that was trained on one farm might not perform well on another farm. Other farms with different environmental conditions, soil types, or crop varieties.

6.2 Limitations of Current Models and Potential Solutions

a. **Overfitting and Under Fitting**

There is always a risk of overfitting, where a model works well on the training data set and may not perform so well on the test data set; or under fitting where the models do not capture the underlying data relationships at all. This is particularly so in agriculture which is inherently characterized by high variability and where often data is scarce.

- **Solution**: Coordinate descent and averaging techniques, validation and verification techniques, and synthetic data creation or data augmentation represent such conservative solutions. Generalization can be also trained with a transfer learning approach: reusing a model for a task for another task, or with dropout, which randomly skips out neurons during training.

b. **Limited Data for Rare Events**

Biological hazards, for instance, Climate change, hail, storms, pests, and diseases are sporadic but produce a massive effect on crops. Such events are a common concern in ML models, provided that these models have sufficient data regarding such events.

- **Solution**: When there are few instances of such events, methods of data generation such as synthesizing data transfer of knowledge, or anomaly detection can be useful. Similar occurrences can also be concluded using simulated data derived from agricultural models.

c. **Delay in Processing Real-Time Data**

A majority of today's ML approaches utilized in agriculture work on a batch-wise data mode, which makes their utilization in time-sensitive decision-making processes, like scheduling of irrigation, or pest identification, impracticable.

- **Solution**: The use of edge computing systems and real-time sensors may lead to real-time data and model deployment which will allow for more real-time decision-making.

d. **Generalization Issue Across Regions and Crops**

This is good for a specific crop or region but models made on one/ some crop/region may not well suit other crops or regions since factors affecting growth and yield may be different.

- **Solution**: Future work can therefore build modular models that can include region-specific data or utilize transfer learning to modify models for diverse crops and numerous regions.

7 Future Directions and Innovations in AI and ML for Agriculture

Nevertheless, here are some developed trends and innovations that can potentially eliminate the existing issues and bring further innovation in agriculture using AI and ML.

7.1 Emerging Trends in AI and ML for Agriculture

- **Autonomous farming systems**: AI and ML are increasingly being adopted in farming systems and the farm of the future is beginning to emerge in practice. They can also incorporate various operations that include (Shaikh et al., 2022); Self-propelled tractors, drones for spraying, and robotics for harvesting, all of which make farming better.
  - **Example**: Computer vision has been applied in robot weeders and robot planters in an attempt to cut on labour costs and increase precision.
- **The specificity of these solutions by using Artificial Intelligence (AI) Decision Support Systems (DSS)**:

Farmers today are learning to use their smartphones and digital devices to connect with decision apps, derived from ML, on when to irrigate, when to fertilize the crops, when to apply pesticides and their opinions on harvesting.

  – **Example**: Applications from Climate FieldView and Granular link AI to IoT devices to help farmers manage their crops and make decisions in real time.

- **Climate and pest prediction or weather and biotic indices**: ML algorithms used for developing predictive models can drive forecasts of the climate and pest infestations, to prevent these.
  – **Example**: There are ML models being used in identifying the likelihood of swarms or pest diseases such as wheat rust so as to make early interventions.
- **Interoperation with the Internet of Things (IoT)**: Currently, through IoT devices in smart agriculture, it is possible to track crops and soils, and even weather conditions, through ML programs. ML models can be fed by smart sensors, drones, and satellites, to help farmers make informed decisions inevitably.
  – **Example**: In an intelligent IoT-based precision agriculture system, soil moisture is sensed and passed into the Reinforcement Learning algorithms for optimizing irrigation schedules.

7.2 Potential Future Applications and Research Areas

- **Genetic optimization and breeding**: The genetics could also be better understood using ML models to help the breeder create new varieties of crops to be more resilient to disease, the dry season, or pests or exhibit higher yields (Mondal et al., 2016).
  – **Research area**: Interactions between genes and the environment: A means of making predictions for crop breeding.
- **AI in vertical farming and controlled environment**: Different forms of farming such as vertical farming and controlled environment agriculture (CEA) are now adopted, perhaps due to the increase in the rate of urbanization. Through integration with IT systems can AI enhance and optimize the lighting, temperature, humidity, and delivery of nutrients.
  – **Future application**: It could also be the reason why reinforcement learning models could decide on plant care in vertical farms to modify the entire environment autonomously.
- **Modelling of soil health and carbon sequestration**: With increases in sustainable agriculture emerging, ML algorithms can be trained to maximize carbon storage in soils to lower the carbon impact of agribusiness.
  – **Research area**: Real-time decision-making on soil fertility, carbon, and other degradative aspects with help of the AI-based soil health monitoring systems.
- **Accurate detection of disease on crops**: Apps based on drones or mobile-based image recognition would for example make the identification of crop diseases in real-time a reality.
  – **Research area:** Real-time, mobile-based deep learning models for identification of plant diseases using only smartphone cameras and low-cost drones.
- **Blockchain and AI for traceability**: Using blockchain technology together with AI can help increase food supply chain traceability and accountability to the consumers of agricultural products.
  – **Future application**: Integration of AI with some of the attributes of block chain technology to enhance solutions for verifying the authenticity of 'organic' or 'sustainably grown' products.

8 Conclusion

Artificial intelligence (AI) and machine learning (ML) play a crucial role in managing the issues of the most advanced agriculture these days. This chapter has endeavored to introduce a plethora of the implications of these technologies extending across yield prediction of crops, determination of resources, and decision making, as well as boosting sustainability. Through achieving supervised learning, clustering, and deep learning farmers can make right decisions to provide right inputs at right place and right time by reducing costs and environmental effects. The use of Remote Sensing and Geographical Information systems has extended the velocities of ML in agriculture for monitoring and predicting the occurrence. Examples show how such tools can be used effectively to optimize water requirements, fertilization, as well as, general farm operations. Topics including issues with data availability, model interpretability, and model scalability remain relevant and current even though new trends and innovations are already on the horizon; including autonomous farming systems, use of IoT, and AI decision support. Hence, several strategies that future studies must undertake so as to enhance model flexibility, foster small-holder farmer inclusiveness, and address environmental concerns. Pursuing the global food demand increases, the advancements described in the chapter prove that AI and ML are essential for forming a sustainable and productive further for agriculture.

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AI Trends Concerning Patterns, Anomalies, and Correlations for Predicting Earthquake Patterns

Shalini Kumari and Chander Prabha

Abstract

The utilization of Artificial Intelligence (AI) in earthquake prediction, emphasizing its capacity to transform seismic forecasting. The research investigates several AI methodologies, including rule-based systems, shallow Machine Learning (ML), and Deep Learning (DL) techniques, and their utilization in analyzing seismic data and precursory events. Significant focus is placed on Anomaly Detection (AD) techniques, which have demonstrated efficacy in recognizing patterns in geophysical data that may precede seismic occurrences. The study examines the evaluation of precursors, including radon concentrations, geomagnetic variations, and crustal deformations, by applying AI algorithms. Although AI exhibits considerable potential in uncovering concealed patterns and connections within intricate seismic data, obstacles remain. This encompasses the inadequate comprehension of seismic mechanics, the potential for false positives and negatives, and the constraints of existing monitoring equipment. The document examines the amalgamation of many data sources and the capacity of machine learning to enhance the precision and promptness of earthquake forecasts. Notwithstanding persistent hurdles, the study determines that amalgamating AI with conventional seismological techniques offers a viable pathway for enhancing earthquake prediction abilities, potentially resulting in more efficient early warning systems and superior disaster preparedness.

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Keywords

Artificial Intelligence · Deep Learning · Rule-based · Tsunami · Machine Learning · Anomaly Detection

1 Introduction

Earthquakes are significant events that can cause landslides, fires, liquefaction, and tsunamis. The complex character of seismic occurrences highlights their potential to cause considerable losses and damages (Hamdy et al., 2022). There is growing interest in predicting earthquakes and understanding their causes, yet they are the least predicted natural disasters. Earthquakes from stress and energy release along fault zones cause tectonic plate failure, slide, and shift (Ni et al., 2023; Pwavodi & Doan, 2023). Studying earthquake nucleation, tectonic fault ruptures, slip mode interactions, slow slip events, and fluid-induced earthquakes is crucial. Subduction zones, mid-Atlantic ridges, and transform fault zones are the main earthquake locations. Many of the most significant earthquakes in history have occurred in subduction zones, including the 2011 Tohoku earthquake (M9.1), 1964 Alaska earthquake (M9.2), 1960 Chilean earthquake (M9.5), 1946 Nankai-do earthquake (8.2), and 1944 Tonankai earthquake (8.3). Additional earthquakes occur on the submerged mid-Atlantic Ridge and the Alpide earthquake belt, spanning Java to Sumatra, the Himalayas, the Mediterranean, and the Atlantic. Peru, China, Mexico, Hawaii, Philippines, Papua New Guinea, Morocco, Turkiye, and Syria experienced minor and deadly earthquakes in 2023. The devastating 2023 Turkiye-Syria doublet occurred on February 6th, with a magnitude of M7.8 along the East Anatolian Transform Fault (EAF) and numerous aftershocks (Alexander, 2010). The Arabian and Anatolian plates are separated by a 1200 km left-lateral displacement transform fault. Pressure and energy accumulation may break the fault zone, causing this earthquake. The Disaster and Emergency Management Authority

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reported 56,000 deaths, 125,000 injuries, 2 million displacements, and over 200,000 building destruction from the earthquake. Damages may surpass USD 100 billion. EAF has had thousands of earthquakes of all magnitudes. In the aftermath of previous earthquakes, notably the devastating Turkiye-Syria doublet in February 2023, scientists worldwide prioritize developing accurate earthquake prediction technologies. To better comprehend earthquakes, scientists are developing methods to forecast them. Three primary factors are used to predict earthquakes: date, time, location, and magnitude.

There are two types of earthquake prediction: short-term and long-term. Predicting earthquakes within days or weeks is challenging. Therefore, it should be precise and accurate, with fewer false alarms valued. Short-term projections are typically employed for earthquake evacuation. The periodic arrival of earthquakes provides information for predicting long-term earthquakes. They can still promote building codes and catastrophe response planning. A 5.9 magnitude earthquake near L'Aquila, Italy, in 2009 claimed 308 lives. The Italian earthquake forecast commission projected no harm. Thus, the city was not evacuated. Mispredictions can cause mass massacres, resulting in loss of life and infrastructure damage. Six years of imprisonment were imposed on the scientists engaged in the incident (Adeli & Panakkat, 2009). Prediction algorithms work well for medium-sized earthquakes but not high-magnitude ones. The largest earthquakes cause the most damage and concern. Because there are few high-magnitude earthquakes, good prediction is difficult without data. Historical earthquake catalog data on energy, depth, location, and magnitude is used in earthquake prediction research. Use completeness value magnitude to calculate area-specific earthquake measures like b-value. Gutenberg Richter b-values, time latency, earthquake energy, and mean magnitude are calculated using ML (Patterson & Gibson, 2017). DL models can independently calculate hundreds of complicated features (Ma et al., 2018; Yang et al., 2019). ML and DL models are data-driven, yet major earthquakes are infrequent, making data-driven prediction problematic. Some algorithms can predict large earthquakes by training or adding weights, although they need refinement (Cicerone et al., 2009). Finding significant earthquake precursors is a successful forecast tool.

Precursors are natural changes before an earthquake. Scientists connect earthquake precursors to Radon gas concentration, anomalous cloud formation, earth's electromagnetic field changes, humidity, soil temperature, and crustal alteration. There have been cases where precursors existed without an earthquake, but earthquakes nevertheless happened. Precursor-based earthquake research should comprise many sites and instrumentation and be related to earth stress and stressors, according to IASPEI (Wyss & Booth, 1997). Evaluation of earthquake prediction methods includes metrics like (P1, P0), specificity (Sp), sensitivity (Sn), accuracy, False alarm rate (FAR), R-score, root mean square error (RMSE, MSE), relative error (RE), mean absolute error (MAE), area under the curve (AUC), chi-square testing, and more. A standard earthquake dataset is necessary for researchers to develop assessment metrics and compare their models to earlier studies. Several review articles have assessed earthquake prediction studies. In certain evaluations, precursory research is critiqued for its scientific worth. Radon concentration for earthquake prediction has also been studied (Woith, 2015). The paper (Galkina & Grafeeva, 2019) discusses classical ML approaches and associated assessment methods. The effectiveness of rule-based strategies in this subject is examined in (Jiao & Alavi, 2020). Mignan and Broccardo (Mignan & Broccardo, 2019) explored DL approaches in this sector. A comprehensive investigation of these strategies is lacking, providing valuable resources for AI researchers in earthquake prediction. The prediction uses AI classifiers, input parameters, and preprocessing.

Recently, numerous studies have utilized the intricate prediction capabilities of machine learning algorithms to examine complicated patterns in past seismic activity, meteorological data, and acceleration and velocity metrics to forecast earthquakes. ML algorithms have forecasted short-term earthquakes, but statistical and mathematical methods predicted medium to long-term earthquakes. Studies on earthquake prediction with ML and DL employed classification or regression techniques. The antecedent for earthquake prediction is unknown. AI-based earthquake prediction is shown in Fig. 1.

This workflow utilizes many data sources and ML techniques for earthquake prediction. The procedure commences with input signals, encompassing seismic indicators, earthquake precursors, seismograph data, and satellite information. The inputs are subjected to pre-processing before their incorporation into classification and regression methods. The algorithms utilize rule-based techniques, shallow ML, and DL methodologies. The final result delivers forecasts regarding earthquake timing, location, and magnitude. This methodical strategy integrates several data sources and sophisticated analytical approaches to enhance earthquake prediction abilities.

2 Related Works

Research in earthquake prediction began at the end of the nineteenth century. Geller (Geller, 1997) reviewed a century of seismic research and its quality. He classified the research into a few periods: before 1960, after 1960, and from 1962 to 1997. He asked about the precursors of an earthquake and acknowledged the IASPEI principles of precursory study. He acknowledged the contributions of the VAN group (Uyeda, 1998) to the electric signature of the Earth but criticized the

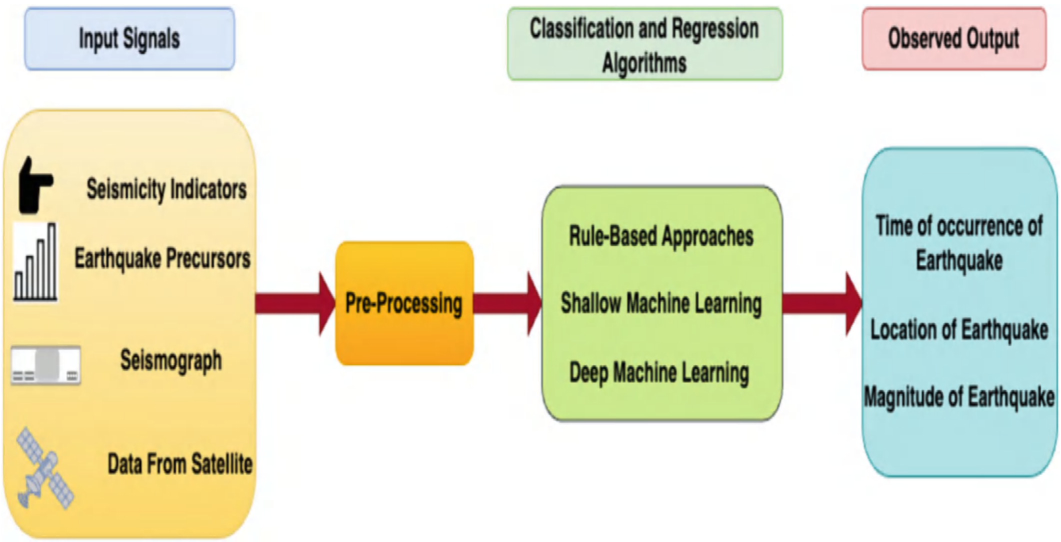

Fig. 1 AI-based general earthquake prediction model

methods applied. Since this review, several models of AI have been developed.

The authors Uyeda et al. (2009) reviewed short-term earthquake forecasting using seismo-electromagnetic signals. They considered the history of short-term predictions, and the proposal to include nonseismic factors was made. They have also studied the Earth's emissions before earthquakes, including telluric currents and high-frequency electromagnetic waves. They mentioned that this electric signal is not an earthquake precursor. Alvan and Azad (Alvan & Azad, 2011) discussed earthquake prediction based on space and ground sensors, providing most of the precursors. This research categorized various factors such as Earth's crust, temperature, cloud formations, humidity, and Radon gas. They also proposed a satellite image review to understand ground conditions. Woith (2015) researched earthquake prediction methodologies using the concentration of Radon gas emissions. He noted that Radon anomalies do not always precede the earthquakes. He reviewed 105 papers and their methodologies. He also talked about how models should discriminate between seismic events.

For instance, Huang et al. (2017) investigated earthquake precursors in China from 1965 to 2015 and divided the research into time intervals. Seismic, geo-electromagnetic, geodetic, gravity, and ground fluids were identified as earthquake precursors. They then discussed China's current earthquake prediction initiatives. Mubarak et al. (2009) investigated earthquake precursors like changes in gravity, temperature, and humidity; variation of concentration in Radon; and electric field variation. They investigated seven countries that use satellites to make predictions. The literature indicates that air humidity may be lower, Radon higher, and electric field strength greater before an earthquake occurs. Bhargava et al. (2009) reviewed works concerning abnormal animal behaviour and its relationship with earthquakes; they also pointed out that "resources in China, Japan, and the USA were in place for such investigations." They excluded studies that predicted earthquakes based on historical data.

In the year 2018, Goswami et al. (2018) discussed data mining for predicting and managing natural hazards such as earthquakes and tsunamis, proposing a Twitter-based disaster management framework for India. Galkina et al. (2009) reviewed deep learning studies and predicted future trends. DNN can independently handle unstructured input and calculate various features. They outlined the operational processes of these systems. Mignan and Broccardo (2020) reviewed 77 articles on neural networks from 1994 to 2019, categorizing them into ANN and DNN. Despite their complexity, Deep Neural Networks are seen as the future of earthquake prediction, although they face overfitting issues.

The reviewed articles focused on short-term earthquakes with precursors or specific AI methods. No review covers short- and long-term earthquakes, Earth's electromagnetics, ANN methodologies, fuzzy studies, clustering techniques, DNN, bio-inspired algorithms, and ML strategies for prediction. This study includes all three areas for a comprehensive analysis of earthquake prediction. The catalogue of earthquakes, their magnitudes, and their corresponding locations from 2005 to 2023 are presented in Table 1.

This table provides a chronological account of significant earthquakes from 2005 to 2023, specifying their magnitudes, locations, and, in certain instances, whether they induced tsunamis. The earthquakes enumerated have magnitudes between 7.6 and 9.1 on the Moment Magnitude (MW) scale. The data encompasses a broad geographical spectrum,

Table 1 Catalog of earthquakes, their magnitudes, and corresponding locations from 2005 to 2023

Year	Magnitude (MW)	Tsunami	Location
2005	7.6	X	Pakistan (Muzaffarabad, Baramula)
	7.7		Papua New Guinea (New Ireland) Chile (Tarapaca)
2007	7.7	✓	Chile (Tocopilla)
	7.8		Maria Elena, Kermadec Islands,
	8.0		Peru (Ica, Pisco, Lima)
	8.4		Solomon Islands
2009	7.6	✓	Vanuatu Islands, Papua New Guinea (Near North Coast),
	7.8		Tonga Islands, New zealand (Off West)
	8.1		Coast of South Island, Samoa Island
2010	–	✓	7.8, 8.8 Indonesia (Sumatra), Chile (Maule) Talcahuano
2011	7.6	✓	New Zealand (Kermadec Islands)
	7.9		Japan (Off East Coast Honshu)
	9.1		Japan (Honshu)
2012	7.6	✓	Phillipines (Cagayan De Oro Tacloban)
	7.7		Canada (queen charlotte Islands)
	8.2		Indonesia (sumatra)
2013	7.7	✓	Scotia sea (south Orkney Islands)
	7.6		Pakistan (Awaran Kech)
	7.9		Solomon Islands (Santa Cruz Island)
	8.3		Russia (Severo Kurilskiye)
2014	7.6	✓	Solomon Islands
	7.7		Chile (Iquique)
	7.9		Alaska (Aleutian Islands)
	8.2		Alto Hospicio
2015	7.6, 7.8, 7.8, 8.3	X	Peru-Brazil, Nepal: Kathmandu, India, Chile
2016	7.6		Chile, Indonesia (Sumatra),
	7.8		New Zealand (Amberley), Solomon Islands
2017	7.7	✓	Russia (Bering Island)
	7.9		Papua New Guinea (Bougainville Island)
	8.2		Mexico (Oaxaca), Chiapas, Tabasco (Guatemala)
2018	7.9, 7.8 and 8.2	✓	Alaska (Kodiak Island), Fiji Islands
2019	8.0	X	Peru (La Libertad), Cajamarca (Equador)
2023	7.8	X	Turkey (South Eastern Anatolia)

covering nations and areas such as Pakistan, Chile, Indonesia, Japan, New Zealand, and other Pacific island nations. Significant occurrences encompass the 9.1 magnitude earthquake in Japan in 2011 and several high-magnitude earthquakes in Chile. The table denotes tsunami occurrences for specific years (2005, 2015, 2019, and 2023) with a "X" symbol. This compilation offers a comprehensive overview of notable seismic activity over nearly two decades, emphasizing the frequency and distribution of big earthquakes worldwide.

3 The Role of Artificial Intelligence in Earthquake Prediction

This sub-discipline of computer science simulates human functions, including memory and learning, decision-making ability, and problem-solving capabilities. The word "AI" was coined by John McCarthy (2006). It has been developed and utilized superbly in various fields and services. Artificial Intelligence (AI) and Machine Learning (ML) are sometimes used synonymously; however, ML is a subset of AI that involves algorithms that autonomously learn from data, enhance performance, identify patterns, and generate predictions. These algorithms use the math principles of linear algebra, calculus, and probability to formulate predictive models of different patterns. The three broad approaches include supervised learning (SML), unsupervised learning (UML), and reinforcement learning, representing trial-and-error reward-based learning.

Supervised learning applies labels to data to match actual against expected outputs, mainly for regression and classification models for linear, non-linear, multiple, and logistic regression. Unsupervised learning methods like k-means clustering and PCA discover patterns in unlabeled data. UML uses real-time data in its use. It is also user-friendly and inexpensive, but it may give unexpected results and challenge evaluating the model's effectiveness. Table 2 presents AI algorithms that have an important role in earthquake prediction.

4 Use of AI in Earthquake Forecasting

Rule-Based Approaches: In the rule-based methodologies for earthquake prediction, rules formulated in light of a knowledge base or expert opinion are effective. Input signals are fuzzified by certain membership functions to enable their comparison with the rules. The result of this comparison is defuzzified to yield the output. This process is illustrated in Fig. 2, in which the training and testing data follow different paths to produce an earthquake forecast. The studies are grouped into two categories: those analyzing the characteristics of earthquakes for rule-based methods and those investigating the forecast of earthquakes and aftershocks for rule-based methods.

Shallow Machine Learning: Shallow ML comprises conventional ML methods, clustering techniques, and neural network-based approaches. Classical ML methods include Support Vector Machines (SVM), Support Vector Regression (SVR), (K-nearest neighbour (KNN), Random Forest (RF), and Decision Tree (DT), which use handmade characteristics in earthquake prediction. Feature selection is important in this predictive process because they cannot generate features separately. Figure 3 shows a basic diagram of the algorithm for classifying earthquake events.

Deep Learning (DL): AI-based research is mainly focused on DL. This ML technique automatically generates thousands of advanced features without the help of a human, and it is tough to get for humans. The models with several hidden layers are time-consuming. Because of advanced features, some models may experience overfitting. Therefore, dropout and regularization concepts are applied. Figure 4 represents earthquake prediction using DL-based methods. A fully connected layer seeks features for classification purposes involving multi-layer hidden layers.

5 Anomalies and Correlations for Predicting Earthquake Patterns

Researchers have investigated anomalies preceding earthquakes, particularly on radioactive materials such as radon. Radon levels in soil, water, and air vary due to tectonic activity. A study employed Random Forest analysis to juxtapose observed atmospheric radon concentration data with anticipated values derived from standard annual patterns. The investigation utilized data from Kobe Pharmaceutical University (KPU) before the 1995 Kobe Earthquake and Fukushima Medical University (FMU) before the 2011 Tohoku-oki Earthquake. Substantial disparities were identified between expected and actual data during particular intervals preceding both earthquakes (Tsuchiya et al., 2024). The definition of anomaly detection (AD) is understanding the accumulation of stresses and separation of signs from the crust. Shallow earthquakes are often caused by the displacement of the crust. Such deformations can be found with the help of land-based (CORS) and satellite-based (GNSS) monitoring data. The number of installations of GNSS in Japan and Indonesia has rapidly increased in the last few years (Zakaria & Ahmadi, 2020).

AD in CORSdata is long, medium, or short. Long anomaly detection uses pre-seismic deformations and velocity changes generated by long tresses to detect megathrust earthquakes. In 1996, 2003, 2008, and 2013, seismic activity was linked to the 2011 Tohoku Japan earthquake (Chen et al., 2020). Long AD is necessary to identify mega-thrust earthquakes. Multiple big earthquakes may add noise to long AD. Second-type medium AD occurs days or months before an incident. Surface displacement features helped Bedford find the pre-earthquake anomaly months before the 2011 Tohoku and 2010 Maule earthquakes (Bedford et al., 2020). Murai analyzed triangular deformation patterns 1–9 days before earthquakes, including the 2004 Sumatra and 2008 Wenchuan and Japanese earthquakes over 6.0 magnitude. Multiple Taiwanese earthquakes were evaluated utilizing the Hilbert-Huang transform

Table 2 AI algorithms

Rule based approaches	**Fuzzy Logic**: Human decision-making differs from machines. When deciding between "yes" and "no," humans consider alternatives. Fuzzy-logic systems mirror this process. They use modules to make decisions. The fuzzification module creates membership degrees from inputs through a membership function. Degrees include large positive, medium positive, small, mid negative, and large negative. The knowledge base has IF–THEN rules reflecting human behavior. The inference engine analyzes input and provides reasoning through rules. Defuzzification clarifies this logic. Fuzzy logic is valued for its simplicity and adaptability
	Fuzzy Neural Network (Fnn): In the optimization of fuzzy networks portrayed as Artificial Neural Network (ANN) through methods like genetic algorithm (GA) or backpropagation. One way to achieve such a system is by using Mamdani's technique which was proposed by Ebhasim Mamdani (López et al., 2019). The method demands that inputs and outputs of the system are fuzzy. Owing to its basic structure of min–max operations, it serves as a good model for human inference systems. This model can be understood by humans, but when there are more input rules, it becomes increasingly difficult to understand
Shallow machine learning	**Support Vector Machine (SVM)**: SVM is an effective ML-based classification technique for classification, pattern recognition, and prediction. A hyperplane in an N-dimensional plane is used to organize classes, ensuring maximal margin distance between data points (Sun et al., 2021). Support vectors, data points near the hyperplane, and determine its orientation and position. If a linear hyperplane cannot distinguish classes, a higher-dimensional nonlinear hyperplane is required. Kernels such as polynomial, sigmoid, and radial basis function (RBF) are available for these scenarios. SVM classifiers are computationally expensive and require longer training times. It has regularization capabilities and can handle linear or nonlinear data
	Support Vector Regression (SVR): SVR algorithm functions differently from most regression methods (Aljarah et al., 2018). While other regression methods aim to reduce the sum of squared error, SVR focuses on the error within a specific range. This regression method functions like SVM, but outputs a real number instead of a class. SVR provides flexibility to minimize coefficients (E-value) and optimize performance in case of errors. It is trained with symmetrical loss function to equally penalize low and high miss estimations
	K-Nearest Neighbor (Knn) Algorithm: It is a supervised ML approach in which data points in close proximity are presumed to share the same output class (Application of k-nearest neighbor (knn) approach for predicting economic events: Theoretical background). The value of k is initially established, ensuring it is neither excessively little nor large
	Random Forest (RF) Algorithm: This classifier comprises a set of randomly chosen decision trees that operate using a voting mechanism (Lulli et al., 2019). The final class is determined by aggregating votes from various decision trees. This method integrates the outputs of various random decision trees to yield a categorization result. Each tree of the Random Forest is created from distinct bootstrap samples. It alters the creation technique for a regression tree. RF closely resembles bagging, yet incorporates an additional layer to enhance randomization. It possesses the capability to attain high precision and manage extensive datasets effectively
	K-Means Clustering: Clustering is an unsupervised learning method that partitions data into distinct subsets. K-means clustering is a widely used iterative approach that identifies local maxima in each iteration. Initially, the value of k is predetermined for this algorithm. The optimal value can be determined with the elbow approach. The algorithm initially allocates random centroids to each cluster and categorizes the data according to its distance from these centroids. Typically, Euclidean or Manhattan distances are employed for distance calculation. The mean is recalculated for each given cluster, and the data is subsequently classed
Deep machine learning	**Deep Neural Network (DNN)**: This is a non-linear artificial neural network, which does not need to be built manually, it derives complex features from the input data directly. Deep Neural Networks (DNN) are most effective for unstructured data. A DNN model is a very dense architecture with multiple layers of hidden (Wang et al., 2019). Each layer contains neurons, which have connections through linkages and biases. The goal of the network is to maximize its performance to have higher classification accuracy. An error function such as the Mean Squared Error (MSE) is used to this effect. Among deeply learned models, one may find deep belief network, convolutional neural networks (CNNs), and recurrent neural networks (RNNs)
	Recurrent Neural Network (RNN): Typically, neural networks do not contain any feedback connections from the output layer; hence these methods are not suitable for tasks requiring time-series data. RNN is better suited for tasks that involve time-series data. Typically, an RNN contains many recurrent layers. The recurrent layers consist of feedback connections from the output of the model
	Long Short-term Memory (LSTM): RNNs suffer the vanishing or exploding gradient problem, where the error gradient becomes too small or too large and prevents the network from learning. In addition, there are serious problems in handling long-term dependencies for RNNs. To overcome these issues, LSTM networks have been designed. LSTMs have an architecture that is essentially chain-like with memory cells within an input gate, a forget gate, and an output gate

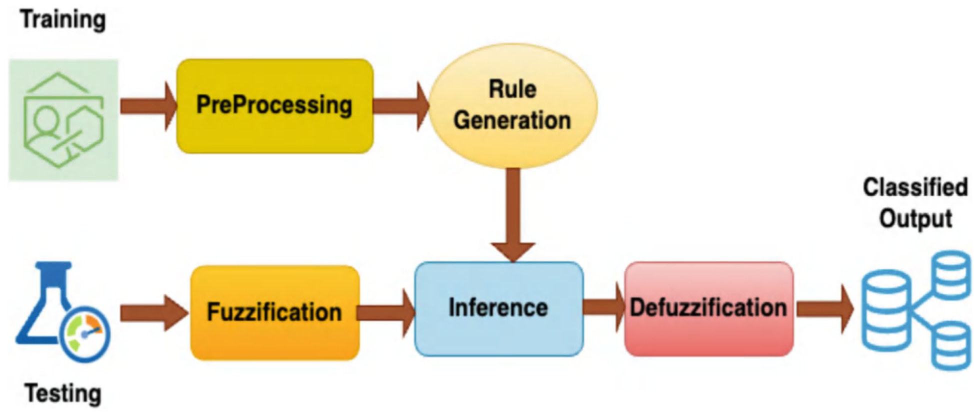

Fig. 2 Rule-based prediction

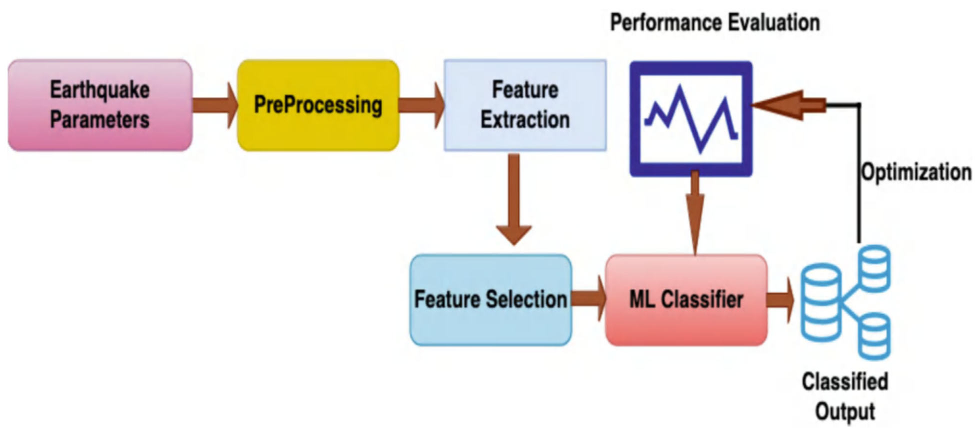

Fig. 3 Classical machine learning earthquake prediction

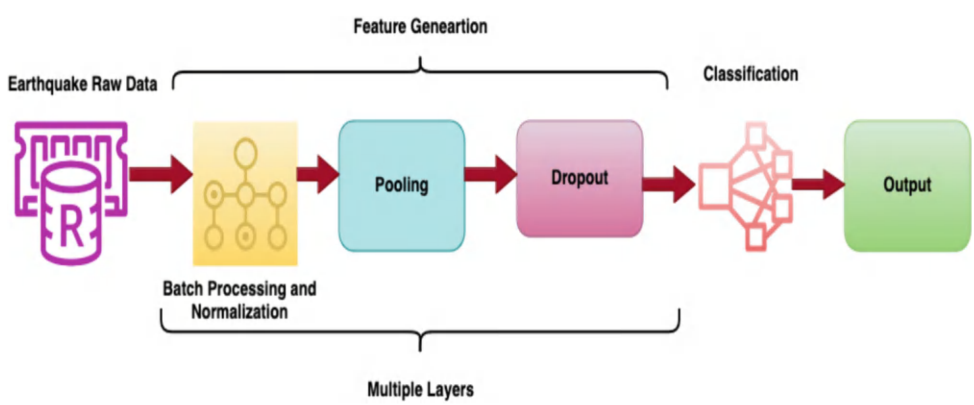

Fig. 4 Prediction process of an earthquake using DL-based approaches

medium AD. Daytime medium anomaly detection is exciting and requires little examination.

Short AD analysis takes hours to a day and requires fast sensors. Kiani captured the Tohoku earthquake in minutes and days with a 1 Hz signal resolution (Kiani et al., 2020). Early warning systems benefit from brief anomaly detection studies' rapid noise pre-processing. Many studies investigate earthquake features utilizing local-scale case studies and crust-deformation analysis, plastic strain analysis, Hilbert-Huang transform processing, and time-specific analysis like Tohoku-Oki 2003e2011 (Xu et al., 2022). Machine learning-driven pre-earthquake anomaly research requires uniform processing. Displacement velocity features and data-driven analysis let Gitis detect Japanese and US earthquakes. This work has not examined how low alert levels affect false alarms. Western China used the receiver operating characteristic curve to assess medium strain anomalies days before a large earthquake (Yu et al., 2021). Machine learning is needed to analyze enormous earthquake data since this study only covers a few large earthquakes. Historical data is typically utilized to predict earthquake patterns with ML. To improve prediction, combine pre-cursors from multiple stations. Tree-based ML algorithms excel in enormous, unlabeled data sets like earthquakes. Information gain reduces classification uncertainty in small datasets with tree-based methods. In addition, tree-based algorithms extract learning rules.

Geomagnetic Anomalies

A study implemented a magnetic monitoring network in seismically active regions of Sichuan, China, to detect pre-earthquake geomagnetic anomalies. The researchers devised an innovative technique to aggregate geomagnetic anomaly energy and utilize its gradient as an indicator for forecasting earthquake occurrence timings. The proposed method attained around 75–85% accuracy in forecasting earthquake occurrence periods based on geomagnetic anomalies (Wibowo et al., 2023).

Key Considerations

The correlation between anomalies and earthquakes may differ based on geographical location and seismic intensity. Prolonged data analysis (exceeding 11 years) is essential to consider the impacts of solar activity. Integrating seismic quiet times into the analysis can mitigate bias in anomaly detection. Additional research is required to comprehend the mechanisms underlying earthquake-related abnormalities.

6 Machine Learning-Based Earthquake Prediction

Figure 5 summarizes the methodology. The pre-processed data structure of raw monitoring data, with filtering of features and expansion of the dimensionality, prepares it for study purposes in earthquake prediction. Data cleansing and sorting by time are part of this pre-processing stage. Once an algorithm is chosen and its parameters are set, a model is created for anomaly detection, selecting outliers from the pre-processed data set. By using temporal continuity, outliers are classified into anomalous periods, and their relevant sampling time is recorded. Finding the thresholds for earthquake response times also helps predict possible occurrences.

The image depicts three concurrent processes associated with data processing and forecasting, specifically about seismic events. The uppermost row illustrates a data processing pipeline: The process commences with “Original Data,” which is subjected to “Data Cleaning,” resulting in a refined dataset. The cleansed data subsequently undergoes “Data Dimension Expansion” before being input into “Anomaly Detection Algorithms.” The central row illustrates the procedure for earthquake prediction: The process commences with an “Earthquake Catalog,” utilized to identify “Earthquake Events,” culminating in the “Time of Earthquake Prediction.” The bottom row delineates an assessment procedure: Evaluation indicators are employed to examine both success and failure predictions, ending in evaluating prediction performance, symbolized by a graph icon.

6.1 Set of Parameters

The two critical parameters of this earthquake prediction model are the AD rate and the earthquake reaction time threshold. The AD rate, P, is defined in this paper as the number of outliers to the total data volume, which is an important parameter in controlling the percentage of outliers in the outputs. For the application of this study based on the response time of hydrogeochemical anomalies for earthquake prediction, a suitable selection of the parameter’s value becomes very significant. A value too low would result in several hydrogeochemical anomalies from the monitoring data that are far too inadequate, thus lowering the rate of earthquake prediction. On the other hand, a value that is too high would result in several hydrogeochemical anomalies that are far too high, thus leading to the elongation of the earthquake prediction time up to unreasonable periods. Therefore, a suitable value choice must be made to achieve accurate earthquake prediction. The maximum temporal lag between the onset of an earthquake event and the hydrogeochemical anomaly is defined by the hydrogeochemical anomaly earthquake response time threshold parameter, M. This parameter is important for predicting the range of times before an earthquake occurs. Although anomalies and earthquakes do not happen simultaneously, they have a temporal relationship. Earlier investigations indicated that pre-earthquake anomalies occurred at any moment in a very broad timescale range from days to one year. This shows that heterogeneity in anomalous times of seismic events signifies that seismic events cannot be predicted based on hydrogeochemical parameters at hot springs.

6.2 Algorithms for Anomaly Detection

AD algorithms are extensively studied and utilized techniques for finding irregular data within normal datasets across diverse domains. These algorithms can be categorized into four distinct groups based on their operational principles (Muruti et al., 2018).

Statistical-based AD algorithms: The correctness of the assumptions can be relied upon for the formulation and validity of such assumptions. Standard assumptions are followed by fitting a model to the distribution of data of a given dataset. A common approach is followed by the detection of outliers as objects located in the low-probability region of that model. This is because of their simplicity and ease of handling, which has led to their extensive use in the sphere of mechanics, medicine, and internet security.

Clustering-based and classification-based AD algorithms: Develop an ML model to analyze the provided data and build a classifier that classifies normal and abnormal data for outlier detection. There are two types of approaches, namely, clustering-based (without training data) and classification-based (with training samples), for anomalies and algorithms for AD.

Nearest neighbor-based AD algorithms: The main unsupervised AD methods assume that normal data clusters in local neighborhoods, whereas abnormal data is spread out and further away from their local data. One uses the basic premise to design an algorithm such that for each sample of data within the dataset, an anomaly score will be computed, and, using these scores, the degree of oddity will be ascertained.

Regression-based AD algorithms: First, they apply a regression technique to the entire data set, then use the fitting error as the criterion to identify and eliminate anomalous data. Such techniques need high accuracy in fitting the regression procedure; overfitting and underfitting can cause huge errors in outcomes.

6.3 Evaluating and Categorizing Performance Metrics

True Positive Values (TP): In earthquake prediction, the instances where the model's predictions of earthquakes align with the actual recorded occurrences are referred to as true positives (TP).

True Negative Values (TN): The instances in which the model predicts no earthquake and no earthquake occurs are called true negatives (TN).

False Positive Values (FP): This statistic indicates the frequency with which the model predicted an earthquake that did not occur in reality.

False Negative Values (FN): The frequency of instances where the model failed to forecast an earthquake, yet an earthquake occurred, referred to as false negatives (FN).

7 Challenges and Potential Trajectories of AI and the IoT in Earthquake Prediction

Present Status of Earthquake Prediction

- Conventional techniques for earthquake prediction have predominantly failed, resulting in distrust within the scientific community.
- Current earthquake early warning systems depend on identifying the preliminary phases of an earthquake to issue short-term alerts, although they cannot predict earthquakes in advance.
- Scientists do not possess direct observation of subterranean processes; instead, they depend on indirect measurements such as seismology, geodesy, and paleoseismology.

Capabilities of ML and AI

- ML is rapidly utilized in diverse facets of earthquake prediction and research. Forecasting seismic magnitudes. Identifying aftershocks. Eliminating background noise to identify faint seismic signals. Examining data from artificially generated seismic events.
- AI methodologies demonstrate the potential to reveal concealed patterns and causal connections within intricate seismic data.
- Researchers are investigating atypical data sources, like animal behavior and electromagnetic signals, to obtain insights into earthquake precursors.

Challenges and Limitations

- The mechanics of earthquakes are inadequately comprehended, rendering precise prediction challenging.

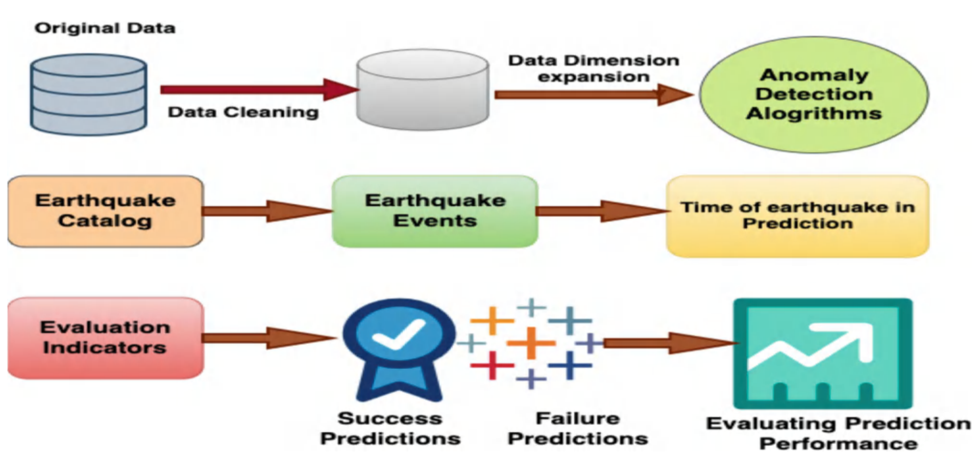

Fig. 5 Earthquake prediction using anomaly detection methods

- False positives and false negatives continue to pose challenges in contemporary early warning systems.
- Identifying minor precursory indications before an earthquake is difficult due to constraints in monitoring equipment.
- Experts assert that the intricate nature of earthquake creation renders accurate prediction improbable.

8 Discussion

Artificial Intelligence in earthquake prediction represents a critical milestone forward in seismological research, improving the odds of fine-tuning and the speed of the projections. In selecting a comprehensive range of AI methodologies, from simple rule-based systems to shallow machine learning and deep techniques, researchers have been able to analyze complex seismic data-in ways, for instance, impossible even quite recently. AI-driven methodologies have proven promising in the anomaly detection process since they often identify subtle patterns and precursors that may be missed through more conventional analytical practices. AI algorithms that can process huge volumes of data from various sources have improved examining precursory events such as changes in radon levels, geomagnetic fluctuations, and crustal deformations. A significant advance over this is the outstanding ability of machine learning techniques, particularly deep networks, to discover concealed patterns and causal links in complex seismic datasets, leading to more reliable models for predicting such events.

Nevertheless, despite these advances, there is still an enormous drag within the domain of earthquake prediction. The intricacy and often tumultuous nature of earthquake mechanics continue to pose difficulties toward accurate prediction, and the possibility of false positives and negatives is an issue with AI-powered models. In addition, weaknesses in the monitoring technology often prevent any detection of weak precursory signals that may prove critical in making a prediction. While the infusion of AI with traditional seismology methods appears to hold much promise, many important questions surround data integrity, model interpretability, and practical implementation of AI-based early warning systems. As research in this field advances, there is a growing need for multidisciplinary collaboration among seismologists, data scientists, and experts in AI to enhance these models and build practical applications.

Future developments in this area may involve the design of new deep learning architectures for the specific application to seismic data analysis, investigating new sources of precursory signals, and developing hybrid models by exploiting the advantages of several AI approaches simultaneously. Although actual earthquake prediction has, to date, remained elusive, continuous improvement in AI-infused seismology continues to come up with a promise for significant improvements in early warning systems, mitigating the devastating impact of seismic events on world communities.

9 Conclusion and Future Direction

The entrenchment of AI in earthquake prediction marked a significant stride in seismological research by opening new avenues through which our understanding and abilities to predict seismic events may be enhanced. Compared with earlier techniques, which sometimes fail to give timely or accurate predictions, an AI-based system seems to produce excellent results in seismological data analysis, where subtle precursors of earthquakes are detected, and hidden patterns may be better revealed than by traditional analysis. By using a broad range of AI methods, from rule-based systems to shallow machine learning techniques and complex deep models, researchers could now analyze and interpret big sets of data derived from various sources, such as seismographs, geodetic measurements, and geochemical indicators. It has been found that many AI algorithms prove quite promising in their ability to detect anomalies so that unusual patterns in geophysical data might be identified with strong predictive capability regarding seismic events. Despite these advances, several significant obstacles still lie ahead in the realm of earthquake prediction. Earthquake mechanics continues to be heavily complex and sometimes violently dynamic, so problems in accurate prediction still abound, and false positives and negatives in AI-driven models are a potential problem. In addition, current monitoring methods have limitations that prevent the recognition of small precursory signals, which could be crucial in making real predictions. The prospect of AI in earthquake prediction is vast and encouraging. There does exist a clear and urgent need to continue research and development within various critical areas. Indeed, if an improved deep learning architecture in deep learning specially customized for seismic data processing is developed, more accurate predictive models may be obtained. Exploring innovative sources of data and precursor signals, which could conceivably feature a form of non-typical signs, such as the comportment of animals or electromagnetic anomalies, may better explain the mechanism of an earthquake. Hybrid models that combine the best of AI-based technologies with traditional seismological methods may also provide more solid and intelligible predictive schemes. Further, there is still significant potential in capitalizing on the development of IoT to establish wider, more real-time monitoring networks. The incorporation of AI and extensive sensor networks could allow for more accurate and timely collection of data, which could facilitate making more accurate and timely predictions for earthquakes.

Development in this discipline can be explained well by stating that the requirement for multifaceted collaboration between seismologists, data scientists, and AI specialists is rising to serve the solution to complex problems existing in this area. Potential novelties that are expected to emerge range from new techniques for data pre-processing, feature extraction, and model interpretation needed to make AI-based earthquake prediction systems better and practically useful. While obtaining an accurate forecast for earthquakes is a challenging matter, continued breakthroughs in AI-driven seismology hold in store much-needed improvements in the effectiveness of early warning systems. Such gains promise to reduce the severely devastating impact of seismic events on global communities and, therefore, save lives and economies from suffering extreme damage. Ongoing research in this area shows the inclusion of AI in human understanding and prediction of seismic activities and, therefore, advancing the development of more resilient and prepared communities in earthquake-sensitive regions.

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Future Trends and Challenges of AI and IoT for Earth Sciences

Buram Sanjana, Shugufta Fatima, C. Kishor Kumar Reddy, and Jothi Paranthaman

Abstract

In the face of challenges like climate change and natural disasters, the integration of AI, IoT, and Earth Sciences transforms our understanding of the earth. This chapter looks into how these technologies enhance decision-making, predictive modeling, and environmental monitoring. With its ability to process large datasets, AI can identify patterns that a human cannot see, allowing for more accurate climate models and earlier disaster alerts. This is enhanced with IoT, connecting networks of intelligent sensors and gadgets to enable real-time data gathering even from the most remote locations. Satellite remote sensing, environmental monitoring, and disaster risk management represent the current applications that reflect the revolutionizing power of AI and IoT. The newer areas in machine learning, edge computing, and sensor technologies will provide new and innovative tools for anticipating and reducing the dangers of the environment as well as enhancing resource management. The chapter advocates for managed steps that will enable these technologies to be used over the long term. Research, policymakers, and industry leaders should build robust legislative bodies that address issues such as accessibility, privacy, and security of data. Stakeholders should optimize the benefits of AI and IoT while reducing hazards by encouraging ethical innovation. While these technologies open new horizons with such tremendous potential, ethical integration provides the necessity for uprooting urgent global concerns and responsible development of the Earth Sciences.

Keywords

Artificial Intelligence (AI) · Internet of Things (IoT) · Earth sciences · Geospatial data analysis · Smart sensors · Machine learning

1 Introduction

Understanding Earth Sciences can help in mitigating the present global concerns. Complex earth systems are the source of climate change, natural disasters, resource depletion, and degradation of the environment. Thus, to mitigate these problems, earth scientists design models and plans that can aid in better management of natural resources, predict earthquakes and storms, and help in the process of sustainable development. Earth sciences are also crucial for creating policies that address disaster risk reduction, environmental preservation, and sustainable practices. As Earth Sciences is diverse, geologists, meteorologists, and environmental scientists can work together to advance a comprehensive understanding of our world. The application of cutting-edge technology like artificial intelligence and the Internet of Things (IoT) is revolutionizing the earth sciences. New technologies are improving the capacity to gather, handle, and process gigantic datasets that were too difficult or too time-consuming to deal with. Specifically, artificial intelligence (AI) is transforming how scientists analyze earth systems, predict extreme weather occurrence events, and quickly and accurately gauge environmental repercussions. However, the technology of IoT appliances

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makes it possible to access the data in inaccessible and remote locations to keep monitoring geological as well as ecological processes. Besides the introduction of IoT, AI further contributes to developing advances in resource management in areas of disaster mitigation and prediction but supports the path of attaining general global sustainability goals.

1.1 Role of AI and IoT in Earth Sciences

AI techniques make it possible to process large amounts of geographic data, allowing the study of topographical features and the recognition of high-resolution objects. The availability of IoT devices, which offer real-time data from remote sensors, improves this (Janowicz et al., 2020). Artificial intelligence is becoming increasingly popular in the geoscience field as a means of explaining machine learning and deep learning black-box models that are not inherently interpretable (Mamalakis et al., 2022). The use of AI and machine learning techniques in the earth sciences are just at its start. Perhaps the biggest impact of these processes until now has been in using data collected through remote sensing from images of the surface of the Earth (MacLEOD, 2019). The Earth sciences are now rapidly being called upon to take on more complicated environmental and geological problems, and two revolutionary technologies transforming these fields are AI and IoT. These developments transform how we collect, analyze, and understand information about Earth's systems, which in turn will improve our ability to predict the future and manage environmental problems.

IoT-Based Data Collection and Monitoring: The Internet of Things has greatly enhanced our ability to monitor and acquire real-time environmental data in Earth sciences. By definition, the Internet of Things is an associated system of devices consisting of software, actuators, and more embedded technologies that communicate via the internet.

Remote Sensing and Environmental Monitoring: It is possible to deploy IoT-sensorial sources of information in the woods, oceans, atmospheres, and many more environments for extracting reliable data on all sorts of variables, like air quality, temperature, humidity, and ocean currents. For example, real-time data on atmospheric conditions are provided by weather stations in equipment IoT devices, enabling meteorologists to make more accurate forecasts. Networks of IoT are also critical in monitoring tremors, volcanic eruptions, storms, and floods. **Disaster Prediction and Response**: They are also applied to predict as well as react toward catastrophes. For instance, sensors installed next to fault lines or coasting regions susceptible to earthquakes or tsunamis can be able to notice even minute indicators of either tsunamis or earthquakes. The technologies help provide early warnings and thus make responses more prompt in reducing loss of life and property.

Horticulture and Water Management: Precision agriculture uses IoT to monitor soil health, control crop growth, and optimize water use. IoT sensors in hydrology monitor the amounts of water in lakes, rivers, and reservoirs, assisting scientists in better managing water resources—particularly in areas that are at risk of drought.

1.2 Artificial Intelligence for Data Analysis and Modeling

Collecting and Interpreting Data for All Water Facilities: Water utilities collect data from various sources, including computerized maintenance management systems and ex-situ laboratory information management systems. However, traditional methods are insufficient for quick fault detection, control, and decision-making due to their reliance on statistics (Zhong et al., 2021). Machine learning models, on the other hand, are flexible and can update themselves with dynamic data, making more accurate predictions.

Climate Prediction: Climate models in prediction and modeling increasingly improved by using AI more and more. Huge amounts of information from sensor networks, historical climate data, or satellite images can be further processed by machine learning to produce very accurate models. These models predict long-term temperature trends, extreme weather situations, or the way the ecosystems and human societies will change due to climate alteration.

Natural Hazards Prediction: Artificial Intelligence is the most effective tool in fighting natural disasters. Improved seismic activity predictions may be based on training machine learning algorithms with historical data regarding both earthquakes and volcanic eruptions. Likewise, AI-based models—which study conditions in the atmosphere and oceans—become even better at predicting storms and floods.

1.3 Importance of Emerging Technologies in Environmental Monitoring

As they allow researchers to handle large amounts of information for more precise risk and resource evaluation, big data and AI are creating techniques that contribute to environmental monitoring revolutions. The primary improvements introduced by machine learning and the Internet of Things relate to increasing our abilities to observe the quality of air and water, detect pollution, and predict natural disasters with new anomaly detection methods and almost real-time evaluations of environmental threats. AI and IoT are crucial in monitoring the quality of air and water, an important environmental issue. New technologies have come in to allow real-time monitoring and analysis of environmental changes, which increases our ability to mitigate and deal with problems like pollution and climate change. Cloud computing, and AI-based platforms enable accessibility and scalability for environmental monitoring systems. These technologies provide infinitely scalable and economically scaled infrastructures for both local and worldwide environmental monitoring.

2 AI in Earth Sciences: Current Applications

Evidence of being the backbone of critical applications among various disciplines, AI has shown through its functionality in assessing data about geography, climate trends, and environmental changes in fields such as improvement and prediction of natural disasters. Artificial Intelligence is currently being applied in Earth Sciences fields like remote sensing, biodiversity monitoring, climate change modeling, disaster prediction, and water resource management. In addition to all these applications in the understanding of Earth processes, it ensures the quality management of resources and minimizes environmental concerns. It also gives an early warning for all approaching disasters. Apart from these applications in the understanding of Earth processes, it assures the quality management of resources and minimizes environmental concerns. Moreover, it gives an early warning for all approaching disasters, as illustrated in Fig. 16.1.

2.1 Remote Sensing and Geospatial Analysis

AI-Driven Identification of Objects and Image Categorization: Using AI and deep learning, the automation of object detection and classification in images significantly transformed remote sensing. AI programs classify land cover, identify urban structures, and monitor changes in ecosystems from satellite and aerial photographs. Environmental assessments both qualitatively and quantitatively improve.

Optimized Spatial Resolution: One salutary circumstance is that we can now make reasonably fair comparisons between the consequences of aggressive undersampling and deteriorating data quality because, although such sampling is restricted to the earth's surface, Even at this small scale, we may acquire a comprehensive and detailed geographical mapping of atmospheric variables of significance (Trevisani & Omodeo, 2021).

Machine learning methods enhance analysis of high resolution satellite imagery. AI makes it possible to realize finer spatial resolution leading to a better identification of small-scale geographical elements, such as vegetation patterns and

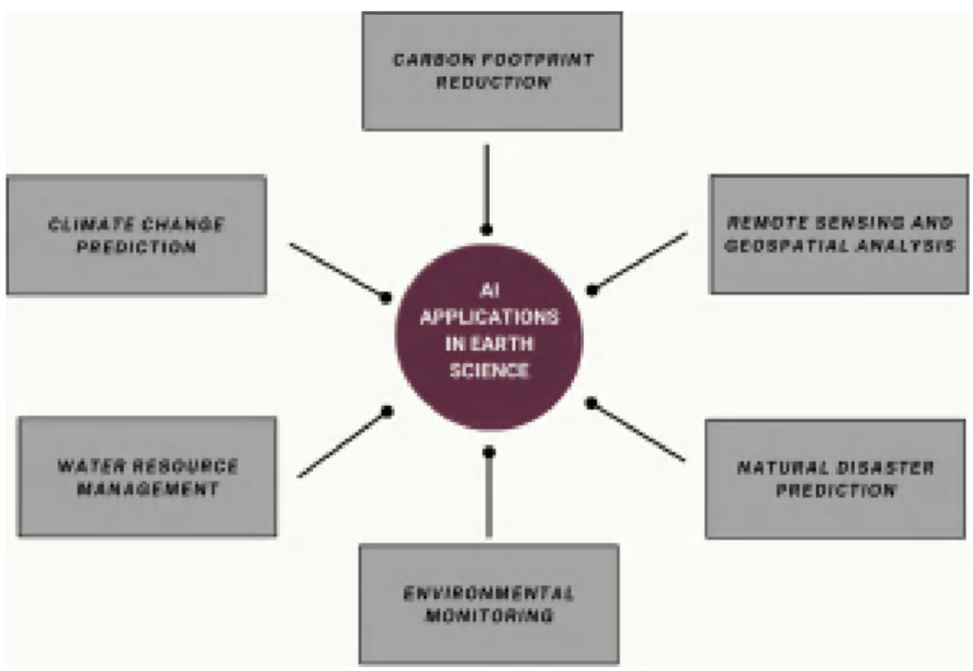

Fig. 16.1 Key AI applications in earth science

water bodies, as well as urban expansion. These interpretations have important uses in the monitoring of ecosystems and land use planning. **Data Fusion and Multimodal Analysis**: The calibration equation, that has been used in the model development, has managed to incorporate multiple sensor nodes inputting through the data fusion technique (Okafor et al., 2020). To produce thorough geospatial models, AI combines data from multiple sources, including sensor networks, networking sites, and satellite photography. Such integration of data streams is likely to lead to better decisions in resource management, urban planning, and disaster response.

AI in Temporal and Spatial Pattern Recognition: Artificial intelligence models can differentiate between changes in geospatial patterns that are either temporal or geographical, thus making it easier to track changes over time. For example, by looking at the time-evolved data from satellite photography using artificial intelligence, one would find a pattern related to trends of deforestation, glacier melting, or urban spread.

2.2 AI in Climate Change Prediction Models

Although less used in the past, machine learning has been heavily used to analyze climate change. In recent analyses, it has become important, focusing attention on its applications such as mitigation of climate change, identification of teleconnectivity, and adaptation. AI is used in creating high-resolution data that helps combine many predictors with climatic conditions (Cheng et al., 2020).

Random Forests (RF) and related machine learning techniques have been employed to enhance the parametrization of atmospheric processes in General Circulation Models, particularly in applications related to moist convection (Bochenek & Ustrnul, 2022). This AI model also recovers extreme precipitation events-the tail events that are crucial for good climate predictions.

Extreme Weather Forecasting: It is proposed to develop 2D Convolutional Neural Networks (CNNs) for the extreme quantities over a region-precipitation and discharge-extreme, with synoptic-scale projections for identifying essential regional and seasonal differences. Intensity–duration–frequency curves, which are basic for the forecast of occurrence of extreme weather events, such as floods, are developed through machine learning.

2.3 Earthquake and Natural Disaster Prediction Using AI

Various research works are taken on forecasting methodologies to predict earthquakes, including ANN, SVM, DNN, and FNN. The trend of seismic data, earth's electromagnetic fields, and environmental precursors like radon gases levels, temperature of the earth, and the formation of clouds can all be used to predict earthquakes (RP 10 Earthquake). It also checks precursors that have been associated with earthquake events among other phenomena such as seismic electric signals and total electron content (Jiang et al., 2020).

Integration with Environmental Data: AI models coupled seismic data with variations in humidity, electromagnetic fields, and cloud formations for better predictive accuracy. Though less reliable, parameters act as precursors to the effects of storms. Predictive models need further research to improve its workability.

2.4 AI-Driven Water Resource Management

Three components make up this wireless sensor network-based aquatic environment monitoring system: data monitoring nodes, a centralized monitoring center, and data center. Its performance is very well with complex and vast water environments, such as ground waters, both shallow and deep ones, lakes, rivers, marshes, and reservoirs (kanta Samal & kanta Choudhury, 2017). When it comes to evaluating various information from numerous sources such sensor networks, satellite images, and weather reports, artificial intelligence is crucial. This connection can analyze historical data, meteorological conditions, and season variations for the AI system to properly estimate the consumption of water. This system uses artificial intelligence algorithms to analyze the tremendous amount of data produced by its components. It can extract useful insights from the data using trends, abnormalities, and correlations detected with these algorithms. Using machine learning and predictive modeling techniques, it can predict water consumption and its effective distribution along with possibly detected leaks or loss in it (Nova, 2023). In this manner, the resource of water can be wisely allocated to prevent shortages and improve readiness in relation to its high demand.

Optimize Water Distribution System: AI systems monitor and adjust for system inefficiencies, pressure changes, and consumption patterns using real-time information from sensor networks. Ultimately, this promotes sustainable water management practices by ensuring equitable distribution of water and minimizing waste.

Water Infrastructure Leak Detection: Artificial intelligence systems analyze the data captured from strategically placed sensors in water distribution networks to be able to identify leaks in the infrastructure. Such algorithms enable early detection through the identification of anomalies that may suggest a leak or abnormal water flow (Kamyab et al., 2023). Early response cuts costs associated with related financial and environmental expenses, damage to infrastructure, and loss of water.

AI in Drought Prediction and Early Warning: AI algorithms are used to anticipate drought using previous climate records, satellite imagery, and atmospheric information. Such models are capable of predicting drought conditions and allow communities and governments to give those communities sufficiently early warnings so they can make proactive steps about conserving water.

2.5 AI in Biodiversity and Ecosystem Monitoring

Monitoring of Forests and Wildlife: The use of AI models in conjunction with Internet-of-Things-enabled sensors leads to identification and online tracking of illicit logging and deforestation, further helping monitor ecosystem health biodiversity conservation, wildlife conservation, forestry, illegal logging, plant inventory and identification, forest classification and mapping, wildlife monitoring and identification, forest conservation and restoration, above-ground carbon stock, forest health, and phenology monitoring, detection and prediction of anthropogenic threats, etc. (Shivaprakash et al., 2022). Examples are species classifications from audio recordings and from camera trap photos with the help of sound recognition and image analysis algorithms.

Automated Species Identification: Armed with multiple sounds, camera traps, and drones, Artificial Intelligence has been exploited to identify species automatically in biodiversity hotspots such as the Indian woods. Conservation efforts have thus become more effective.

2.6 AI and IoT in Geohazard Mitigation

The mitigation of geohazards like tsunamis, volcanic eruptions, and landslides is now revolutionized with the advent of IoT and AI. Ground movements, seismic activity, and atmospheric changes are continually collected as real-time information by setting up IoT sensor networks in sensitive places; AI algorithms will interpret this information to detect the early warning indicators before an event manifests. Alarm bells and preventive measures can thus be triggered in due time. For example, IoT sensors on mountain slopes can monitor soil movement and raise alarms, and AI systems can analyze seismic patterns and volcanic gas emissions to predict eruptions more precisely. Improving the accuracy in predicting disasters as well as enhancing emergency response speed and efficiency lower the risk to infrastructure and human life. Since geohazards are inherently dynamic and complex, the adaptation of AI and IoT technologies leads into a proactive, data-driven disaster management scenario, thereby making it an essential tool to protect those communities at risk.

3 IoT in Earth Sciences: A Technological Framework

One rapidly developing technological framework with enormous potential applications in many other sectors, including earth sciences, is the Internet of Things (IoT). In an effort to solve some of the previously unheard-of difficulties that the world faces today—including resource depletion, climate change, and natural disasters—it is very important that creative solutions be found to monitor and control environmental systems. The Internet of Things shall provide a very promising methodology in gathering, processing, and forwarding near-time environmental data with the use of networked networks of sensors, devices, and data analytics platforms. Integration of IoT into earth sciences can totally change how we understand those complex biological and geological processes by giving earth scientists new sets of tools and insights that can enable them to discover, analyze, and respond to environmental occurrences.

3.1 Definition and Scope of IoT in Earth Sciences

Internet of Things in earth sciences is defined as the web of sensors and devices that collect, transmit, and analyze environmental information in real time. These implanted devices measure temperature, humidity, air quality, and soil moisture within a range of settings, such as woods, oceans, and urban space. Figure 16.2 describes how information flows through an IoT-based environmental monitoring system; sensors collect and send information in real time to be analyzed.

IoT's scope in Earth sciences:

- **Real-Time Environmental Monitoring**: It is made easy by Internet of Things (IoT) to keep track of continuous monitoring of natural systems with constant information regarding a state of air, water levels, or climate conditions.
- **Data-Driven Decision Making**: IoT systems aid the AI models in gathering data for their analysis and forecast generation by streaming data to central hubs or cloud-based platforms, thereby becoming useful for resource management and catastrophe preparedness.
- **Accessibility and Scalability**: With IoT networks, it is much easier to monitor both dense forests and urbanized

areas remotely because the setup is highly scalable over vast geographical areas.

- **Increased Precision and Automation**: IoT predicts environmental processes like soil degradation, deforestation, and rainfall patterns with the help of automation-based high-precision data collection. No human intervention is necessary.

3.2 Environmental Sensors and Data Collection Networks

Low-Cost Environmental Monitoring and Sensors (LCS): As low-cost sensors are capable of producing high-resolution spatiotemporal datasets, they are very important to augment monitoring capabilities in environments. It is with such sensors that dense in-situ monitoring networks are constructed, hence built as requirements for producing accurate environmental data. Accuracy and reliability are still common issues in LCS. Quality of the data is highly sensitive to temperature and humidity levels. Environmental sensors only give accurate data if calibrated. Calibration has traditionally been performed in highly controlled lab-based environments, which quite often does not reflect real-world conditions under which sensor products will be operating. In-field calibration by optimizing sensor outputs based on environmental parameters by means of machine learning techniques, such as ANN, and linear regression can help to achieve a higher accuracy in the data obtained.

Data Fusion Techniques: In a model, these comprise information gathered and displayed from various sensors and environmental factors. Data fusion is an advanced technique of making use in environmental monitoring by filling in gaps where the data collected separately by the sensors are not constant, not so exact, and not very useful.

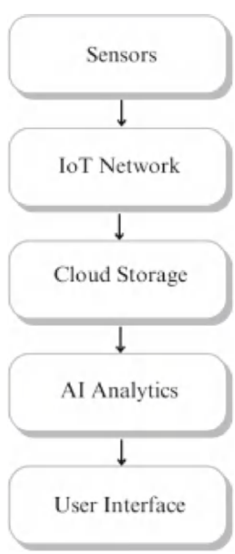

Fig. 16.2 Flow of data in an IoT-based environmental monitoring system

Feature Selection for Quality Improvement of Sensor Data: Techniques like Feature Selection will help decide which environmental variable is most relevant and should be selected, from the point of view of sensor data quality, and therefore humidity and temperature come within this scope. The result is an improvement in the performance of the calibration model and an increase in the efficiency of the process of data acquisition.

3.3 Real-Time Monitoring of Natural Resources

AI-Powered Data Analytics: AI analyzes huge amounts of information that is collected from the sensors that track all resources: soil, water, air, and forests. Powerful computers can analyze this data to look for patterns, predict trends, or identify anomalies such as water pollution, illegal deforestation, or rising air pollution.

Intelligent Decision-Making: With AI providing real-time insights, automated resource management decisions become a possibility. For example, water management through AI will consider soil moisture and meteorological data, with this optimized irrigation schedules or supply distribution; one would utilize resources more effectively.

Early Warning Systems: Improvements in early warnings have also been facilitated through AI, as it recognizes extremely minor changes in data collected from the environment, which could indicate natural disasters or resource depletion in the near future. In turn, this real-time monitoring makes possible rapid reactions to environmental risks, reducing damage which can occur as part of efforts toward conservation.

3.4 IoT for Air and Water Quality Monitoring

The combination of artificial intelligence models with IoT networks enhances environmental monitoring capacities for water and air quality. Large volumes of data from IoT sensors may be processed by integrated systems to provide early warning of harmful environmental changes. This is a critical technology combination working to help tackle climate-related issues. There are IoT devices deployed in the environment for pollution control, which continuously collect data about air and water pollutants. In addition to AI, these systems provide sophisticated analytical tools, such as predictive analysis and real-time reaction to environmental hazards. With the constant sensing of contaminants by IoT, there is instantaneous alerting about the risks associated with pollution. The integration of IoT technology with AI models allows predictive analytics and the identification of anomalies in environmental data. Such integration supports the real-time identification of pollution and contamination in water and air systems. Uninterrupted data collection and analysis, which these advanced monitoring systems ensure, are therefore very critical in supporting quick environmental response measures.

4 Integration of AI and IoT for Earth Sciences

In contrast, the combination of artificial intelligence and the Internet of Things has transformed earth sciences and offers powerful tools for addressing some of the most pressing geological and environmental issues of our day. The complete potential of environmental monitoring, data collection, and analysis is unlocked with the integration of sophisticated processing and predictive capabilities of AI combined with the far-reaching network of sensors and devices in IoT. When AI and IoT are combined, intelligent systems that can autonomously monitor ecosystems, forecast natural occurrences, efficiently manage resources, and respond quickly to environmental changes can be built.

This integration strengthens the ability to understand complex natural processes and make judicious decisions in the earth sciences, where enormous and complex datasets are being continually generated from a number of sources—including air sensors, seismic detectors, and satellite images. How the convergence of IoT and AI is revolutionizing earth sciences, by way of improved climate models, more accurate predictions of natural disasters, and sustainable resource management, shall be discussed in this chapter.

4.1 Synergy Between AI and IoT for Data Analytics

Data might be surveyed considerably more sensitively using AI and the Internet of Things, perhaps exposing intricate environmental trends that would otherwise go undetected. This kind of combination elevates real-time data acquisition and analysis associated with Earth sciences. Such environmental information is processed and used by AI for knowledge of patterns of climate, geologic events, and the health of ecosystems. AI is able to improve decision-making processes if it works over the huge amount of data that IoT networks collect, such as identifying early natural disasters and developing predictive environmental models.

IoT devices collect vast amounts of environmental data, which are consequently processed and analyzed by AI to draw patterns and results for improved monitoring of the environment and further insight to inform decisions. In all, AI and IoT work together to amplify the accuracy and depth of environmental data analyses. IoT sensors result in continuous streams of data which AI systems can make sense of to arrive at predictions and models for monitoring Earth systems. With AI and IoT, massive volumes of real-time environmental data could more easily be gathered, processed, and analyzed. The reason is that the synergy of data analytics between AI and IoT devices continuously gathers streams of data related to weather patterns, ecosystem health, and natural resources, such as field-deployed sensors. In turn, these trends, patterns, and abnormalities are scrutinized by AI systems. This integration allows for real-time decision-making concerning areas as diverse as water management, air quality control, and disaster prediction and offers more accurate and timely insights. It is a very effective system of environmental monitoring when combined with IoT's real-time data collection and AI's complex analysis. It allows proper resource management and sustainability initiatives to be done.

4.2 Smart Environmental Monitoring Systems

Using IoT sensors and AI-driven analytics, smart environmental monitoring systems measure the alterations that take place in the environment and can detect anomalies to improve management towards environmental health. IoT and AI-driven smart monitoring systems provide uninterrupted independent observation of environmental variables such as temperature swings, water levels, and air quality. These technologies have sensors that capture real-time data and AI analyses this data to look for patterns or predict changes in the environment. One of the reasons people are starting to use these technologies is for tracking urban pollution and also towards monitoring water resource management. It is only through the implementation of smart environmental monitoring systems that can offer automatic algorithms that any issues regarding water management, catastrophe forecasting, or other such aspects like air quality monitoring, can be effectively handled. Such algorithms are constantly self-improving and adapt with changes and learn to enhance their predictive ability.

5 Case Studies: AI and IoT Applications in Earthquake Detection, Climate Forecasting and Conservation Efforts

AI in Earthquake Detection: Seismic detection through AI has gone remarkably quick with different types and approaches of machine learning. For example, with deep learning and shallow machine learning offered by SVM, ANN, and RBFNN-based approaches, it is possible to remove patterns from seismic data in order to enhance the rates of earthquake prediction. The location, time, and energy released in an earthquake can be evaluated using AI systems that are capable of processing seismic indicators such as Gutenberg-Richter b-values, seismic electric signals (SES), and P-wave and S-wave patterns. Mamdani fuzzy neural networks (FNN) and adaptive neuro-fuzzy inference systems (ANFIS) are used in a particular earthquake prediction technique to detect high-precision seismic signals (Al Banna et al., 2020). These AI methods can integrate sensor information gathered through IoT networks to detect minute changes in the Earth's electromagnetic field or temperature that could be an earthquake precursor.

AI and IoT in Climate Forecasting: Researchers have demonstrated that AI and IoT in climate prediction work by having several implementations. For example, CNNs and LSTM networks create models from vast climate data sourced by real-time monitoring systems fitted with IoT sensors. Some of the environmental elements monitored include temperature, humidity, and wind patterns, such elements responsible for weather phenomena like storms or cyclones. It would gain predictive accuracy for climate prediction if this model is trained on such data; hence, it would be able to predict severe weather events in anticipation and thus provide early warning with regard to timely alerts. Figure 16.3 shows how data is obtained in an AI-driven climate forecasting system through environmental sensors and fed into the predictive analytics tool to gain proper climate forecasting.

Conservation Efforts Using AI and IoT

Through such processing of vast ecological datasets gathered through IoT environmental sensors, AI technologies play a critical role in conservation efforts. For example, AI-powered image recognition systems integrated into IoT networks can actually monitor the populations of endangered species and detect changes in habitats in biodiversity preservation. AI can also forecast how animal movements, shifting forest cover, variations in water temperatures, and other effects of climate change may affect biodiversity.

6 Future Trends in AI and IoT for Earth Sciences

The future integration of AI into the Internet of Things and resultant outcomes such as the monitoring of ecological systems, climate, among others are expected to emerge into some of the scarce but historic opportunities to radically challenge certain of the most egregious ecological issues facing humankind nowadays. This would revolutionize earth sciences in the future. By allowing it to combine real-time data it collects from sensors and devices using IoT and by processing and analyzing its huge dataset, AI will be able to model climate conditions much better, manage resources much better, and predict natural disasters much better. Future developments in this space include autonomous monitoring systems, scalable IoT networks, and AI-driven predictive analytics to provide deeper insight into complex environmental processes. Actually, the implementation of those technologies may bring with them some issues about data safety, energy consumption, and ethical questions. Yet, the combination of AI and IoT brings up a lot of possibilities for revolutions in earth science and more ecologically friendly developments.

6.1 Advancements in Machine Learning and Deep Learning for Earth Sciences

Deep learning and machine learning are powerful new technologies that may be used to analyze large, multi-dimensional datasets, revolutionizing the field of Earth science. Newer advancements now provide more accurate predictions of natural phenomena, such as the scarcity of resources, extreme

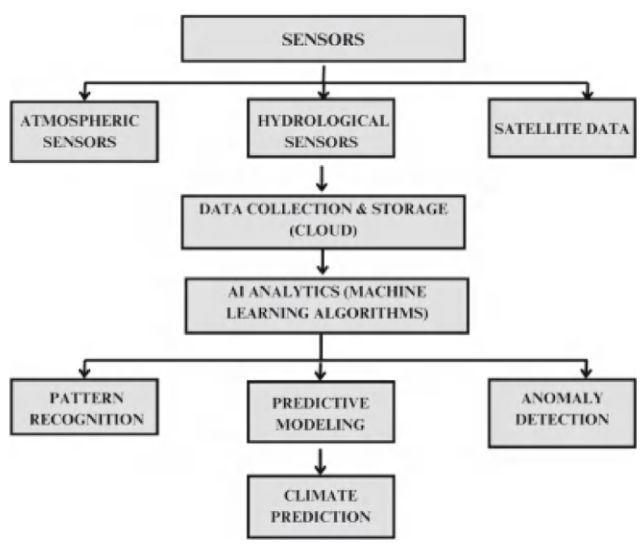

Fig. 16.3 AI-driven climate forecasting system data flow from environmental sensors to predictive analytics

weather, and change in climate. Major datasets, such as satellite imagery and sensor data, have been processed using deep learning models, mainly CNNs, RNNs, or other combinations of network types, to identify items like land-use classification, biodiversity monitoring, or real-time environmental forecasting.

This further changes AI to reveal previously undiscovered environmental changes in large datasets by discovering hidden patterns. DL models are also better at mimicking and forecasting interactions in Earth systems such as atmospheric and oceanic processes much more accurately than ever before. The models provide increased decision-making capacities, more accurate environmental monitoring, and better ability to predict natural disasters as they unfold. Among the emerging techniques include generative adversarial networks (GANs) to generate synthetic data in the face of the problems of data scarcity issues within remote sensing. Applications of ML and DL in earth sciences will be dramatically very significant as AI algorithms continue to develop and as more processing power increases, particularly in preservation of ecosystems, resource management, and disaster prediction.

6.2 Role of Big Data and Cloud Computing in Enhancing AI and IoT Systems

Big data and cloud computing are essential for improving the capabilities of AI and IoT systems in the Earth sciences. As IoT sensors are increasingly being used globally, vast environmental data keeps getting generated almost continually. Big data technologies help store, process, and analyze these datasets, usually too large and intricate for traditional approaches. These massive databases are the basis for the AI algorithms, especially ML and DL, which rely on them to draw patterns, predict outcomes, and insight into phenomena, including resource management, climate change, and disaster forecasting.

The infrastructure required for real-time Big Data processing and analysis is provided by cloud computing. Scalable and flexible cloud platforms make it possible to store and retrieve Big Data from anywhere, thereby applying AI models to analyses related to environmental data. International collaboration over national borders becomes easier by sharing data and models of researchers and companies through the cloud. Not only do these platforms provide tools for more effective management of huge datasets and deployment of models of AI, but also reduce the need for expensive on-site computer resources. Big Data and cloud computing enable performance for AI and IoT systems through collaborative work with large-scale requirements for swift processing and analytics calculations. The following generation of smart environmental systems, including real-time monitoring, decision-making, predictive analytics, and many more services, has been influenced by such emerging technologies.

6.3 AI in Carbon Footprint Reduction Strategies

The total serving carbon footprint includes three types: offline training, online training, and inference. Offline training includes model training from historical data as well as experimentation. In the case of recommendation models involving ever changing parameters relative to new data, online training is highly relevant. The inferred footprint represents the severe traffic emissions. The inferences and online training emissions throughout the life of the training session off the line are comprised of the total serving carbon footprint (Wu et al., 2022), artificial intelligence in terms of model training and application. This suggests that it will generate green and use a lot of energy, emissions of household gases (GHGs) (Wu et al., 2022). AI has been successfully applied to making industries energy efficient and decrease carbon emissions in the areas: petrochemical, shipping, and construction. Techniques of tracking emissions from industry, controlling electrical networks, and optimizing buildings' energy consumption rely on AI-driven solutions. Another area where AI may help reduce energy waste is in an industry such as manufacturing, where operational inefficiencies are leading to losses of immense quantities of energy.

Artificially developed AI models that categorize existing and future trends, for predicting carbon emissions. This gives the ability to identify the major regions that, with appropriate action, could potentially be most effective at reducing carbon emissions. AI technologies can be used to monitor carbon dioxide removal from the air with the help of advanced algorithms. In this manner, reforestation efforts may improve and carbon capture projects become sure-shot successes. AI-based models are increasingly used to test the feasibility of large carbon reduction programs, such as carbon tax plans and emission trading schemes. By way of these simulations, policymakers could maximize the environmental impact of their policies by knowing how those policies will likely influence various industries.

AI for Sustainable Transportation: AI contributes to the creation of green transport through management of the shared electric car networks, streamlining the electric car charging infrastructure, and nudging people to switch towards more environmentally friendly modes of transportation.

6.4 Digital Twins for Environmental Simulations

Digital twins are three-dimensional digital representations of physical systems that can be simulated under any realistic environmental conditions and monitored in real time. Through AI, it has further improved the capabilities of digital twins by providing predictions of future ecosystem states as well as assessing the implications of various scenarios, such as deforestation and climate change.

Integration of Process-Based Models (PBMs) and Machine Learning (ML): Digital twins have to function under diverse circumstances of data availability (Pylianidis et al., 2022). The ML model learns the mapping function from large datasets, whereas the PBM relies on mathematical representations of the underlying processes to tap into the problem domain. There is a possibility for improvement to environmental modeling when these two approaches are integrated as the constraints or the sparsity/resolution problem can be relaxed. Especially in sparse data availability or resolution, digital twins utilize PBMs for simulations and ML for quicker predictions.

Challenges in Environmental Models: Issues are also posed by missing or low-resolution data, especially in the presence of unsampled or infrequently monitored regions in environmental digital twins. Techniques necessary for combining high resolutions into lower resolutions become the major need for operational decision support (Irrgang et al., 2021). For instance, simulation-assisted machine learning creates artificial data and trains models on the data in order to overcome such limitations of data.

Case Study: Pasture Nitrogen Reaction Rate, New Zealand using a Digital twin A case study projects the pasture nitrogen reaction rate of New Zealand using a digital twin. The research outlines how, without real time or future data, digital twins can significantly provide insight in agriculture by bringing simulations and machine learning together.

Within that context, developed models prove to be effective for multi-size operation decision-making: local, regional, and national.

Digital Twin Architecture: It opens a conceptual framework for operational digital twins, emphasizing independent predictability of future data. The approach serves especially well to environmental systems that involve sparse sensor data. The digital twin architecture is shown in Fig. 16.4, which shows how cloud, IoT, and AI are all combined to enhance Earth scientific applications.

7 Challenges and Limitations

Earth sciences integration of AI and IoT is highly promising, but it is not without challenges and limitations. Advanced algorithms are needed to obtain meaningful insights from the vast volumes generated by IoT devices, but data quality, interoperability, and scalability issues often cause effective application problems. Other restrictions for the deployment of AI and IoT in remote or rugged areas include power consumption, network access, and hardware life. Ethical concerns around data security, privacy, and the correct application of AI in decision-making processes further complicate usage. A number of technological and moral concerns need to be resolved in order to fully understand the potential of AI and IoT applications in earth sciences. These will be analyzed in the following chapter. Moreover, there is no standardization of protocols and data formats for IoT devices, which makes heterogeneous ones hard to assimilate, thus complicating the coherence and smooth formation of these networks for environmental monitoring. Another problem is the tremendous processing power needed for AI models to operate, sometimes even a challenge in isolated locations with poor infrastructure. Often, Financial restrictions prevent the implementation of these technologies that impede their scalability and accessibility to several research projects.

7.1 Data Privacy and Ethical Concerns

Indeed, there are significant ethical and data privacy issues with the application of AI and IoT in Earth sciences (Tuia et al., 2021). More and more issues are being flagged with the management of environmental data as it is being accumulated in huge volumes through various sources such as sensors,

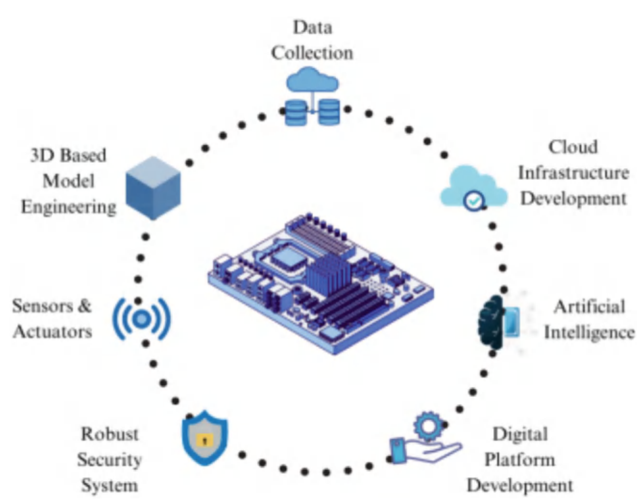

Fig. 16.4 Digital twin architecture: integrating AI, IoT, and cloud in earth sciences

satellite photography, or even personal devices. While large datasets form the basis of AI models to make accurate predictions, it brings private or sensitive data, leading to issues of data privacy.

Data Security Issues: IoT devices may, unwittingly, download private or context-specific information about the individual as they collect live environmental information in an urban area or around research on human interactions within their ecosystems. To ensure this information is kept secure and anonymized becomes all the more important to protect people's private lives in the digital world. However, the Earth sciences are still missing most of the frameworks that would enable effective data privacy management, and therefore, may be victims of exploitation of personal data or violations of laws such as the GDPR.

Ethical Impact of AI: AI in Earth sciences raises two major pressing ethical issues transparency and bias in decision-making. This is mainly because such biased datasets could skew the outcomes and unfavorably affect already very vulnerable ecosystems or communities when applied in AI models. For instance, AI models used to manage resources or predict climate risks are expected to be transparently truthful for unbiased equitable representation such that some areas or populations are not marginalized. Ownership of the data is another issue in terms of ethics. Increased usage of social media and crowdsourced data for environmental sensing raises issues of consent. Users may not necessarily be aware that information is being collected through AI and IoT systems for environmental monitoring thus raising issues of transparency in the presence of informed permissions.

Security Risks: Acquired data has to be secured because AI and IoT devices will gain entry, increasingly into Earth sciences. Data tampering, fake forecast or the stoppage of an environmental surveillance system may affect decision-making due to attacks on environmental databases or on the Internet of Things networks. The concerns over issues associated with stronger ethical standards and legal frameworks to control data gathering, use, and sharing in AI applications of Earth sciences call for stronger and more robust ethical and legal standards. In the sustainable and responsible development of AI and IoT systems in the context of environmental research, data security, transparent AI methods, and the assurance of the safety of sensitive and personal data will be at a premium.

7.2 Limitations of Current AI Models in Earth Sciences

Earth sciences have significantly benefited from AI. However, the current models of AI cannot realize their full potential because of a few major problems: the difficulty of Earth processes, problems with the quality of data, and limitations in AI techniques.

- **Availability and Quality of Data**: More often than not, it is ground-based equipment, aerial sensors, and satellites that generate the data fed into AI. However, firms, scientists, and researchers may not always easily get access to such treasured data. Some of the data can be out of bounds for wider usage because they fall under proprietary rights or because they are owned by government agencies. Certain datasets might not be available for wider usage because they are restricted by government bodies or corporate rights (Janga et al., 2023). In producing credible predictions, AI models require much more high-quality data. Since some regions may be geographically challenging, others may be left out simply because the ways of gathering data may be unbalanced, and some data may go missing. Incomplete datasets or biased ones will lead to wrong or insignificant outputs from the models. For example, remote sensing data could be poor in some areas, hence affecting the models developed for the projections of the global climate or biodiversity.
- **Problems of Generalization**: The produced AI models had been trained on particular datasets. These models may therefore not generalize well to any novel or unforeseen situation. This is very problematic in Earth sciences, given the significant variability in climatic conditions by place and over time. A model trained on data from one particular geographic location in one particular place with a different climate, terrain, or ecological features would not predict the outcomes with any level of accuracy in another different place. That is another fundamental drawback, which makes the case for models that are more flexible and able to deal with uncertainty and variability in Earth systems.
- **Complexity of Earth Systems**: Earth systems are fundamentally complex due to intricate nonlinear interactions involving interactions at many scales. Current AI models, being strong, often oversimplify such interactions and omit crucial information, the linkages between different systems for instance, which would determine the long-term patterns of climate or seismicity, needless to say, not something to be fully accepted by a brittle AI algorithm.
- **Lack of Explanation and Transparency**: Deep learning models in particular are referred to as "black boxes" since it is nearly impossible to comprehend how these models make decisions. Lack of explanation becomes a problem in Earth sciences because scientists will need to know how these models come up with their respective predictions in order to validate and accept the results. That lack of explanation, though, is what places big obstacles in the

way of being able to conduct scientific research and make policies.

devices, will aid in the secure and efficient advancement of AI-driven insights in Earth sciences.

7.3 Technological Challenges in IoT Infrastructure

Technologically, the introduction of IoT in Earth sciences faces several challenges (Cowls et al., 2023). Those IoT sensors are meant to operate under extremely hostile environments, and supply power is usually thin in the areas, while network access may be minimal. It is such a challenge to ensure that the devices have a long lifespan and are robust enough with full security provisions while at the same time dealing with huge amounts of data generated from such a network.

- **Durability and Reliability of Sensors**: The largest component of the Internet of Things systems of the Earth sciences is a distributed network of sensors found in many different environmental settings, which at times are quite hostile, such as mountains, seas, and deserts. These sensors are not really durable because of exposure to the vagaries of weather, temperature extremes, and potential physical impact. Robust constructions and materials, combined with high maintenance cycles that tend to be expensive and logistically challenging, ensure long-term reliability of IoT sensors in such environments.
- **Data Transfer and Access**: The IoT networks in earth science mostly function in remote places where the communication infrastructure is not developed. Reliable access to the internet or satellites in such areas would limit the ability to send large amounts of real-time data into central processing systems. Data transmission delays or interference may compromise the efficiency of AI systems, especially those that use applications for time-related matters such as natural catastrophe prediction or real-time environmental monitoring. These developed communication technologies must therefore be more resilient to guarantee continued data flow, an effort that will include sophisticated satellite communication systems or LPWAN.
- **Data Organization and Storage**: Huge amounts of data from IoT sensors must be recorded, analyzed, and assessed in real time in order to implement AI applications. Big amounts of storage are required in dealing with big datasets, which often necessitates that cloud-based infrastructure be sought. However, cloud storage solutions come with a unique set of difficulties such as latency, cost, and data security. Cloud solutions, which are effective enough to handle the vast amount of data generated by IoT

7.4 Environmental and Sustainability Impacts of AI and IoT

The application of AI and IoT technologies within Earth sciences causes good as well as bad effects on environmental sustainability. Innovative technologies raise questions about their own environmental footprints, even as they offer huge potential to enhance resource management, sustainability initiatives, and monitoring of the environment. AI and IoT technology ensures much more precise and timely monitoring of environmental parameters, like air and water quality, deforestation, wildlife habitats, and climate change. With this IoT technology, the many sensors collect, analyze data from several ecosystems for trends, changes in the environment, and very early warnings on possible natural disasters through AI models. By improving the management of natural resources and minimizing environmental risks, this aids in maintaining initiatives.

Through AI models, there is an optimization of the energy usage with direct carbon emission reduction. Its application takes place, mostly in energy management systems. The IoT devices monitoring the current energy consumption aid in the AI algorithms pointing out areas of inefficiency to come up with proposals on reducing the usage. As such, there is reduced greenhouse gas emission, hence developing support for sustainability and fulfilling global carbon reduction objectives. The amount of electronic waste has increased significantly as a result of the expansion of IoT devices like sensors and cameras. The manufacture, maintenance, and recycling processes should ensure minimal environmental impacts using sustainable approaches. Huge data centers for processing and storage of IoT data cause environmental impacts, despite the shift to renewable energy.

7.5 Ethical Considerations in AI and IoT for Earth Sciences

Additionally, with the advent of AI and IoT in earth sciences, some critical ethical issues come into play. As a result of IoT devices collecting massive amounts of environmental as well as sometimes personal data from most of the remote villages, data ownership and privacy are among the primary issues. This means that the data must be safe and available in its management to avoid abuse or unwanted access. Additionally, an AI model with an obvious bias, which is not infrequently caused by a partially biased or incomplete dataset, can create damaging predictions or environmental assessments for communities and ecosystems most vulnerable. Decisions reached through AI applications also carry ethical implications because findings generated by "black box" algorithms are, although accurate, opaque. Addressing such ethical challenges shall pose to be quite an important requirement for more robust policy frameworks, moral standards, and international collaboration, thereby ensuring the responsible application of AI and IoT in earth sciences so as to maintain trust, ensure secure justice, and promote sustainability while employing such a powerful technology.

8 Conclusion

Earth sciences are in a revolution due to the confluence of AI and IoT technologies that have been bringing game-changing solutions for the monitoring of the environment, model prediction, and catastrophe management. The technological advance brings about better handling capacities in terms of huge volumes of data and, hence, more precise forecasts in resource management, climate change, and an alert on natural catastrophes. However, important questions such as data management, moral dilemmas, and long-term sustainability of IoT infrastructure remain to be addressed. Responsible innovation and cross-disciplinary collaboration would be essential in order to fully exploit AI and IoT and ensure an ethically sustainable implementation in Earth Sciences.

8.1 Future Prospects for AI and IoT in Earth Science

As these AI and IoT technologies progress, they will provide unprecedented possibilities to deepen our understanding and stewardship of the complexity of systems on Earth. AI could progress and enhance resource management and catastrophe-forecasting and climate-prediction models as it advances data analysis capabilities. Meanwhile, through IoT, inaccessible or far-flung areas could be wired to provide real-time environmental data and allow academics and decision makers to make quick responses in an informed way. A confluence of AI and IoT will help solve global concerns in terms of climate change, loss of biodiversity, and natural disasters. New developments in these domains, such as digital twins, AI-driven carbon reduction plans, and intelligent environmental monitoring systems, also hold promise for potentially greater accuracy and effectiveness. However, these technologies are generally associated with certain problems, which include the issues of data privacy and moral dilemmas, not forgetting environmental impacts when implementing a vast IoT infrastructure.

As the AI and IoT technologies advance, the handling of data gathering and processing will be transformed. It will be possible to have more autonomous systems monitoring and governing the environment. Further progress may be in creating more effective AI algorithms able to work with the size of big datasets in real time to deliver more accurate and focused forecasts of impending natural disasters, such as earthquakes, droughts, or floods. Moreover, the IoT networks developed by the progress of 5G connectivity and satellite technologies will ensure the tracking of even the most difficult and distant situations with unprecedented precision. These breakthroughs will give scientists and decision-makers useful information that allows them to take initiatives in terms of conservation, preparation for natural disasters, and sustainable resource management. But the future integration of AI with IoT into earth sciences must be led by ethical frameworks, practices for sustainability, and international cooperation, to minimize technological overreach and ensure fair access to these benefits. Responsible innovation practices, backed by strong regulation and cross-disciplinary collaboration, will become crucial in unleashing AI and IoT for use in Earth Sciences. In the coming decades, AI and IoT can serve as effective instruments for fostering sustainability, catastrophe resilience, and protection of natural ecosystems through mitigation of technological, ethical, and environmental concerns.

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