Tofael Ahamed *Editor*

IoT and AI in Agriculture

Strategies to Develop Smart Agricultural Space for In-field and In-house Crop Production

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Preface

The Tsukuba Conference (TC) and Tsukuba Global Science Week (TGSW) provide global platforms to address future policy challenges, develop solutions, and cultivate future leaders. This book is the outcome of our yearly efforts, stemming from the Tsukuba Conference 2025, aimed at addressing agricultural challenges, new developments to mitigate climate change, and increasing food production to meet global demands. This year, we collaborated on a special session, “AI and IoT to Integrate Automation in Farm Management: A Path to Sustainable Agriculture,” with the University of Tsukuba and the National Agricultural Research Organization (NARO). Investing in the agricultural sector can address not only hunger and malnutrition but also other challenges, including poverty, water and energy use, climate change, and unsustainable production and consumption.

In Chap. 1, high-throughput plant phenotyping (HTPP) is discussed that was initially developed for model plants in controlled environments and that has recently transitioned to the more challenging context of field crop phenotyping. Despite the challenges posed by unstable environmental conditions, technological advancements have made efficient and precise field phenotyping feasible, enabling the assessment of crops in their actual growing environments using platforms such as satellites, unmanned aerial vehicles (UAVs), and ground-based vehicles (UGVs). High-throughput field phenotyping (HTFP) is vital for diverse and structurally complex horticultural crops. These crops are crucial for nutritional security but have received less attention in phenotyping research, resulting in a significant knowledge gap. This chapter reviews key HTFP technologies applied to selected horticultural crops, including advanced imaging sensors deployed on RGB, thermal, and hyperspectral platforms.

In Chap. 2, the development of microcontroller-based semi-automated primary root and shoot length measurement system for tomato (*Solanum lycopersicum*) is discussed. Accurate quantification of root and shoot growth is essential for assessing plant development, but manual measurement methods are laborious and fail to capture the actual geometry of plant structures. This study presents a novel semi-automated system for nondestructive measurement of tomato (*Solanum lycopersicum*) root and shoot growth in an aeroponic setup. The low-cost system integrates a

Raspberry Pi computer for automated image acquisition, custom software for user-guided annotation of root and shoot paths, and algorithms to extract length measurements from the annotated images.

Chapter 3 discusses on the global demand for sustainable agriculture in driving innovations in precision farming technologies. Grapes are a high-value crop, and their cultivation is widespread worldwide. Vineyard irrigation and disease control should be improved to meet the growing demand for grape production in response to an increasing population. This research presents the development and implementation of a smart drip irrigation and fungicide application system designed for grapevine management, integrating Internet of Things (IoT) technologies, cloud-based monitoring, and automated control mechanisms.

Chapter 4 discusses on mini-plant factories that are controlled by Environmentally Friendly Agriculture (EFA) systems, which are reported for small-scale indoor crop production. This chapter will critically review the research on using mini-plant factories for growing homegrown vegetables, herbs, and spices, covering the challenges of design, implementation, and technology integration, as well as the benefits. The chapter will also focus on developing a conceptual model to improve the boundary conditions and achieve more benefits with suitable crops well-suited to mini-plant factory cultivation. Future trends in mini-plant factory design, as well as the application of modern technologies, including AI, the Internet of Things (IoT), and automatic control, are reviewed in the chapter. These systems typically utilize hydroponics or aeroponics to cultivate plants without soil, often incorporating artificial lighting, microclimate controllers, and nutrient management systems.

In Chap. 5, computational intelligence in climate-adaptive agriculture is highlighted with an extensive review approach. Intensifying climate shocks, ranging from unpredictable rainfall to extreme heat, are heightening the vulnerabilities of smallholder farmers, who dominate agricultural landscapes across the globe. Relying on traditional, labor-intensive practices, they are increasingly under-equipped to adapt to the evolving realities of climate change. Small-scale mechanization offers a promising solution, expanding beyond basic tools to include affordable, context-specific equipment integrated with digital technologies such as sensors, IoT, and solar energy systems.

In Chap. 6, the agronomic performance and physiological responses of inbred rice using Drone Seeding Technology are discussed, and a study is presented. A Randomized Complete Blocked Design (RCBD) with a two-factorial structure was employed. The study aimed to evaluate the agronomic and physiological response of inbred rice under different drone seeding parameters through two experiments.

Chapter 7 reported short strategic notes on deep learning strategies for smart agricultural spaces. This note highlights the strategic convergence of deep learning technologies across three critical domains: multimodal plant health diagnostics, autonomous precision field management, and intelligent product quality optimization.

In Chap. 8, feature selection techniques for model development are highlighted. One of the most critical issues in developing the model to analyze real-world problems is the input variable selection problem. Determining the number of input variables the model requires to predict the target variable and gain insight into the research question is one of the most important considerations when developing a model, especially for an Edge-AI model.

Chapter 9 outlined the development of remote autonomy of multi-cluster agricultural machinery. Considering the shortage of the agricultural workforce and the consequent rise in the need for integrated machinery, this chapter presents a study that endeavors to construct a remote autonomous system for multi-cluster agricultural machinery by implementing an IoT-based and AI-based system using the WebSocket protocol and the YOLO deep learning algorithm. Considering the difficulties that contemporary machinery encounters, including substantial operational expenses and arduous learning curves, this research aims to enhance operational efficiency to support labor shortages and increase productivity, with the ultimate goal of achieving autonomy and intelligent machinery.

Chapter 10 discusses the development of a navigation system for the crawler tractor, designed for use on rural roads, to enhance productivity. Labor shortages in the agricultural sector have become a global concern, especially in countries with an aging population. The use of AI technology in agriculture not only addresses the workforce shortage but also increases efficiency by monitoring plant growth and diseases, as well as enabling autonomous transportation. In agriculture, autonomous tractors have been increasingly used, requiring advanced navigation systems to support various agricultural operations.

Chapter 11 reported the development of an orchard autonomous system using Zigbee Communication and Visual SLAM Technology. The orchard management system encounters skilled labor shortages globally. Additional care, such as spraying at the tree location and continuous monitoring, is also required for the site-specific plantation in the orchard. Automation systems can be utilized in the agricultural sector to address labor shortages.

Chapter 12 discusses deep learning-based instance segmentation algorithms for autonomous navigation in orchards. Autonomous navigation in orchards presents unique challenges due to the dynamic environmental conditions and various farming tasks, including monitoring, weeding, spraying, harvesting, and transporting goods. In field operations, GNSS-based navigation systems often experience signal interference caused by dense tree canopies, making them unreliable for precise local environmental perception.

Chapter 13 highlights the intelligent recognition of orchard environment by instance segmentation of trees and roads. Orchard target detection is a key prerequisite for realizing agricultural automation. With the continuous development of agricultural science and technology, agricultural production is gradually moving toward intelligence and automation. As a vital part of the agricultural sector, the management and production of orchards must also utilize advanced technology to enhance efficiency and quality. Deep learning models utilizing instance segmentation, such as Mask R-CNN and YOLACT, can not only detect trees in the orchard but also segment the safe range for vehicles to operate, thereby realizing accurate identification and localization of the orchard environment, as well as guaranteeing vehicle safety during operation.

In Chap. 14, a strategic short note is placed for the prospect of small-scale agricultural mechanization for sustainable agriculture in a climate change context. Greenhouse and orchard fruit harvesting has posed a challenge due to its time-consuming and labor-intensive nature, the seasonal shortage of skilled laborers, and the aging workforce. The high demand for fresh market produce has increased the need for mechanized and robotic harvesting systems in greenhouses and orchards.

Chapter 15 discusses the robotic orchard and greenhouse fruit harvesting and its challenges and future trends. In this regard, greenhouse and orchard fruit harvesting has posed a challenge due to being time-consuming and labor-intensive, as well as the seasonal shortage of skilled laborers and the aging workforce. The high demand for fresh market produce has led to an increased need for mechanized and robotic harvesting systems in greenhouses and orchards. Greenhouse automation applications have a high demand due to their success and the efficiency they bring to fruit production.

Chapter 16 reports on the development of small-scale autonomous seed and fertilizer broadcasting machinery. Fertilizer application in agriculture is one of the essential operations, not only for open-field cultivation but also for orchards and indoor cultivation. Broadcasting techniques can be used not only for seeding but also for fertilizer applications. Small-scale farmers in developing countries need to develop their farming operations through mechanization. Moreover, the agricultural sector faces challenges such as climate change and a labor shortage of skilled workers, so farming operations must be conducted promptly and skillfully.

Chapter 17 discusses the design and fabrication of an autonomous weeder for agricultural fields. Specifically, escalating global warming and shifting temperatures necessitate the implementation of advanced technologies in agriculture to increase farmland productivity. Agricultural systems worldwide rely on seasonal rainfall and other environmental factors to contribute to food production. Farmers in Myanmar and other South Asian countries have recently faced a decrease in crop yields due to the abundance of weeds in their agricultural fields, which is facilitated by subtropical climates. With the increased risk of farm laborers moving to industrial sectors in search of employment, farmers in Myanmar face challenges in securing labor for weed management throughout the year.

Chapter 18 discusses the weeding techniques in tropical places for cassava plantations, which require significant labor input in tropical climates. This comprehensive and detailed review chapter provides a comprehensive overview of weeding techniques available for cassava plantations in tropical areas. It covers mechanical, organic, and chemical methods for weed control, including the timing and density of weeds present in those areas. The chapter also thoroughly examines the weed management efficiency in the chemical, organic, and mechanical aspects of the tropical area and summarizes the most appropriate methods of weed management in cassava plantations.

Chapter 19 placed a strategic short communication note that concisely mentioned the AI agent system for agricultural water resources management. Agricultural water resources face increasing pressure due to climate variability, rising food demand, and limited water availability. Efficient and adaptive management strategies are crucial for maintaining agricultural productivity while ensuring environmental sustainability.

Chapter 20 reported an IoT-assisted dual supply solar food drying system for tropical agricultural conditions. The world's population is projected to expand to 9.1 billion by 2050, necessitating a 70% increase in food production. Post-harvest losses (PHL), estimated at 20–60% of food products, exacerbate the food demand-supply gap, especially in developing countries. PHL is a key issue in global farming, undermining efforts to achieve better food access, poverty reduction, and sustainable development. PHL results in considerable losses in both food quantity and quality, affecting not only the ready accessibility of food for consumption but also the sustained financial health of farmers. Minutes, outperforming single-source systems by reducing drying time by 100 minutes.

Chapter 21 examined the technological advancements in thermal drying, with a focus on microwave and heat pump drying systems that are enhanced by Artificial Intelligence (AI) and the Internet of Things (IoT). By integrating these Industry 4.0 technologies and the concept of Industry 5.0, food drying processes are being transformed into intelligent, adaptive systems that minimize nutrient losses, retain sensory attributes, and improve energy efficiency.

Chapter 22 outlined the challenges and opportunities for AI and IoT Technology in contemporary avian production systems. Artificial intelligence (AI) and the Internet of Things (IoT) can transform poultry farming production systems. Key applications include automated health diagnostics, precise climate control within homes, and advanced tracking of individual animals, as well as quality assessment. As data-driven decision-making technology evolves rapidly, challenges and opportunities for applying novel technologies are surging—driven in part by broader trends in digital transformation (DX) across the agriculture sector. This chapter thoroughly analyzes how recent groundbreaking AI-based algorithms and IoT systems innovations can benefit poultry farming practices. In addition, the chapter addresses broader issues related to adopting these technologies, including the ethical implications of implementing AI-based systems and concerns about the socio-economic impacts on farming communities.

Chapter 23 concluded the discussion on AI and IoT integration in farm management, describing the details of integrating technologies for sustainable agriculture in changing climates. Climate change fundamentally reshapes global agricultural dynamics, threatening food security through rising temperatures, erratic precipitation, extreme weather events, and shifting ecological zones. This chapter comprehensively analyzes how integrating Artificial Intelligence (AI) with climate-adaptive agricultural strategies can revolutionize food production, resource management, and resilience building in the face of climate variability.

This book concludes the chapters discussed in this book. This book highlights four domains: smart outdoor production and indoor production systems, management for increasing productivity, post-harvest management, and 4 non-destructive quality measurements. Overall, this book conveys a message about the intersection of IoT and AI in agriculture, focusing on strategies to Develop Smart Agricultural Spaces for In-field and In-house crop production.

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Acknowledgments

The Tsukuba Conference (TC) and Tsukuba Global Science Week (TGSW) have created a common platform, hosted by the University of Tsukuba, for global communication among researchers, universities, and industry. In 2025, Tsukuba Conference (TC), the joint special session “AI and IoT to Integrate Automation in Farm Management: A Path to Sustainable Agriculture” with the University of Tsukuba and National Agricultural Research Organization (NARO) has consistently contributed to collaboration over the years and has the privilege of hosting experts from diverse countries who generously share their experiences and expertise. Our focus has centered on integrating agriculture with transboundary approaches, including the incorporation of AI and IoT-based big data systems to sustain food security. The invaluable knowledge exchange during these conferences has encouraged me to enhance the third edition of the book by providing additional content and insights from this year’s TC 2025 session.

I would like to express my appreciation to our disguised speakers: Ryozo Noguchi (Kyoto University Japan), Mimin Muhamin (Universitas Padjadjaran, Indonesia), Lin Tao (Zhejiang University), Ming-Che Hu (National Taiwan University, Taiwan), Kriengkri Kaewtrakulpong (Kasersart University, Thailand), Syafiq Fauzi Kamarulzaman (Universiti Malaysia Pahang Al-Sultan Abdullah, Malaysia), Yong-Joo Kim (Chungnam National University), Frevy T. Orencia (Benguet State University, the Philippines), and Genkawa Takuma (National Agricultural Research Organization and University of Tsukuba, Japan) for joining to this session. There are a few strategic short notes from the speakers that played an important role in introducing the concept of each section of the book and fostering interdisciplinary research ideas for readers. Their support during the recent TC2025 as our distinguished speakers has been invaluable, and including their insights in this edited version is indeed a significant contribution.

In addition to the contributions to our laboratory from the University of Tsukuba, I would like to express sincere gratitude and appreciation to our international contributors, Bangladesh Research Council (BARC), and Dr. Shahriar Abdullah Al-Ahmed from the University of West Scotland, United Kingdom, for the time devoted to preparing and reviewing the chapters to provide a comprehensive concluding chapter.

This third edition of the book comprises 23 chapters. Bringing all the concepts together into one cohesive framework required tremendous effort, and this effort would not have been possible without the exceptional dedication of the team. In this regard, I would like to express special appreciation to my committed team of PhD and master's degree students for their tireless efforts in cross-checking, updating, and formatting the book. I extend my hearty gratitude to Bryan Vivas Apacionado who demonstrated exceptional leadership by taking the lead in managing the team, efficiently distributing tasks, editing, creating figures, and overseeing the book's progress from the initial stage to final submission. I believe that I could not have finished this third edition without Bryan's continuous support and dedication. Additionally, R. M. Rasika D. Abeyrathna, Jiang Ailian, Liu Zifu, Nakaguchi Victor Massaki, Opasatian Ithiphat, Sampurno Rizky Mulya, Md. Hanif, and Ottoni Neves Jose Luiz provided invaluable support in the literature review, layout formatting, and cross-checking of the references for this book over the last few months. The success and outcome of this book were made possible by the considerable efforts of each team member. I am grateful for their unwavering support, assistance, and patience in the collaborative process, which ultimately led to the succinct production of this second edition. In addition to my dedicated team, I would like to express my gratitude to Nelundeniyage Sumuduni L. Senevirathne and Katiyape Samarasekarage Hasini Nimanthi, PhD students from our graduate school, for their assistance in reviewing several chapters for formatting and clarity. Special thanks to W. P. Pamoda Madhushani Wijesinghe for developing outstanding figures for this book. I feel incredibly privileged and fortunate to have such an outstanding team, whose contributions were instrumental in ensuring the successful completion of the book.

I would like to acknowledge the support that I have received from the University of Tsukuba, and enabled our researchers to reach other collaborators, motivating us to further extend our networks by sharing knowledge.

Finally, I would like to thank Springer-Nature for collaborating with me by refereeing our TGSW/TC sessions at the University of Tsukuba and extending our session outcomes as the third book.

Tofael Ahamed

Contents

Chapter 1
Field-Based High-Throughput Plant Phenotyping of Selected Horticultural Crops

Bryan Vivas Apacionado and Tofael Ahamed

Abstract High-throughput plant phenotyping (HTPP), initially developed for model plants in controlled environments, has recently transitioned to the more challenging context of field crop phenotyping. Despite difficulties from unstable environmental conditions, technological advancements have made efficient and precise field phenotyping feasible, enabling the assessment of crops in their actual growing environments using platforms like satellites, unmanned aerial vehicles (UAVs), and unmanned ground vehicles (UGVs). High-throughput field phenotyping (HTFP) is vital for diverse and structurally complex horticultural crops. These crops are critical for nutritional security but have received less attention in phenotyping research, creating a significant knowledge gap. This chapter addresses this gap by reviewing key high-throughput field phenotyping (HTFP) technologies and advanced imaging sensors—including RGB, thermal, and hyperspectral—applied to selected horticultural crops. Moreover, this chapter highlights practical, "fit-for-purpose" strategies powered by machine learning, from 3D yield estimation in apples to stress and disease detection in mangoes, tomatoes, grapes, and chili peppers. While significant challenges in cost, data standardization, and analysis remain, future advances in sensor fusion, AI-driven autonomy, and the deep integration of phenomic with genomic data are anticipated. This synergy is poised to accelerate the development of resilient, high-quality horticultural crops, ultimately strengthening global food systems.

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1.1 Introduction

In the quest to feed a growing global population under the pressures of a changing climate, a central challenge for modern agriculture lies in establishing a clear connection between a plant's genetic blueprint (genotype) and its observable characteristics (phenotype) (White et al., 2012). This understanding is paramount for selecting the high-yield, stress-tolerant cultivars required to meet future demands. Plant phenotyping, which refers to the detailed evaluation of complex plant traits like development, growth, stress resistance, and yield, is the key to unlocking this relationship (Li et al., 2014). It plays an essential role in plant science and agriculture by allowing researchers to accurately assess how plant traits respond to environmental conditions, genetic diversity, and stress factors, thereby supporting the development of more resilient and better-adapted crops (Hamidon & Ahamed, 2024).

Crop phenotyping traits are commonly categorized according to their relevance to the four principal goals of modern agriculture: yield enhancement, stress resistance, product quality, and nutritional value (Fig. 1.1). These primary phenotyping goals are strongly associated with crops' morphological and structural

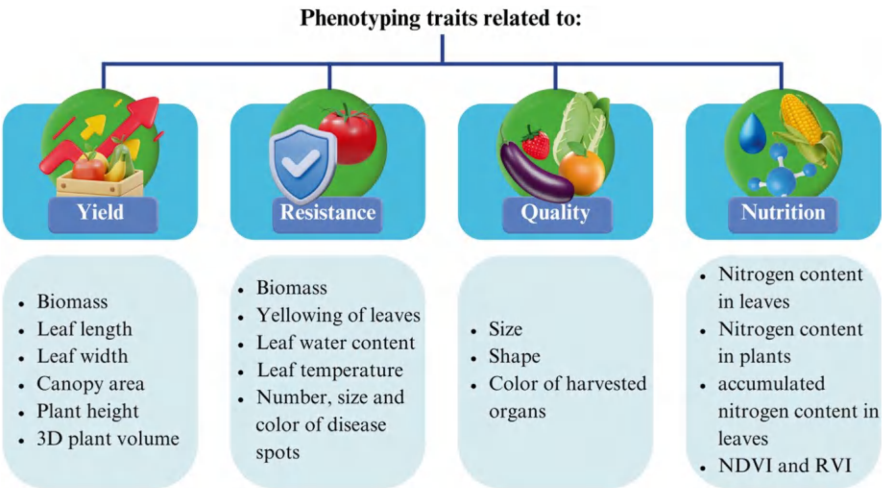

Fig. 1.1 Classification of crop phenotyping traits and their typical characters based on Yuan et al. (2023)

characteristics, such as crop height, crown breadth, coverage, biomass, leaf length, leaf width, and fruit characteristics (Yuan et al., 2023). The resulting data can guide germplasm selection in early-stage breeding and later serve as a critical foundation for the precise management of crop growth (Yang et al., 2020).

Historically, the advent of high-throughput genotyping revolutionized plant breeding by providing unprecedented access to the genetic blueprints of crops. However, the ability to rapidly and accurately measure the corresponding physical traits lagged significantly, creating a significant "phenotyping bottleneck" (Ninomiya, 2022). This gap hindered the progress of genomic-assisted breeding techniques like genome-wide association studies (GWAS) and marker-assisted selection (MAS), which depend on robust phenotypic data to connect genetic information to real-world performance (Jangra et al., 2021).

To bridge this divide, high-throughput plant phenotyping (HTPP) has emerged as a critical and transformative discipline (Sheikh et al., 2023). Initially, the development of HTTP was focused on indoor applications for model plant species under controlled environments. However, this focus subsequently shifted to the more challenging context of field-grown crops. While phenotyping in the field is considerably more difficult due to unstable environmental conditions, recent technological advances have made it increasingly feasible.

The evolution from controlled indoor settings to real-world field conditions represents a significant leap forward. Indoor HTPP allows for precise measurements of individual plant architecture and physiological traits, which is particularly valuable for genetic mapping and understanding specific stress responses (Yang et al., 2020). However, the ultimate test of a crop's performance is in the field. Field-based HTPP, often employing ground-based platforms, unmanned aerial vehicles (UAVs), and even satellites, enables the assessment of crops in their actual growing environments (Li et al., 2014). Though complicated by environmental variability, this approach provides invaluable data on how crops perform under real-world conditions (Araus & Cairns, 2014).

Recent advances have begun to replace costly, labor-intensive, and destructive traditional methods with automated, high-throughput systems enhanced by artificial intelligence (Gill et al., 2022). HTTP employs sophisticated imaging technologies, sensor networks, robotics, and advanced data analytics to conduct rapid, non-invasive, and scalable assessments of plant systems (Yang et al., 2020). By enabling the quick and precise evaluation of traits like development, productivity, and disease resistance across extensive populations, this approach provides the comprehensive data needed to break the phenotyping bottleneck. Ultimately, by synergizing advancements in genotyping with these powerful new phenotyping capabilities, both in controlled environments and in the field, researchers are better equipped to develop the superior crop varieties needed to ensure future food security.

1.2 Importance of High-Throughput Field Phenotyping in Horticultural Crops

Horticultural crops, such as fruits, vegetables, and ornamentals, are vital to global food systems for their significant contributions to economic development and nutritional diversity. However, their immense morphological diversity and complex growth habits present unique challenges for trait assessment. Consequently, these crops have received comparatively less attention in high-throughput plant phenotyping (HTPP) research than major cereal and grain crops, creating a notable knowledge gap (Amby et al., 2025).

High-throughput field phenotyping (HTFP) offers a transformative opportunity to bridge this gap. While field analysis introduces hurdles like fluctuating environmental variables and complex plant architectures, modern HTFP technologies are increasingly able to overcome these issues. They enable the rapid, non-destructive, and precise measurement of complex traits—such as fruit size, color, maturity, and stress tolerance—directly in their natural growing environments (Furbank & Tester, 2011). This capability is particularly crucial for perennial fruit crops that cannot be easily evaluated in controlled indoor settings.

Ultimately, integrating HTFP into research and breeding programs is critical for advancing the productivity and sustainability of horticulture. By providing reliable, high-resolution data on critical traits, these technologies enhance breeding efficiency, support precision agriculture, and accelerate the development of resilient, high-quality cultivars tailored to meet both market and climatic demands.

1.3 Technologies and Tools for High-Throughput Field Phenotyping

High-throughput field phenotyping (HTFP) leverages a variety of advanced equipment and tools to capture extensive, precise data across large-scale agricultural fields. Each tool plays a specific role in measuring traits that impact yield, quality, and stress resilience. The technologies described in this section—imaging systems, UAVs, ground-based vehicles, and Internet of Things (IoT) devices—create an integrated system to automate and streamline data collection and analysis for horticultural field crops.

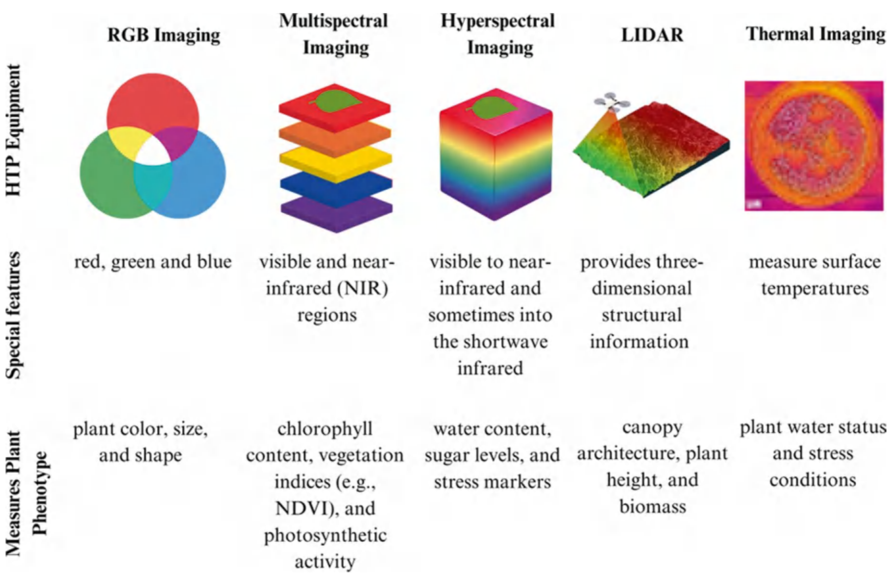

Fig. 1.2 Standard imaging systems used in high-throughput plant phenotyping

1.3.1 The Sensor Toolkit: From Photons to Phenotypes

HTPP relies on multiple imaging techniques to capture various plant traits at different resolutions. These imaging systems include RGB, multispectral, hyperspectral, LIDAR, and thermal cameras, each contributing unique data insights essential for accurate phenotyping (Fig. 1.2).

RGB Imaging Visible light sensors operate within the 400–700 nm wavelength range, capturing reflectance in the red, green, and blue (RGB) spectrum. RGB cameras are widely used in high-throughput phenotyping because they capture high-resolution color images that reflect visible plant traits. Due to their affordability, ease of use, and widespread availability, visible light imaging has become a common and practical tool for high-throughput phenotyping applications (Kim & Chung, 2021). These cameras are particularly effective for assessing morphological features such as plant size, shape, and color, indicative of growth stage, leaf area, and overall plant health. Their relatively low cost and ease of deployment make RGB imaging a practical and scalable solution for field-based phenotyping, especially in large-scale or resource-limited settings. However, in field applications, the effectiveness of RGB imaging may be limited by subtle color differences between plant leaves and the background and by variations in ambient lighting conditions, which can hinder the accuracy of automated image processing (Kim & Chung, 2021).

Multispectral Imaging Multispectral imaging is a non-destructive and cost-effective technology that captures reflectance across a limited number of spectral bands, typically including the visible and near-infrared (NIR) regions (Cao et al., 2024). This capability allows for assessing physiological traits such as chlorophyll content, vegetation indices (e.g., NDVI), photosynthetic activity, essential indicators of plant health, nutrient status, and stress conditions. The technology also enables the extraction of morphological and textural features from plant surfaces, as well as the characterization of biochemical components using spectral information from red-edge and NIR bands (Wang et al., 2018). Additionally, multispectral imaging has demonstrated effectiveness in crop quality monitoring, varietal identification, plant health, nutrient status, and disease symptoms underscoring its broad utility in precision agriculture and high-throughput phenotyping.

Hyperspectral Imaging Hyperspectral imaging acquires detailed spectral information across a broad wavelength range, typically spanning from the ultraviolet (UV) through the visible (VIS) and near-infrared (NIR) to the shortwave infrared (SWIR) regions (approximately 250–2500 nm). This technique simultaneously captures both spatial (x, y) and spectral (λ) data at each pixel, resulting in a three-dimensional dataset known as a hypercube (Sarić et al., 2022). The hypercube enables comprehensive analysis of plant traits by providing high-resolution spectral signatures that reflect biochemical and physiological characteristics with high sensitivity and precision. With these hyperspectral data, researchers can obtain detailed information on plant biochemical properties, such as sugar levels, moisture content (Bai et al., 2024), and stress markers. This imaging type is susceptible to subtle variations in leaf composition, enabling early detection of diseases (Shao et al., 2024) and nutrient deficiencies, which is especially valuable for precision agriculture and crop management.

LIDAR Light Detection and Ranging (LiDAR) is a remote sensing technology that employs laser pulses to measure the distance to target surfaces, enabling the construction of precise three-dimensional representations of plant structures (Tang et al., 2024). By capturing the return time of emitted laser beams, LiDAR provides detailed spatial information and surface contours, making it a powerful tool for analyzing plant architecture with high accuracy. This technology is particularly valuable in high-throughput phenotyping for quantifying plant height, canopy architecture, volume, and shoot biomass. LiDAR is especially beneficial for horticultural crops, where structural traits are closely linked to yield potential and disease susceptibility. Its capture of detailed growth dynamics and complex morphological features supports precise monitoring and analysis. However, the widespread adoption of LiDAR is hindered by several limitations, including high operational costs, sensitivity to slight variations in path length, the requirement for specific illumination in certain systems, and the computational demands of processing large datasets (Abebe et al., 2023). These challenges may restrict its practical application in extensive or time-sensitive field phenotyping programs.

Thermal Imaging Thermal imaging uses infrared sensors to capture surface temperature variations, offering valuable information on plant water status and stress responses. Thermal cameras generate spatially resolved temperature maps of plant surfaces by detecting emitted radiation in the thermal spectrum—typically within the 3–5 μm or 7–14 μm range (Abebe et al., 2023). These images visualize heat distribution at the pixel level, enabling non-invasive monitoring of physiological processes related to transpiration and drought stress. Thermal cameras measure surface temperatures, providing insights into plant water status and stress conditions (Mertens et al., 2023), transpiration, and stomatal behavior (Vialet-Chabrand & Lawson, 2020). Differences in leaf temperature often correlate with transpiration rates, which can indicate drought stress. This data helps farmers optimize irrigation schedules and detect early signs of water stress, contributing to resource-efficient agriculture practices.

1.3.2 Platforms for Field Phenotyping

Low-orbiting satellites, ground-based vehicles, and unmanned aerial vehicles (UAVs) have revolutionized HTPP by enabling rapid and scalable data collection across extensive fields (Fig. 1.3). These platforms can have various imaging systems, allowing for efficient, high-resolution data acquisition over different spatial and temporal scales.

Low orbiting satellites (LOS), particularly constellations of small satellites like CubeSats, represent a rapidly evolving frontier for field plant phenotyping, offering unprecedented spatial coverage and temporal frequency for monitoring agricultural systems at a large scale. These satellites are typically equipped with multispectral imaging sensors that capture data across various spectral bands, including the red-edge and near-infrared regions, which are crucial for assessing plant health and vigor (Johansen et al., 2022). By analyzing vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) derived from this imagery, researchers can estimate key phenotypic traits like canopy development, photosynthetic activity, biomass, and overall crop condition across thousands of plots simultaneously (Sishodia et al., 2020). The primary advantage of LOS is its ability to repeatedly monitor vast geographical areas, enabling the standardization of data collection for multi-location trials and reducing the costs and labor associated with ground-based or aerial methods (CIMMYT, 2022). However, limitations include a lower spatial resolution (e.g., ~3 m for PlanetScope) compared to UAVs, which may not be sufficient for individual plant analysis, and the data quality can be affected by atmospheric conditions such as cloud cover (Mudereri et al., 2019). Despite these challenges, the increasing availability of high-resolution, high-frequency satellite data is proving invaluable for large-scale genetic screening and enhancing the efficiency of breeding programs by enabling season-long monitoring of crop performance.

Ground-based vehicles have advanced field plant phenotyping by enabling critical plant trait data's high-throughput and non-destructive collection. These platforms, which range from manually pushed carts and tractor-mounted systems to

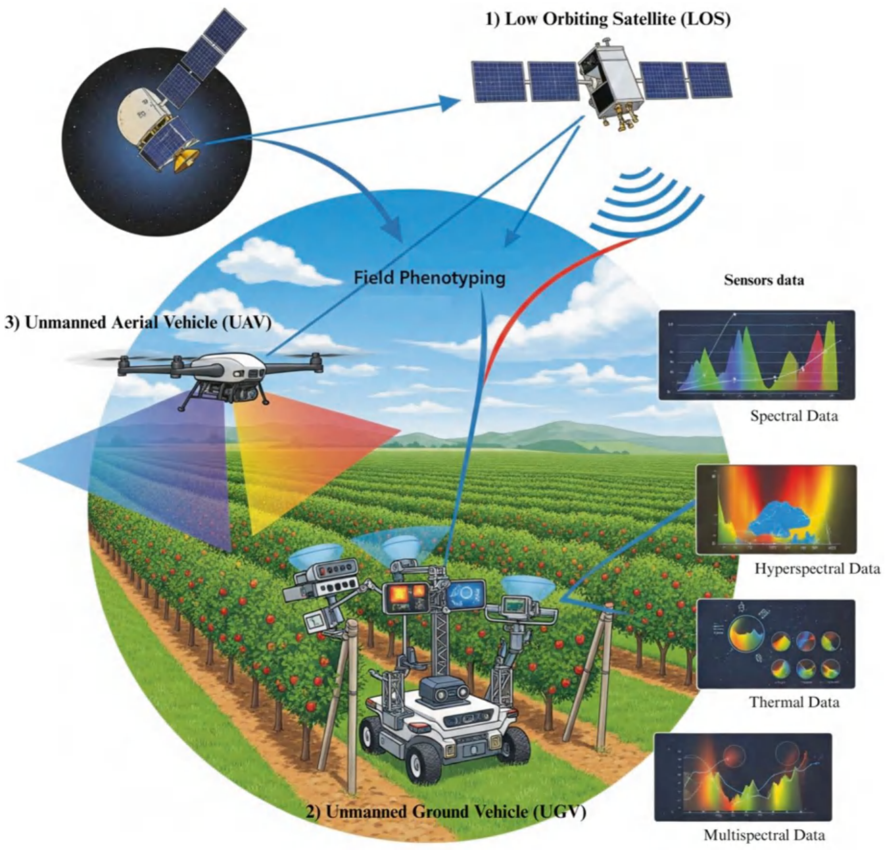

Fig. 1.3 Platforms for field phenotyping equipped with standard imaging sensors: (1) low orbiting satellite, (2) ground-based vehicle, (3) unmanned aerial vehicle

sophisticated autonomous robots, unmanned ground vehicles (UGVs), and large-scale gantry systems, are equipped with a diverse array of sensors to monitor plant growth, health, and development with high spatial and temporal resolution (White et al., 2012). Commonly deployed sensors include RGB cameras for morphological traits like plant height and canopy cover, multispectral and hyperspectral imagers for assessing physiological status and nutrient content, thermal cameras for monitoring canopy temperature as an indicator of water stress, and LiDAR for 3D architectural analysis and biomass estimation (Araus & Cairns, 2014). The primary advantage of these ground-based systems lies in their ability to capture detailed, plot-level data under fluctuating field conditions, providing valuable insights for genetic research, breeding programs, and precision agriculture (Busemeyer et al., 2013). However, challenges remain regarding the operational scalability for vast fields, potential soil compaction, and the complexity of data processing and interpretation. Despite these limitations, the continuous development of more autonomous and robust ground vehicles, coupled with advanced sensor technologies and data analytics, is overcoming many of these obstacles, solidifying their role as a cornerstone of modern field phenotyping.

Unmanned aerial vehicles (UAVs) or drones equipped with cameras and sensors are widely used in HTFP for aerial data collection to serve as a practical remote sensing tool that bridges the gap between time-consuming ground-based measurements and large-scale satellite or aerial observations (Gago et al., 2015). Researchers can monitor crop health, estimate canopy cover, and analyze spatial variations in plant growth by capturing high-resolution images of plant canopies. UAVs are particularly advantageous for measuring canopy-level traits, such as leaf area index, canopy temperature, and vegetation indices, which help identify stress patterns and growth dynamics across large areas (Sankaran et al., 2015). The ability of UAVs to rapidly survey extensive trial plots at high spatial and temporal resolutions provides unprecedented insights into plant growth dynamics and their response to environmental conditions, which is invaluable for breeding programs and precision agriculture (Araus & Cairns, 2014). While challenges related to data processing, sensor calibration, and regulatory constraints exist, the scalability and flexibility of UAV-based phenotyping offer significant advantages over ground-based systems, particularly in terms of coverage and speed, making it a pivotal technology in modern agricultural research.

1.4 Phenotyping in Practice: Crop-Specific Applications and Methodologies

The theoretical capabilities of HTFP platforms and sensors are best understood through their practical application to specific horticultural challenges. The following sections detail recent research demonstrating how these technologies are deployed to phenotype apple, mango, tomato, grapes, and chili pepper.

1.4.1 Apple Orchards: 3D Reconstruction for Yield and Quality

A primary challenge in apple production is the accurate pre-harvest estimation of yield. The complex 3D structure of apple trees and the significant occlusion of fruit by leaves make simple top-down imaging approaches ineffective (Hobart et al., 2025). To overcome this, researchers have developed methodologies centered on 3D reconstruction using low-cost UAV platforms (Fig. 1.4).

The typical methodology involves conducting low-altitude flights, for instance, 10 m above the canopy, using a consumer-grade RGB camera mounted on a UAV (Atefi et al., 2021; Hobart et al., 2025). To capture the sides of the tree crowns where

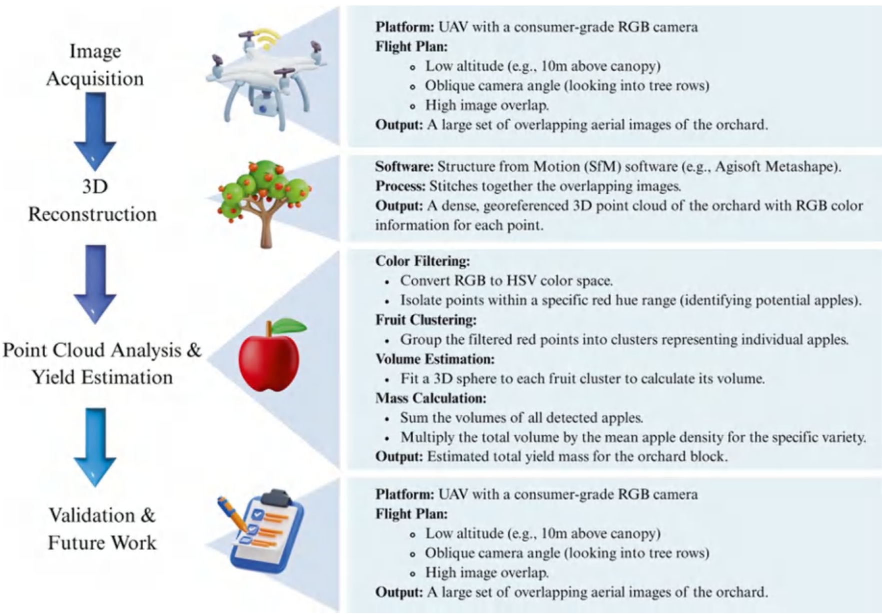

Fig. 1.4 Apple 3D reconstruction for yield and quality

many fruits are located, flights are often performed with the camera at an oblique angle, looking into the neighboring tree rows rather than straight down. A high degree of image overlap is maintained to ensure robust 3D reconstruction. The collected images are then processed using SfM software (e.g., Agisoft Metashape) to generate a dense, georeferenced 3D point cloud of the entire orchard block, where each point retains its original RGB color information (Hobart et al., 2025).

Analysis of this point cloud leverages color information and 3D spatial data. An algorithm first filters the point cloud to isolate points corresponding to ripe apples, typically by transforming the RGB color data into the Hue-Saturation-Value (HSV) color space and selecting points within a specific red hue range. These red points are then clustered to identify individual fruits. A key component of yield, a 3D sphere, is fitted to each fruit cluster to estimate fruit volume. Finally, the total yield mass for a block of trees is calculated by summing the volumes of all detected apples and multiplying by a pre-determined, variety-specific mean apple density (Hobart et al., 2025; Atefi et al., 2021).

This UAV-based 3D modeling approach has shown remarkable success, achieving a coefficient of determination (R^2) as high as 0.76 when correlating the estimated yield mass with actual, manually harvested yield data. Research has also provided practical insights into optimizing the methodology; for example, a flight altitude of 10 m was found to produce more accurate yield estimates than a lower altitude of 7.5 m, likely due to a more stable image acquisition and better overall model geometry (Hobart et al., 2025). Despite these successes, challenges remain, including the persistent underestimation of apple counts due to occlusion and difficulties separating clustered fruits. To address this, emerging research explores using coordinated multi-UAV systems to simultaneously capture data from more angles, thereby improving canopy coverage and reducing data loss (Melnychenko et al., 2024).

1.4.2 Mango Groves: Fused Sensing for Canopy Structure and Water Stress

Mango trees present a different challenge: their large, structurally complex canopies make it difficult to assess overall plant health and, in particular, water status, which is critical in the tropical and subtropical regions where they are grown. Research on mango phenotyping exemplifies the power of fusing data from multiple platforms to achieve a more comprehensive assessment (Fig. 1.5).

The methodology centers on combining the strengths of high-spatial-resolution multispectral UAV imagery with the superior spectral range of satellite data. A multispectral UAV can capture images at a resolution of 5 cm, but its sensors may not cover the SWIR bands crucial for water content assessment. In contrast, the Sentinel-2 satellite provides these SWIR bands with a spatial resolution ranging from 10 to 60 m. Using an AWT fusion algorithm, these two datasets are merged to create a single, high-resolution (5 cm) dataset that contains the full range of spectral bands from the satellite (Liu et al., 2025).

This robust fused dataset calculates a suite of vegetation indices sensitive to water content—such as the Normalized Difference Water Index (NDWI) and Moisture Stress Index (MSI). These indices and structural information are then fed into various machine learning models (e.g., Random Forest, SVM, GABP neural networks) to predict canopy water parameters measured on the ground (Liu et al., 2025). In addition to water status, researchers are also developing mango-specific indices derived from UAV imagery, such as the Mango Tree Yellowness Index (MTYI) and the Normalized Automatic Flowering Detection Index (NAFDI), to precisely track key phenological stages like flowering, which is directly linked to final yield (Afsar et al., 2025).

The results of this data fusion approach are compelling. The fused data consistently and significantly outperforms models trained on UAV data alone. The Genetic Algorithm Backpropagation Neural Network (GABP) model proved to be the most effective, achieving an R^2 of 0.859 and an RMSE of 0.001 g/cm^2 for estimating EWT, a key measure of water content at the leaf level. The research also found that Canopy Water Content (CWC), which integrates EWT with LAI, was the most sensitive indicator of environmental changes and provided the most reliable representation of the overall water status of the mango canopy (Liu et al., 2025).

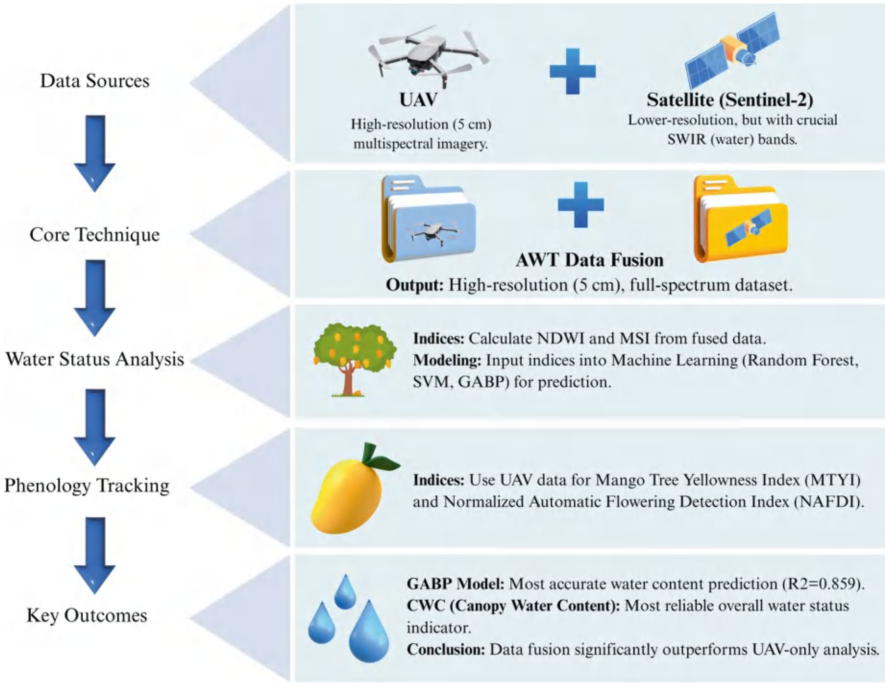

Fig. 1.5 Fused sensing for canopy structure and water stress of mango

1.4.3 Tomato Systems: Multi-Platform Assessment of Fruit and Disease

Tomatoes are a globally significant horticultural crop grown in diverse systems, from open fields to high-tech greenhouses. HTFP in tomatoes addresses the dual needs of monitoring fruit development and quality and managing a high susceptibility to various diseases (Fonteijn et al., 2021).

UGVs have proven highly effective for fruit detection and quality assessment, particularly in controlled greenhouse environments. Robotic platforms like the “Phenobot” are equipped with multiple RGB-D (depth) cameras, such as the Intel RealSense, and are programmed to autonomously navigate the rows of a greenhouse (Fonteijn et al., 2021). Stopping at regular intervals, the UGV captures close-range, side-view images of the plants. These images are then analyzed using advanced deep learning models. The Mask R-CNN architecture, in particular, has become a state-of-the-art method for segmentation, allowing it to detect and precisely delineate the boundaries of each tomato. This technique has been used to detect and count both ripe (red) and unripe (green) tomatoes with outstanding accuracy, achieving precision and recall rates greater than 0.90 at a standard 0.5 Intersection-over-Union (IoU) threshold. Beyond simple counting, non-destructive spectroscopic methods are also being explored. Handheld Raman spectrometers, for example, can analyze the chemical composition of the fruit surface to quantify key quality compounds like lycopene and other carotenoids, offering a rapid tool for breeders to select for enhanced nutritional profiles (Akpolat et al., 2020).

A multi-platform approach is often necessary for disease and stress management in the field (Fig. 1.6). UAVs equipped with multispectral and thermal sensors screen for abiotic stresses like salinity. By monitoring changes in plant growth rates and canopy temperature, researchers can identify stress responses; one study found that a Crop Water Stress Index (CWSI) value greater than 0.36 was a reliable indicator of salinity stress in tomato plants (Stutsel et al., 2021). For disease detection, which often requires higher resolution, deep learning models are applied to images to identify symptoms. Architectures like YOLOv5 and custom-built CNN-based Single Shot Detectors (SSD) have been used to identify foliar diseases and fruit rot with very high accuracy, in some cases exceeding 98% for detecting diseases on the fruit itself (Nyarko et al., 2023). Recognizing the complementary strengths of aerial and ground platforms, projects like HuskyBot2.0 aim to create a coordinated system where a UAV performs initial large-scale screening for potential problem areas, which then directs a UGV to perform detailed, inside-canopy inspections with its robotic arm and endoscope for definitive diagnosis (Karkee et al., 2024).

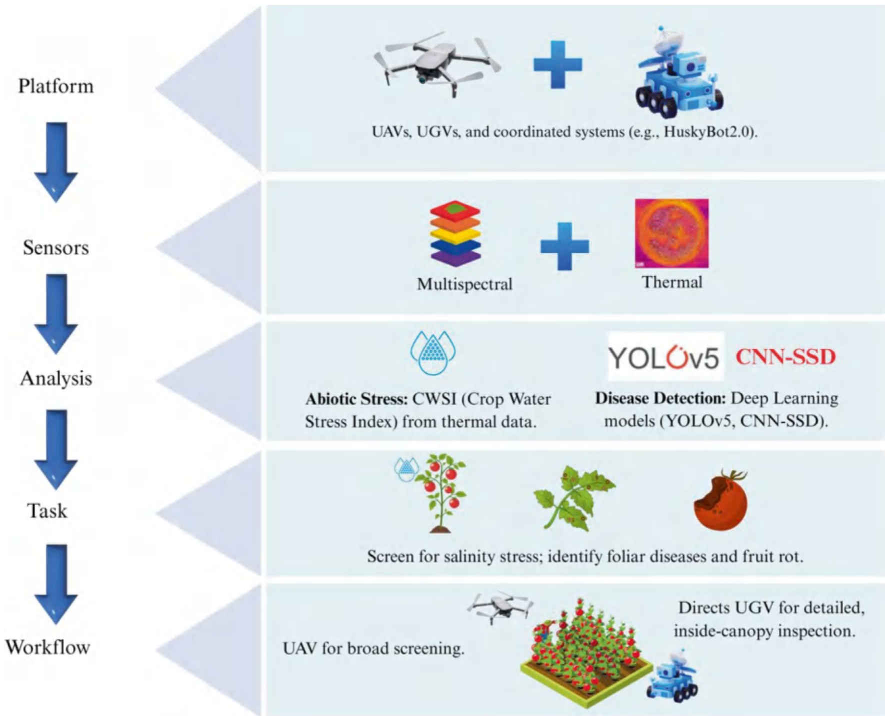

Fig. 1.6 Multi-platform assessment of fruit and disease of tomato

1.4.4 Grapes: Thermal Imaging for Precision Irrigation

In viticulture, water availability is arguably the most critical manageable factor influencing both grape yield and the final quality of the wine (Atencia Payares et al., 2025). Therefore, a primary focus of HTPP in vineyards has been the development of tools for precision irrigation management, which requires an accurate, spatially explicit assessment of vine water status (Fig. 1.7).

The principal technology for this application is thermal imaging deployed on UAVs (Santesteban et al., 2017; Pineda et al., 2021). Grapevines experience a water deficit, and they respond by closing their stomata to reduce water loss through transpiration. This reduction in evaporative cooling causes the canopy temperature to rise, a signal that is effectively captured by high-resolution thermal cameras mounted on UAVs (Santesteban et al., 2017).

The Crop Water Stress Index (CWSI) calculation is the most widely used analytical method. This index normalizes the measured canopy temperature by comparing it to the temperatures of theoretical "wet" (entirely transpiring) and "dry" (non-transpiring) reference surfaces, providing a standardized measure of stress that accounts for ambient environmental conditions (Santesteban et al., 2017; Pineda et al., 2021). UAV-derived CWSI values have been shown to correlate strongly with ground-truth physiological measurements. For example, studies have reported coefficients of determination (R^2) as high as 0.91 between CWSI and stomatal conductance, a direct measure of stomatal opening (Sagan et al., 2019).

More advanced, physically based approaches like the Two-Source Energy Balance (TSEB) model are also gaining traction. Instead of relying on empirical reference temperatures, the TSEB model uses thermal and multispectral data to partition the energy fluxes between the vine canopy and the soil surface. This allows for a direct estimation of canopy transpiration, which is a more direct and robust indicator of the plant's physiological water use than bulk canopy temperature

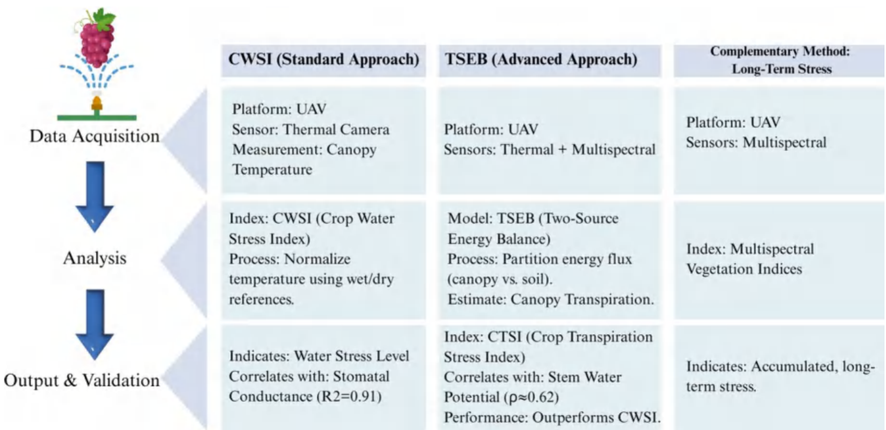

Fig. 1.7 Thermal imaging for precision irrigation of grapes

(Ortega-Farias et al., 2021). Stress indices derived from these partitioned canopy fluxes, such as the Crop Transpiration Stress Index (CTSI), have demonstrated even stronger correlations with physiological ground-truth data like stem water potential (Spearman's ρ = 0.61–0.62) compared to traditional CWSI ($\rho \approx 0.55$). Research also suggests that while thermal imaging is excellent for detecting short-term, dynamic changes in water status, multispectral indices can serve as reliable long-term indicators of accumulated water stress over the season (Atencia Payares et al., 2025).

1.4.5 Chili Pepper Fields: Advanced Sensing for Covert Stress

Chili pepper phenotyping showcases the application of the most advanced sensing technologies to detect "covert" or hidden stresses—physiological problems that are not yet visible to the naked eye but can lead to significant yield and quality loss if left unmanaged (Pineda et al., 2021; Shao et al., 2024).

One such challenge is the early detection of root rot, a soil-borne disease that impairs the plant's ability to transport water and nutrients but whose initial symptoms on the leaves are subtle (Shao et al., 2024). UAV-based hyperspectral imaging has emerged as a powerful tool for this task (Fig. 1.8). By capturing the detailed spectral reflectance of the leaves, it can detect minute changes caused by the underlying stress. Another critical application is monitoring nutrient status. Hyperspectral imaging has created detailed spatial maps of Total Nitrogen Content (TNC) within pepper plants, identifying the narrow wavelengths most sensitive to nitrogen-related compounds and allowing for targeted fertilizer application (Yu et al., 2014). Thermal imaging has also been applied to detect biotic stress, successfully identifying the distinct temperature anomalies caused by viral infections like the Pepper Mottle Virus (PMMoV), in some cases before visual symptoms fully develop (Pineda et al., 2021).

The analysis of this complex, high-dimensional data relies heavily on machine learning. For hyperspectral data, a typical workflow involves using a feature selection algorithm, such as the Successive Projections Algorithm (SPA), to reduce the hundreds of spectral bands to the few most informative for the task. These key wavelengths are then used as inputs for classification models like Partial Least Squares Discriminant Analysis (PLS-DA), Support Vector Machines (SVM), or Backpropagation (BP) neural networks to classify the plant's health status. This approach has yielded impressive results for root rot detection, with an SPA-BP model achieving a classification accuracy of 92.3%. Demonstrating the potential for developing rapid field tools, a simpler model based on a Normalized Difference Spectral Index (NDSI) using just two key wavelengths (R445 and R433) still achieved a high accuracy of 89.7%, making it suitable for implementation in a portable, real-time detector (Shao et al., 2024). Similarly, for nitrogen assessment, Partial Least Squares Regression (PLSR) models based on key wavelengths selected

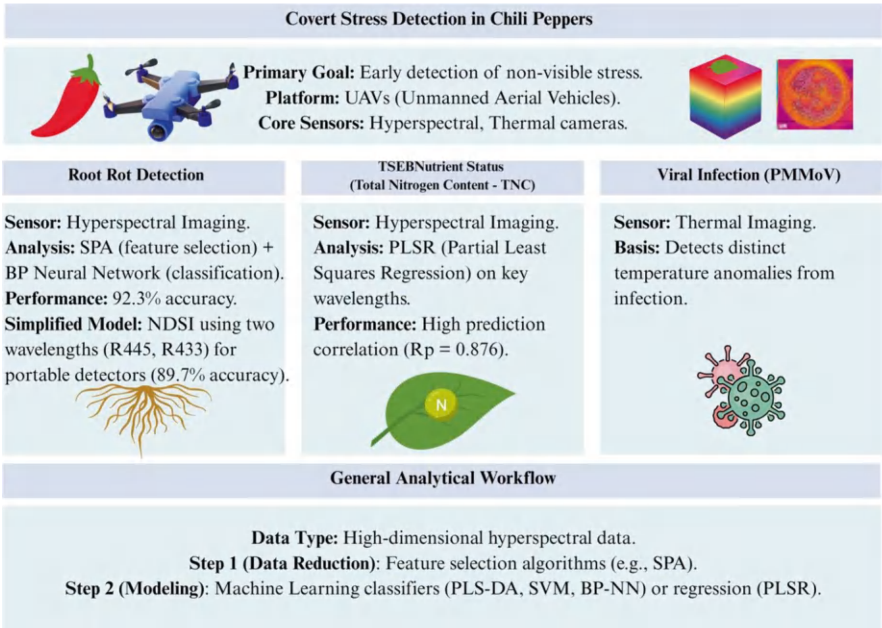

Fig. 1.8 Advanced sensing for the covert stress of chili pepper

from hyperspectral data can predict TNC with a high prediction correlation coefficient (Rp) of 0.876 (Yu et al., 2014).

1.5 Challenges and Opportunities in High-Throughput Field Phenotyping

Despite rapid progress, several significant challenges must be addressed to unlock the full potential of HTFP in horticulture (Fig. 1.9). A pressing need exists for standardized protocols for data acquisition and management, as the current lack of common standards hinders the comparison of results and the creation of extensive, robust "big data" repositories needed for training advanced AI models (Jangra et al., 2021). Cost and accessibility also remain significant barriers. At the same time, basic UAVs are more affordable, advanced sensors like research-grade hyperspectral and LiDAR systems are prohibitively expensive for many, limiting their widespread adoption. This influx of technology has created a new data analysis bottleneck, where the sheer volume and complexity of HTFP data require significant computational power and specialized expertise, highlighting a need for more user-friendly and automated analytical pipelines (Jangra et al., 2021). Finally, all remote sensing estimations depend on rigorous validation against laborious and

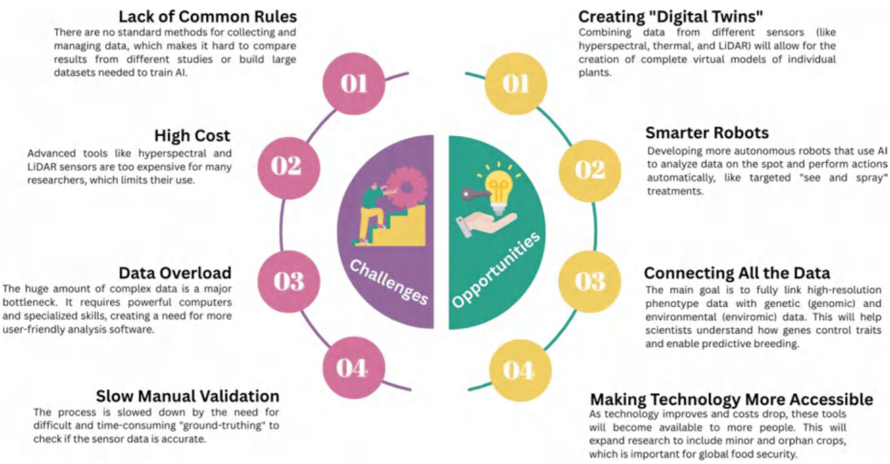

Fig. 1.9 Challenges and opportunities of high-throughput field phenotyping

time-consuming "ground-truthing," which remains a fundamental constraint on the overall throughput of the phenotyping process (Jangra et al., 2021).

The future of horticultural phenotyping is poised for further transformation, driven by advancements in sensor technology, artificial intelligence, and data integration. Key prospects include enhanced sensor fusion, moving beyond two-stream data to integrate multiple modalities like hyperspectral, thermal, and LiDAR to create comprehensive "digital twins" of individual plants. The next generation of robotic platforms will feature greater AI-driven autonomy, enabling data collection, real-time analysis, and automated interventions such as "see and spray" applications (Partel et al., 2019). The ultimate goal is the deep integration of this high-resolution phenomic data with genomic and enviromic data. This will allow researchers to finally unravel the complex genetic architecture of critical traits, enabling truly predictive breeding. As these technologies mature and costs fall, their democratization will expand HTFP tools to a broader range of users and, crucially, to minor and orphan crops, which is vital for enhancing global food security and promoting agricultural diversity (Jangra et al., 2021).

1.6 Conclusion and Prospects

High-throughput plant phenotyping marks a transformative shift in horticultural science, moving beyond the constraints of traditional, destructive measurements toward an era of non-invasive, data-rich crop assessment. The successful implementation of HTFP relies on a dynamic, multi-scale ecosystem of platforms, from the expansive view of satellites to the detailed aerial perspective of UAVs and the intricate, close-range view of UGVs. As demonstrated across diverse and structurally complex crops—apples, mangoes, tomatoes, grapevines, and chili peppers—there is no universal solution. Instead, effectiveness is achieved through a "fit-for-purpose" strategy, where the selection of platforms and sensors is meticulously tailored to the specific crop architecture and biological question. The immense volume of data generated by these systems is translated into meaningful biological knowledge through the essential power of machine learning and deep learning. These analytical engines are indispensable for tasks ranging from 3D yield estimation in dense apple canopies to the pre-symptomatic detection of disease in chili peppers. While significant challenges related to cost, data standardization, and analytical bottlenecks persist, the future trajectory is clear. The field is advancing toward enhanced sensor fusion for creating comprehensive "digital twins" of plants, greater AI-driven autonomy for real-time field interventions, and the ultimate integration of phenomic, genomic, and enviromic data. By continuing to address these challenges, HTFP is poised to break the phenotyping bottleneck, accelerate genetic gains, and empower precision management, ensuring the development of more resilient and productive horticultural crops for the future.

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Chapter 2
Development of a Raspberry Pi-Based Semi-Automated Primary Root and Shoot Length Measurement System for Tomato (*Solanum lycopersicum*)

W. P. P. M. Wijesinghe, K. S. H. Nimanthi, and Tofael Ahamed

Abstract Accurate quantification of root and shoot growth is essential for assessing plant development, but manual measurement methods are laborious and fail to capture the actual geometry of plant structures. This study presents a novel semi-automated system for non-destructive measurement of tomato (*Solanum lycopersicum*) root and shoot growth in an aeroponic setup. The low-cost system integrates a Raspberry Pi computer for automated image acquisition, custom software for user-guided annotation of root and shoot paths, and algorithms to extract length measurements from the annotated images. Tomato seedlings were grown aeroponically and imaged at regular intervals. Root and shoot paths were manually traced on the images using a mouse interface, enabling measurement of actual curved path lengths. The semi-automated system yielded shoot and root length measurements that were 30% and 40% longer, respectively, than manual linear methods by accounting for the contorted geometry of shoots and roots. It reduced measurement time by approximately 50% while increasing consistency threefold compared to conventional destructive techniques. This open-source platform provides a novel tool for researchers to efficiently and reliably quantify critical plant phenotypic traits in a non-destructive manner. Integration with aeroponic culture enables temporal studies of dynamic growth responses to environmental conditions. The framework can be readily adapted for phenotyping diverse crop species and will accelerate plant biology and breeding research efforts.

Keywords Agricultural automation · Image processing · Root and shoot length measurement · Root and shoot growth dynamics · Phenotyping · Aeroponic · Raspberry Pi

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2.1 Introduction

Accurate root and shoot growth measurement in plant science is crucial for understanding plant development, health, and responses to various environmental factors. However, traditional manual methods for quantifying these growth parameters are time-consuming, labor-intensive, and often destructive to the plant. Furthermore, they fail to capture root systems' actual geometry and complexity, leading to an underestimation of root lengths and surface areas. There is a growing need for advanced, non-destructive techniques that can efficiently and accurately measure plant growth traits to address these limitations (Hou et al., 2021).

2.1.1 Importance of Quantifying Root and Shoot Growth

Root and shoot development are critical aspects of plant growth that directly impact agricultural productivity and plant responses to environmental stresses (Furbank & Tester, 2011). The root system architecture, including the spatial arrangement, branching patterns, and total length of roots, determines a plant's capacity to acquire water and nutrients from the soil. Shoot growth, encompassing stem elongation and leaf expansion, influences a plant's photosynthetic capacity and yield potential.

Quantitative phenotyping of root and shoot traits illustrated in Fig. 2.1 can provide valuable insights into the genetic basis of plant growth, responses to abiotic and biotic stress factors, and the efficacy of agricultural management practices (Blaha, 2019). In particular, root phenotyping has been highlighted as a key bottleneck in improving crop resource use efficiency and stress tolerance. However, root systems are notoriously difficult to study due to their underground nature and complex three-dimensional architectures.

Conventional methods for measuring root growth rely on destructive sampling, soil excavation, and manual measurements of the longest root or total root length. These techniques are time-consuming and labor-intensive and fail to capture the dynamic nature of root development over time. Shoot growth is often measured similarly, with manual plant height measurements or total leaf area at discrete timepoints. New tools are needed to enable non-destructive, high-resolution, and high-throughput quantification of root and shoot development.

2.1.2 Advantages of Aeroponic Systems for Studying Plant Growth

Aeroponic culture systems offer several advantages over soil-based systems for studying plant root and shoot growth. In aeroponics, plant roots are suspended in a nutrient solution rather than soil, allowing for direct visualization and measurement

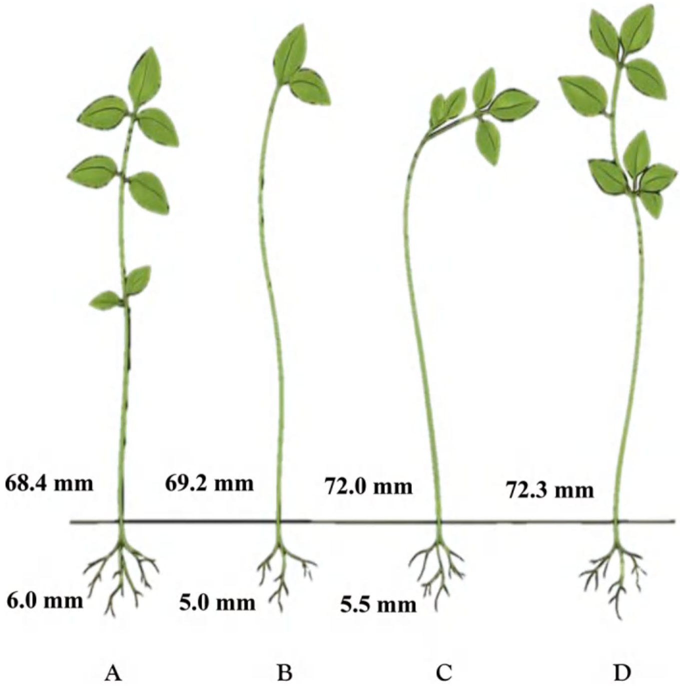

Fig. 2.1 Shoot and root length measurement

of root system architecture (Salma et al., 2024). This eliminates the need for destructive sampling and allows for non-invasive monitoring of root development over time.

Aeroponic systems in Fig. 2.2 also enable precise control over nutrient and water availability, pH, and other environmental factors influencing plant growth. This makes them ideal for studying plant responses to specific stresses or treatments in a standardized and reproducible manner. The ability to easily manipulate and monitor the root zone environment in aeroponics facilitates studies of root-shoot communication and whole-plant physiological responses.

For these reasons, plant biology research has widely used aeroponic systems to investigate nutrient uptake and transport, abiotic stress responses, root-microbe interactions, and plant growth regulation. Integration of novel phenotyping technologies with aeroponic culture has the potential to accelerate discoveries in these areas and advance our understanding of plant development.

2.1.3 Study Objectives

Building on these prior efforts, this study aimed to develop and evaluate a low-cost, semi-automated system for quantifying root and shoot growth of tomato plants grown in aeroponic culture. Specific objectives were to:

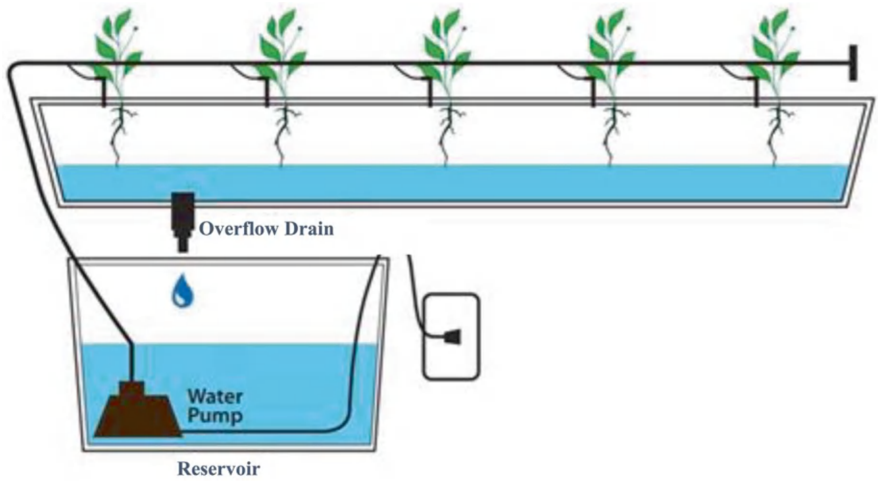

Fig. 2.2 Aeroponics system

(a) Integrate a Raspberry Pi camera with an aeroponic growth system to enable automated, non-destructive imaging of plant root systems and shoots over time.
(b) Develop custom software to facilitate user-guided annotation of root and shoot paths in the captured images and automatically extract length measurements.
(c) Compare the accuracy and efficiency of the semi-automated measurement approach to conventional manual techniques.

By coupling the non-destructive imaging capabilities of aeroponics with the flexibility and affordability of the Raspberry Pi platform, we aim to provide a new tool for enhancing plant growth studies and accelerating efforts to understand and improve plant form and function.

2.2 Methodology

The proposed system shown in Fig. 2.3 for measuring tomato plant primary root length integrates a Raspberry Pi with advanced image processing algorithms. The block diagram illustrates the system's architecture, which is designed to monitor and measure plant growth using a Raspberry Pi as the central processing unit. The Raspberry Pi receives real-time data from the camera that captures images of the plants. It then processes the data and sends control signals to a relay module, which regulates the pump operation that delivers nutrient solution to the plants.

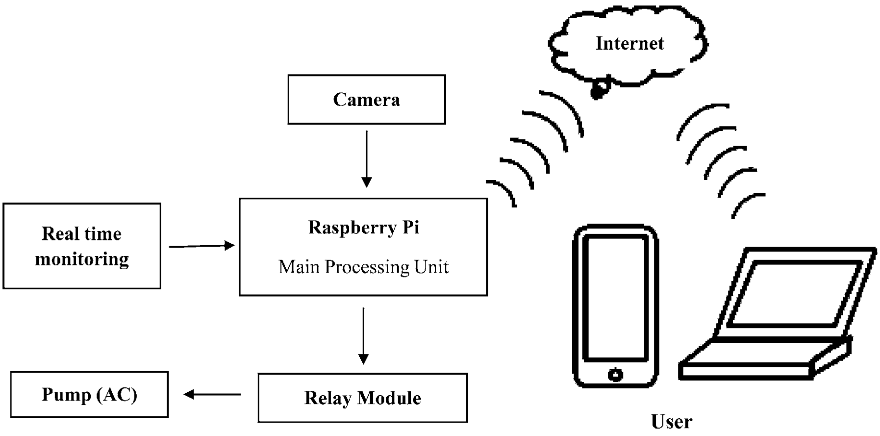

Fig. 2.3 Block diagram of the system

2.2.1 Experimental Setup

The experimental setup consists of an aeroponic system that provides a controlled environment for cultivating tomato plants. The system was constructed using a fiberglass cubicle, which creates a self-contained growth environment for the tomato plants. The cubicle features transparent walls, enabling clear visibility of the root systems without disturbing the plants. Inside the cubicle, a nutrient delivery system was installed, consisting of misting nozzles that provide a fine spray of nutrient solution to the roots. The aeroponic system incorporates precise environmental control mechanisms such as temperature, humidity, and light intensity to ensure consistent and ideal growing conditions for the tomato plants. Tomato seeds were germinated under controlled conditions, and after 14 days, seedlings at the two true leaf stage were transplanted into the aeroponic system.

2.2.2 Hardware and Software Implementation

As illustrated in Fig. 2.4, the Raspberry Pi single-board computer serves as the system's central processing unit. It is integrated with various hardware components and programmed to control image capture, data processing, and system operations. The Raspberry Pi model was selected based on its computational power, memory capacity, and compatibility with peripheral devices. A high-resolution camera module was connected to the Raspberry Pi, the primary imaging device for capturing root and shooting images. The cameras were fixed 50 cm from the plant holder surface to ensure consistent imaging conditions. The Raspberry Pi runs on the Raspbian operating system, a Debian-based Linux distribution optimized for the Raspberry Pi hardware. Python is the primary programming language for developing image

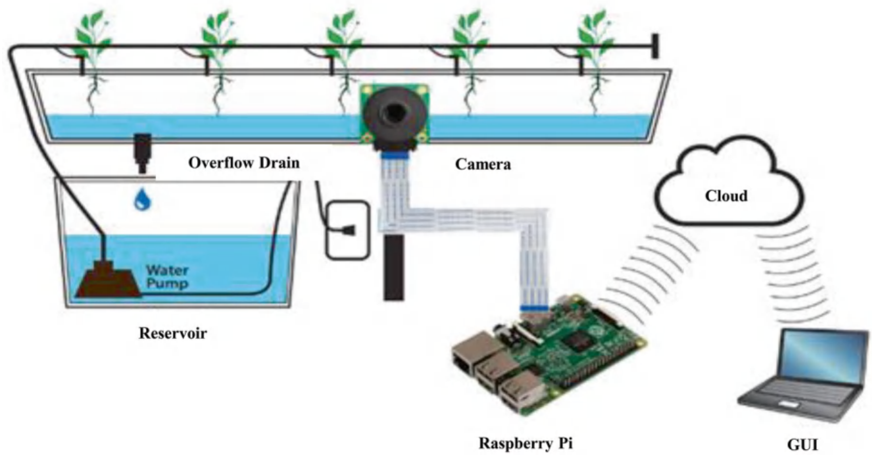

Fig. 2.4 Shoot and root growth measuring system

capture, processing, and analysis algorithms. Libraries such as OpenCV, NumPy, and scikit-image are utilized for image manipulation, computer vision tasks, and scientific computing.

2.2.3 Root and Shoot Annotation

Custom software was developed in Python to facilitate the annotation of the root and shoot images and the extraction of quantitative growth metrics. The software consisted of a graphical user interface (GUI) for annotating root system skeletons and measuring root lengths, as well as for annotating shoot silhouettes and measuring shoot heights.

For root annotation, the user was prompted to load a series of root images and manually traced the path of the primary roots using a computer mouse. The annotation process involves clicking points along each root to define line segments approximating the root's shape. After tracing the origins in an image, the system can save the annotated image and proceed to the next time point. The software automatically calculates the length of each traced root based on the pixel coordinates of the annotation points and the known pixel-to- millimeter conversion factor (CF) at the imaging distance. For shoot annotation, the system follows a similar process. The shoot annotation calculates the plant's maximum height (distance from the base of the stem to the highest leaf tip).

2.2.4 Length Calculation and Data Output

The root length measurements were calculated using a pixel-to-millimeter conversion factor determined during the system calibration. A calibration target with known dimensions, such as a ruler or a grid of known size, is placed in the camera's field of view at the same distance as the plant shoots and roots. An image of the calibration target is captured, and the number of pixels corresponding to a known length (10 mm) is determined using image processing software as shown in Fig. 2.5.

The pixel-to-millimeter conversion factor (CF) is then calculated using the following formula:

$$\mathrm{CF} = \mathrm{Known\ Length}\left(\mathrm{mm}\right) / \mathrm{Number\ of\ Pixels} \tag{2.1}$$

When a 10 mm section of the calibration target corresponds to 100 pixels in the image, the conversion factor would be:

$$\mathrm{CF} = 10\,\mathrm{mm} / 100\,\mathrm{pixels} = 0.1\,\mathrm{mm} / \mathrm{pixel} \tag{2.2}$$

To calculate the length of a root in millimeters, the number of pixels along the root path is multiplied by the conversion factor:

$$\mathrm{Root\ Length}\left(\mathrm{mm}\right) = \mathrm{Number\ of\ Pixels} \times \mathrm{CF} \tag{2.3}$$

The calculated root lengths are then associated with the corresponding plant ID and timestamp information to create a comprehensive dataset. The data is exported in a structured format, such as CSV (Comma-Separated Values), for further analysis and integration with other experimental data. The output file includes columns for plant ID, timestamp, root length (mm), and any additional relevant metadata. Output in CSV is shown in Table 2.1.

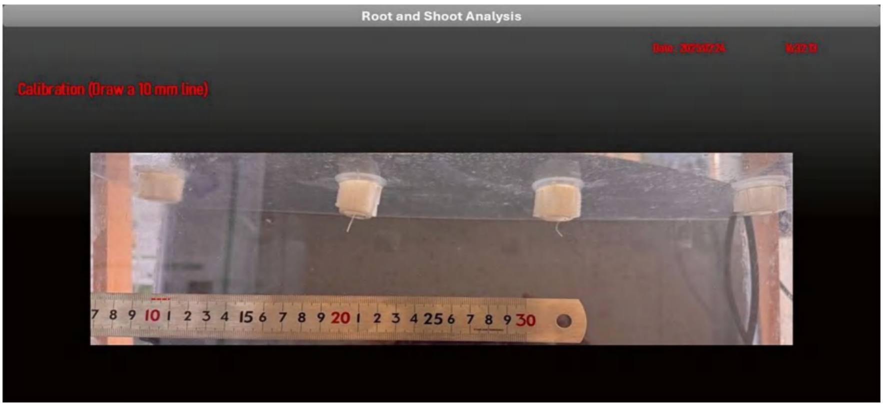

Fig. 2.5 System calibration

Table 2.1 Output CSV

Plant ID	Timestamp	Shoot length (mm)	Shoot length (mm)
1	2024-02-01 09:00:00	68.4	6.0
2	2024-02-01 09:00:20	69.2	5.0
3	2024-02-01 09:00:45	72.0	5.5
4	2024-02-01 09:01:00	72.3	7.0

2.3 Automated Versus Manual Measurement Comparison

The same set of tomato seedlings was analyzed using both methods to demonstrate the differences between the semi-automated and manual measurement approaches. Figure 2.6 presents the results obtained using the semi-automated system, while Fig. 2.7 shows the manual measurements of the identical seedlings. Using the graphical user interface, the semi-automated system (Fig. 2.6) determined the root and shoot lengths by manually tracing their respective paths. The software automatically calculated the lengths based on the pixel coordinates and the predetermined pixel-to-millimeter conversion factor. Table 2.2 presents the system-measured root and shoot length results.

These results demonstrate the system's ability to capture the fine details and curvature of the roots and shoots, providing precise measurements of their lengths.

In contrast, the manual measurements Fig. 2.7 were obtained by directly measuring the roots and shoots using a ruler placed alongside the seedlings in the aeroponic chamber (Tian et al., 2024; Islam et al., 2021). Due to this method's limitations, it was impossible to accurately trace the curved paths of the roots and shoots. Instead, measurements were taken straight from the base to the tip of each root and shoot. The manual measurements yielded the following results, which are shown in Table 2.3.

Compared to the manual method, the semi-automatic method provides accurate measurements of shoot and root lengths and is more convenient for the user. As a result, this new method saves the researcher half the time compared to taking manual measurements.

2.4 Conclusion and Future Works

In this study, we developed and evaluated a semi-automated system for non-destructive, high-throughput measurement of tomato root and shoot growth in an aeroponic setup. Integrating a low-cost Raspberry Pi computer, custom image analysis software, and an aeroponic culture system enabled efficient and accurate quantification of plant growth dynamics. The semi-automated system demonstrated clear advantages over manual measurement methods, capturing the non-linear geometry of roots and shoots and yielding length measurements that were, on average, 30% and 40% longer for shoots and roots, respectively. The approach also reduced

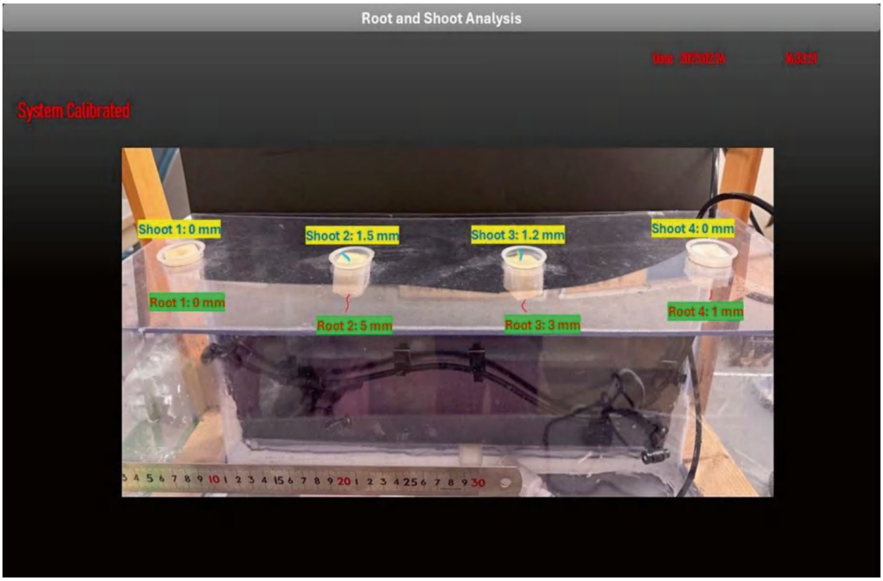

Fig. 2.6 Measurements of the semi-automated system

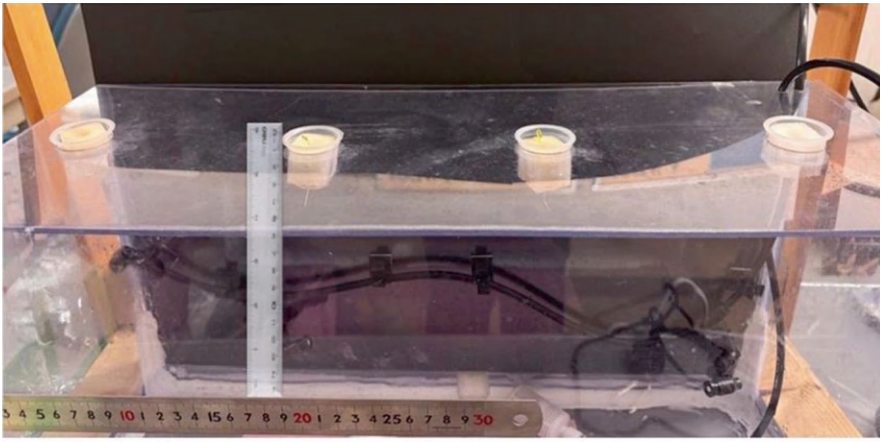

Fig. 2.7 Measurements of roots taken manually for confirmation

Table 2.2 Shoot and root lengths measurements by the system

Shoot 1	0 mm	Root 1	0 mm
Shoot 2	1.5 mm	Root 2	5.0 mm
Shoot 3	1.2 mm	Root 3	3.0 mm
Shoot 4	0 mm	Root 4	1.0 mm

Table 2.3 Shoot and root lengths measurements by the manual method

Shoot 1	0 mm	Root 1	0 mm
Shoot 2	1.0 mm	Root 2	3.5 mm
Shoot 3	0.9 mm	Root 3	2.0 mm
Shoot 4	0 mm	Root 4	0.8 mm

measurement time by approximately 50% per plant while improving consistency threefold compared to manual methods.

The non-destructive, imaging-based approach allows researchers to capture detailed temporal data on root and shoot growth dynamics, which is particularly valuable for investigating the effects of environmental factors on plant development. Integrating the semi-automated system with aeroponic culture enables precise control over the root zone environment, facilitating studies of plant responses to specific experimental treatments. The modular design and open-source nature of the Raspberry Pi-based platform make the system adaptable and accessible for a wide range of plant species, growth systems, and research questions.

In conclusion, this study's semi-automated root and shoot measurement system significantly advances plant phenotyping capabilities. By providing a non-destructive, high-throughput, and cost-effective solution for quantifying plant growth dynamics, this system can accelerate plant biology research and inform the development of improved crop varieties and sustainable agricultural practices.

Future work will focus on further improving and expanding the capabilities of the semi-automated phenotyping system. Key areas for development include automated image segmentation, integration of additional imaging modalities, expansion to other plant species and growth systems, integration with environmental sensors, and the development of user-friendly interfaces and databases. By addressing these aspects, the system can be refined to meet the evolving needs of plant biology and agricultural research, ultimately enhancing crop productivity and resilience in the face of global challenges.

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Chapter 3
Development of Smart Drip Irrigation and Fungicide Application System for the Grapevine Management

Hikmatullah Malik and Tofael Ahamed

Abstract The global demand for sustainable agriculture is driving innovations in precision farming technologies. Grapes are a high-value crop, and their cultivation is widespread worldwide. Vineyard irrigation and disease control should be improved to meet the demand for grape production for the increasing population. This research presents the development and implementation of a smart drip irrigation and fungicide application system designed for grapevine management, integrating Internet of Things (IoT) technologies, cloud-based monitoring, and automated control mechanisms. The innovative irrigation system involves the coordination of soil moisture sensors deployed in the soil and DHT22 to gather required real-time information, such as soil moisture, air humidity, and environmental temperature, and Arduino R4 as a microcontroller. To address fungal disease management, the fungicide application system uses an ESP8266 microcontroller and the Blynk app for remote control, coupled with a YOLO-based object detection model for accurately identifying grapevine diseases. A cloud-based dashboard was developed using HTML, CSS, and JavaScript, fetching data from ThingSpeak and Blynk. The system provides alerts and notifications for critical moisture levels, ensuring timely interventions. Integration with Citronics cameras also allows for visual plant health monitoring and improved management practices. The findings show that combining IoT-enabled smart irrigation with advanced disease detection offers a novel, user-friendly framework for sustainable grapevine management.

Keywords Smart irrigation · Fungicide application · IoT · Deep learning · Precision farming

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3.1 Introduction

Grapes are one of the most important crops, grown not only for fresh consumption but also for wine and raisins; a variety of other products, each has an average yield of 10.2 tons per hectare. The world's vineyards, covering around 7.3 million hectares, produced 74.8 million tons of fresh grapes in 2021 (OIV, 2021). Viticulture is a major contributor to the agricultural economy in most regions where climate conditions are favorable. In 2016, a record was achieved with 77.4 million tons of grapes from 7.1 million hectares of vineyards, resulting in approximately $68.3 billion at farmgate value (Cantu & Walker, 2019). On the other hand, grape production is one of the most sensitive crops to environmental factors, particularly regarding water needs and disease management.

Irrigation is crucial for farming; the acres of farmland that will have to be irrigated to feed the estimated 9-billion-strong global population by 2050 could reach several billion acres, way higher than scientists projected. An estimated quantity of farmland needing irrigation may be prolonged between 240 million and 450 million hectares (from 590 million to 1.1 billion acres) within the next 30 years (Puy et al., 2020). On the other hand, fungal diseases have always been serious threats to grapevines, directly and indirectly influencing the fruit quality and yield rate. Anthracnose is among the most serious diseases of grapevines during its favorable conditions (warm conditions, high humidity, and precipitation). This disease is caused by the *Elsinoe ampelina* fungus (Ellis, 2011). Fungicides are commonly used to control these diseases, but their application is often not optimized, which is critical to ensuring sustainable and profitable cultivation.

As growers worldwide struggle to sustain vineyard production during hot summer temperatures and limited water resources, emerging technologies like electronic soil moisture sensors coupled with automated irrigation may provide some opportunities for consideration. Using soil moisture sensors can aid in irrigation scheduling to sustain crops such as wine grapes, helping to prevent heat damage to vines and impacts on fruit yield before visual symptoms appear on the vine (Jacoby, 2023). Intelligent irrigation systems can enhance water use efficiency, supplying the right amount of water at the right time, based on up-to-date information on weather and soil conditions. Similarly, variable rate fungicide application systems can precisely target infection areas, reduce chemical usage, and minimize environmental impacts. Therefore, this research focuses on developing a comprehensive, innovative system that integrates irrigation and fungicide application for efficient and sustainable grape production.

3.1.1 Challenges in Grape Production

Water management and disease control are among the most important challenges for efficient grape production. Most existing irrigation practices lead to inefficient water use due to over- or under-irrigation. Over-irrigation leads to waterlogging, nutrient leaching losses, and high vulnerability to diseases, while under-irrigation causes water stress, reducing yield and quality (Chaves et al., 2010). Smart irrigation is considered one of the significant parts of precision agriculture and a solution for water conservation.

Additionally, fungicides are applied to grape production to control diseases and increase yield. The application of conventional fungicides in vineyards leads to poor agricultural practices. Therefore, the residues of these fungicides in or on grapes at harvest are higher than those permitted by regulation. Furthermore, excessive application may lead to fungicide resistance among fungal strains, environmental contamination, and added production cost (Brent & Hollomon, 2007).

Moreover, traditional methods of applying fungicides are not optimized; either the chemical is overapplied, which poses environmental and health risks, or there is too little to provide effective disease control. Therefore, an integrated smart irrigation and fungicide application system is needed to solve these problems by optimizing irrigation and application of fungicides.

3.2 Objective of the Research

To address the above challenges, the primary objective of this research was to develop a smart irrigation and fungicide application management system using IoT-based sensing technologies that can help to increase grape production and reduce losses of agricultural inputs.

3.3 Materials and Methods

3.3.1 Overall Research Design and Layout

The research was conducted in the Laboratory of Bioproduction and Machinery, Tsukuba, Japan. Three grape plants of the Shine Muscat (Vitis vinifera L.) variety, incredibly famous in Japan due to their high quality, were grown in wooden crates sized $70 \times 60 \times 60$ cm (Fig. 3.1). The soil of the experiment was organic with a high water-holding capacity. The experiment consisted of two crucial smart irrigation and smart fungicide application systems. The pump controller was integrated with a cloud-based platform for remote access.

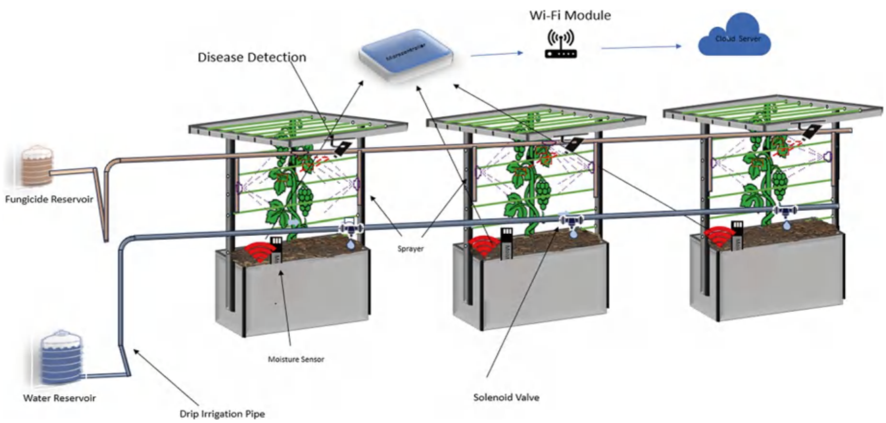

Fig. 3.1 Overall structure of the system

Soil moisture sensors and DHT22 were deployed to detect soil moisture content and monitor temperature and humidity data. Moreover, CTRONIC cameras were installed to collect images of plants for disease detection. The Arduino UNO R4 Wi-Fi was used as a microcontroller for the irrigation system, and the ESP 8266 was used for the fungicide application system. Solenoid valves were installed for individual plants, and a 12 V power supply was connected to the relay. Irrigation was performed based on the threshold 34% (MAD) and 56% (FC) values. The irrigation and fungicide applications were controlled for each plant based on the soil moisture level and disease detection results. Figure 3.2 shows the system's overall flow chart.

The irrigation and fungicide spraying applications were controlled for individual plants through solenoid valves operated through the relay. Irrigation water was applied through drip irrigation pipelines, and fungicides were used through the sprayers installed on the tops and sides of the plants. Moreover, individual pumps were installed for each system to apply irrigation water and fungicides when needed.

3.3.2 Sensors Deployment and Calibration

Capacitive soil moisture sensors buried 15 cm below the surface were used to track soil moisture content. Extensive calibration was made before each sensor deployment, as suggested to improve the accuracy of the readings. Throughout the season, the percentage of soil moisture was continuously monitored. If the moisture percentage fell below 34%, then irrigation would automatically be triggered in the system to prevent stressing the water in the plants. Irrigation stopped at 56% moisture content. Since the soil's nutrient level was already good enough to make the plants grow well, no fertilizer was added throughout the experiment. DHT22, in addition, was added to a capacitive soil moisture sensor to monitor environmental factors like temperature and humidity.

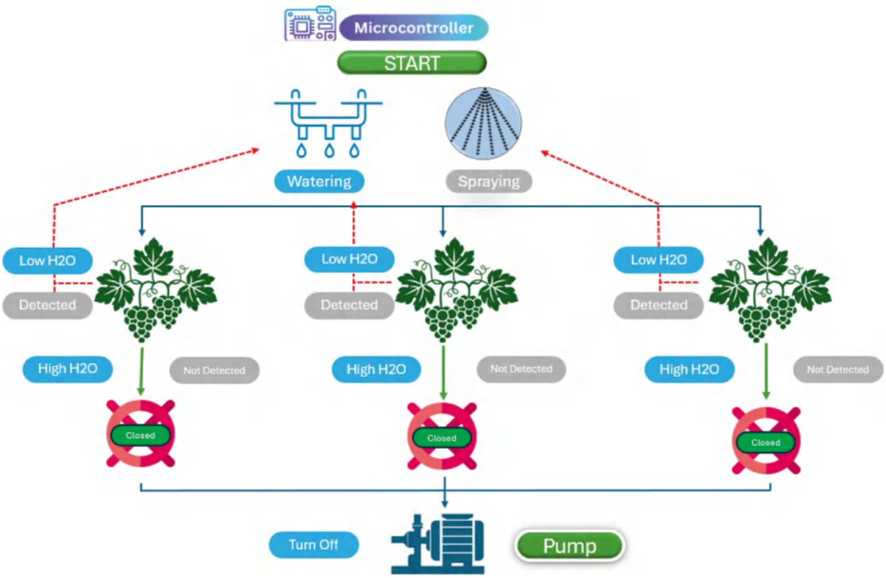

Fig. 3.2 Flow chart of the irrigation and fungicide spray system

3.3.3 Calibration Process

Sensors were placed 15 cm below each plant to measure soil moisture content. Three soil moisture sensors were deployed, so each plant was equipped with one soil moisture sensor. A DHT22 was installed near the vineyard to monitor atmospheric conditions, such as temperature and relative humidity. All the sensors were interfaced with a low-cost data logger or microcontroller, namely, Arduino Uno R4, placed inside a small plastic box. Sensor's data was uploaded onto the cloud server (ThingSpeak) on a 15-min basis of 15 min. Cloud displays and stores the data so it can be accessed and downloaded later. The whole system and the sensors employed are illustrated in Fig. 3.3.

The fungicide application system used an ESP8266 microcontroller and the Blynk app for remote control, coupled with a YOLO-based object detection model to identify grapevine Anthracnose diseases accurately. The YOLOv8n and YOLO11n algorithms were employed using the CNN (Convolutional Neural Network) within the Pytorch framework for training to develop and integrate the fungicide application system with the existing irrigation system. Two image datasets containing 2,277 images (for diseased leaf detection) and 2,126 images (for diseased leaf and branch detection) were collected using different devices—a Citronics CTIPC-530C and smartphone cameras (Apple iPhone & Android). Images were captured in various conditions (sunny, cloudy, morning, and evening) from three grape plants grown in wooden boxes. The datasets were then labeled with a single class "Anthracnose" using LabelImg®, and the annotated dataset was trained with YOLOv8n and YOLO11n models.

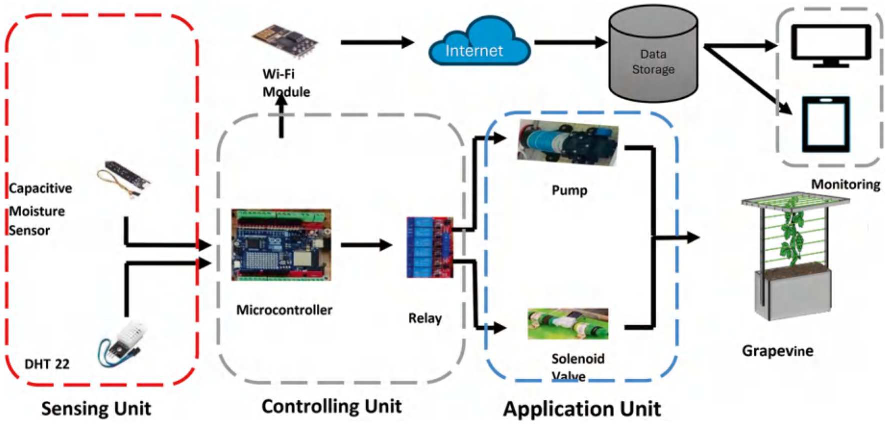

Fig. 3.3 Components of the prototype system

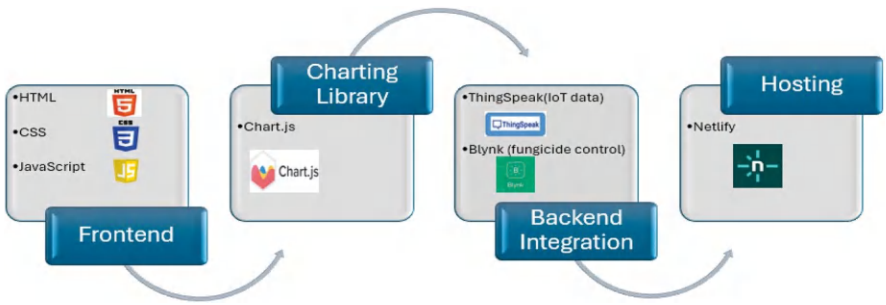

Fig. 3.4 Dashboard development structure

3.3.4 Online Data Storage and Monitoring

The data gathered through the innovative irrigation system is consolidated, visualized, and analyzed on the ThingSpeak Cloud server. The fungicide application system was connected to the Blynk app for the fungicide application in a user-friendly way. Additionally, a web-based cloud dashboard was created to monitor and control a smart irrigation and fungicide application system for grapevine management. It aims to integrate real-time data monitoring and actuating functions based on IoT technologies and cloud-based services.

The structure of the dashboard was based on HTML, CSS, and JavaScript to implement an interactive, responsive, user-friendly interface. The dashboard was built by integrating ThingSpeak and Blynk using their API keys. Chart.js library was used to generate different charts for visual monitoring, and Netlify was used to host the dashboard online (Fig. 3.4). The key components of the dashboard were date range Selector, graph customization options, real-time alerts, fungicide application control, and camera feed access to access grape images.

3.4 Results and Discussion

As stated, our research consisted of two subsystems: one for controlling irrigation and the other for applying fungicide. This section critically reviews all the findings we obtained from both systems.

3.4.1 Performance of Smart Drip Irrigation System

The innovative irrigation system effectively maintained soil moisture within the 34–56% range. Automated responses were triggered within 15 s of detecting low soil moisture levels, demonstrating the system's real-time efficiency. Sensor's calibration results indicated a strong correlation ($R^2 = 0.96$) between sensor readings and actual soil moisture levels, confirming the reliability of the sensors. The system's ability to sustain consistent soil moisture levels reduced water wastage and minimized grapevine stress. The readings among the soil moisture content level and the capacitive sensors reading showed good correlations (Fig. 3.5).

The prototype setup for the irrigation component used soil moisture sensors, DHT22 sensors, and an Arduino R4 microcontroller. Sensors for soil conditions were monitored, and the information was forwarded via an Arduino to the cloud server for storage and monitoring. Temporal variations in the environmental conditions were assessed with data obtained for 2 months on soil moisture (Fig. 3.6).

The data show the system effectively sustained soil moisture within the optimal range. Moisture levels slightly differed from the threshold, indicating accurate and reliable sensor data. In other cases, significant discrepancies were noted in the moisture level measurement, which were regarded as sensor failures. The faulty sensor was replaced, again pointing out one of the opposing sides of using low-cost sensors. One of the significant issues with capacitive moisture sensors is that they tend to drift, which can result in inaccurate readings over time. Furthermore, inexpensive capacitive sensors will rapidly deteriorate through electrolysis if continuously forward-biased. This means that such low-cost sensors may cause damage or incorrect readings, thereby affecting their reliability in the longer term (Ferrarezi et al., 2015).

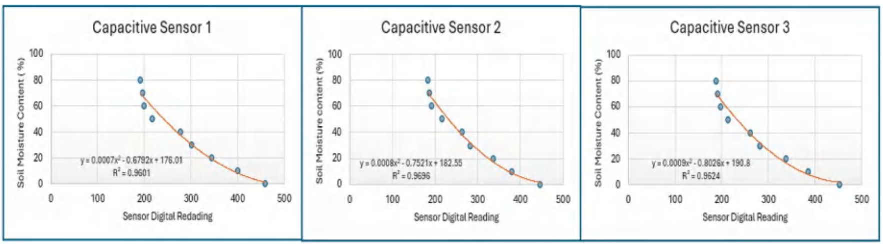

Fig. 3.5 Relationship between moisture content in the soil and the soil moisture sensors

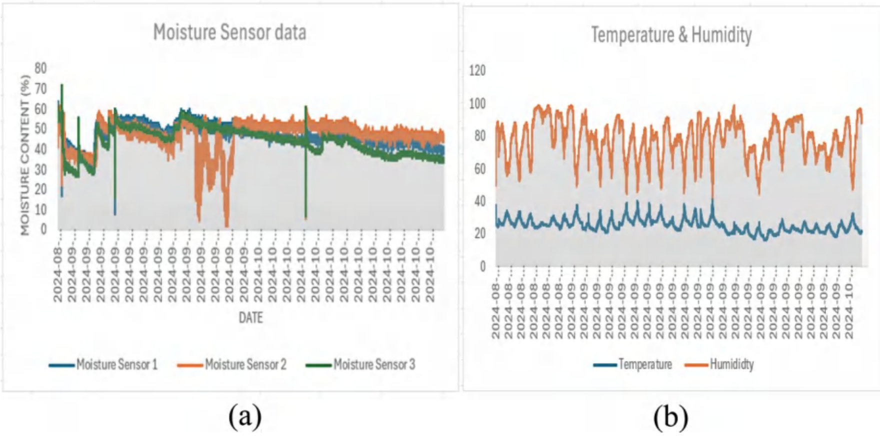

Fig. 3.6 Temporal variation of (**a**) soil moisture, (**b**) temperature and relative humidity over a 2-month period

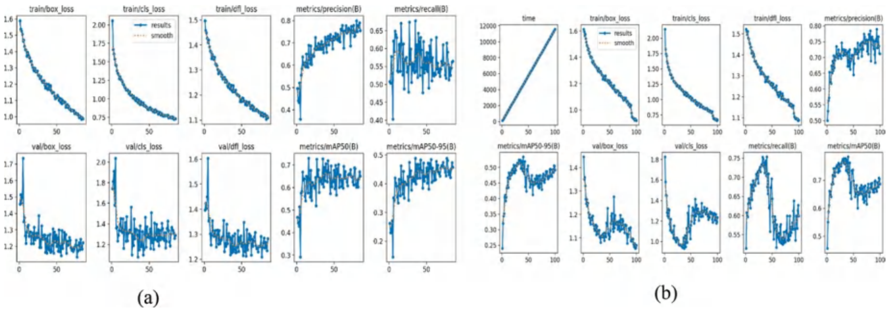

Fig. 3.7 Training configuration for diseased leaf detection (**a**) YOLOv8n and (**b**) YOLO11n

3.4.2 Detection Model Development

To develop and integrate the fungicide application system with the existing irrigation system, the YOLOv8n and YOLO11n algorithms were employed using the CNN (Convolutional Neural Network), within the Pytorch framework, to develop a disease detection model. An image dataset of 2277 and 2126 images of grapes was trained and labeled with a single class, Anthracnose, in LabelImg. After successful model training and validation, the model detected anthracnose disease in each frame. The YOLOv8n model achieved a mean average precision (mAP) of 72.2% and a recall of 66.6% for the first dataset, while YOLO11n showed better results with an mAP of 78.3% or 0.783 and a Recall of about 75.3% from this trained model (Fig. 3.7).

The second data set (diseased leaf and branch detection) was also trained with YOLOv8n and YOLO11n with the same parameters. The results showed mAP of

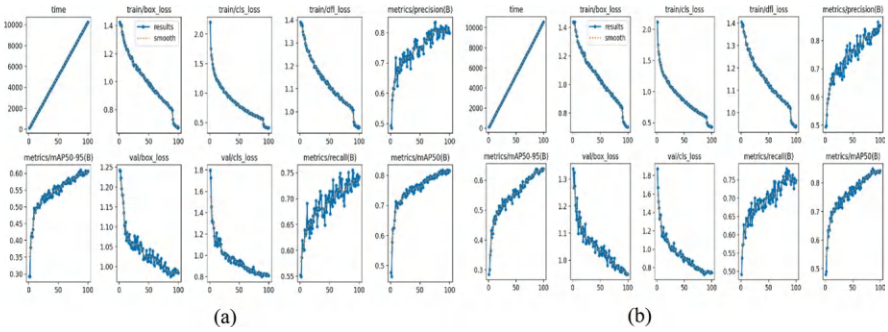

Fig. 3.8 Training configuration for diseased leaf and branch detection (**a**) YOLOv8n and (**b**) YOLO11n

81.5 and a recall of 74.2% for YOLOV8n, while the YOLO11n model performed better, with mAP of 84.2% and a recall of 75% for the second dataset, respectively (Fig. 3.8).

3.4.3 Visual Representation of Detection Outcomes

To clearly show the effectiveness of the two trained models in detecting Anthracnose precisely, a set of different images of grape leaves infected by the disease was used for testing as input by using the weight-best trained from each model to showcase the algorithm's capability in extracting grape disease features within the natural environment. For YOLO11n, the bounding boxes were consistent and covered most diseased leaves and branches with reasonable confidence. It also appeared well in variable lighting conditions. However, some overlaps and false positives were observed in the images. The detection results are visually presented in Fig. 3.9.

3.4.4 Cloud-Based Dashboard for Monitoring and Control

The cloud-based dashboard was instrumental in managing the irrigation and fungicide application systems (Fig. 3.10). The dashboard is secure with a login system, where credentials are verified, and only authorized users can access the functionality. The dashboard integrates seamlessly with ThingSpeak, fetching and displaying real-time sensor data, such as the soil moisture sensors and DHT22.The soil moisture sensors provide data from three variable locations, enabling spatial monitoring of soil conditions. Meanwhile, the DHT22 measures ambient temperature and humidity, updating every few seconds to reflect environmental changes, which allows smooth charts to be generated and loaded efficiently. Sensor data has been made available in line and bar format on the dashboard.

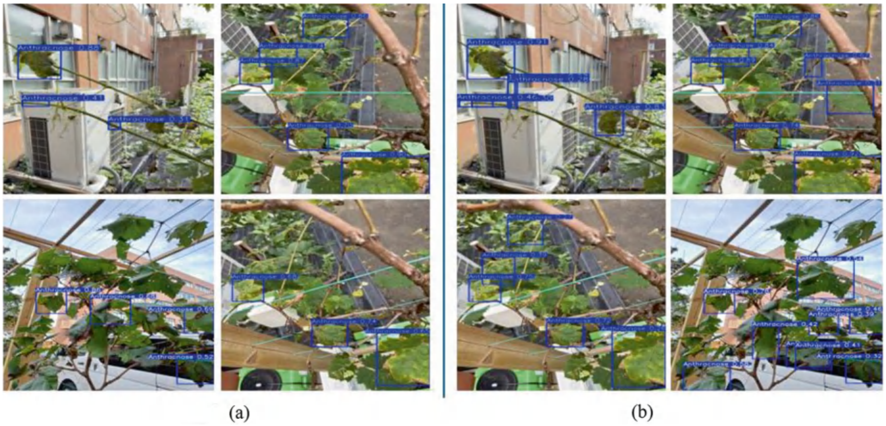

Fig. 3.9 Visualization of detected results for (**a**) YOLOV8n and (**b**) YOLO11n (leaf and branch detection)

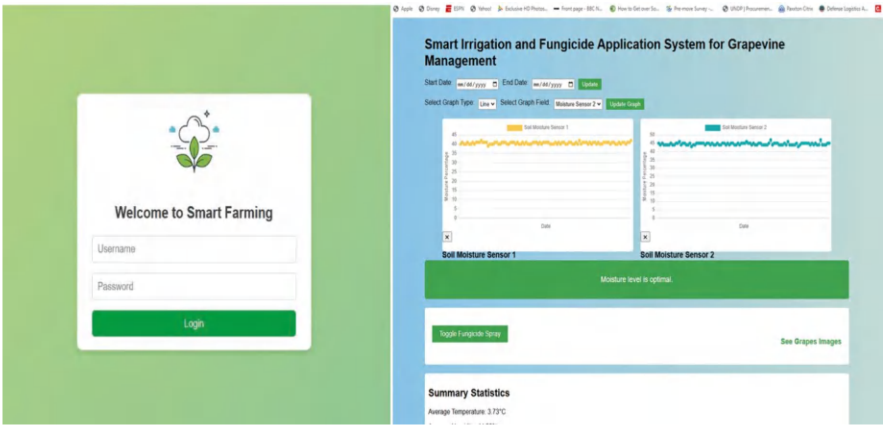

Fig. 3.10 Cloud-based dashboard for irrigation and fungicide application systems

Compared to the work by Hamdoon and Zengin (2023), who developed a mobile app for the irrigation monitoring system, the smooth update rate in our dashboard and predefined threshold in our system made it more reliable, which helps to make rapid responses in decision-making.

Other features included on the dashboard are visual notifications of moisture levels less than the threshold value of 34%; these are color-coded, where red is for low levels and green indicates that the levels are adequate. Moreover, it also sends an alert notification to the user's WhatsApp number using the Twilio platform. This has been presented much like the findings by Hassan et al. (2022), in which the system provided relevant real-time notifications that could keep the soil moisture within the optimum range (Fig. 3.11).

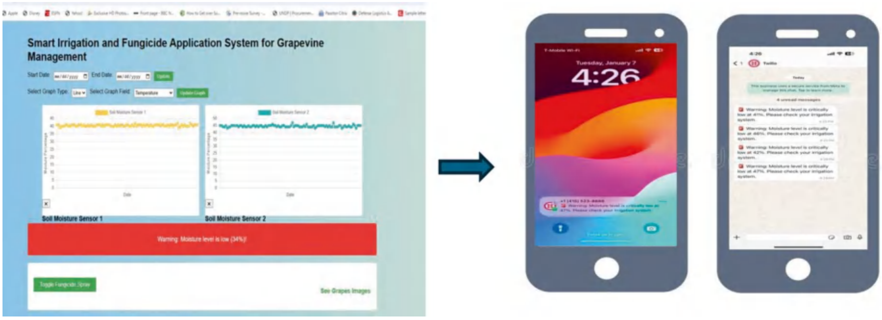

Fig. 3.11 Dashboard alert notification feature

Another feature is that the fungicide control system in our dashboard permits users to operate the spray system remotely through a single interface on the dashboard (Fig. 3.12). Such a design aligns with previous work by Dodgson et al. (2021), indicating that IoT-enabled remote control is necessary to control farming operations promptly, thus resulting in increased yields and less wastage of resources.

3.4.5 User's Feedback on Dashboard

To understand the efficiency of the cloud-based dashboard, a group of 17 prospective users was formed and given a questionnaire. A vote was taken on the most prominent aspects of the dashboard: its visual components, functionality, and overall satisfaction. These findings provide critical insight into user feedback and evaluation of weaknesses and strengths.

Figure 3.13 shows that 94.1% found the dashboard easy to understand, and 64.7% rated its visual design as "very good" or "good," while 35.3% remained neutral for the visual design, indicating potential opportunities for further customization. Moreover, 94.1% rated navigation as easy or very easy, and 88% rated it as showing the data accurately, indicating a highly user-friendly interface. 76.5% considered the fungicide control intuitive, 17% remained neutral, and 6% rated it negatively, suggesting a need for minor improvements.

3.5 Conclusions

Smart drip irrigation and fungicide application management systems have been developed and proven very important for effectively managing grapevine crops. This cloud-based system can help solve two challenges: water and disease management in grapevine cultivation using components of the IoT, such as soil moisture sensors, DHT22 temperature and humidity sensors, and a combination of Arduino

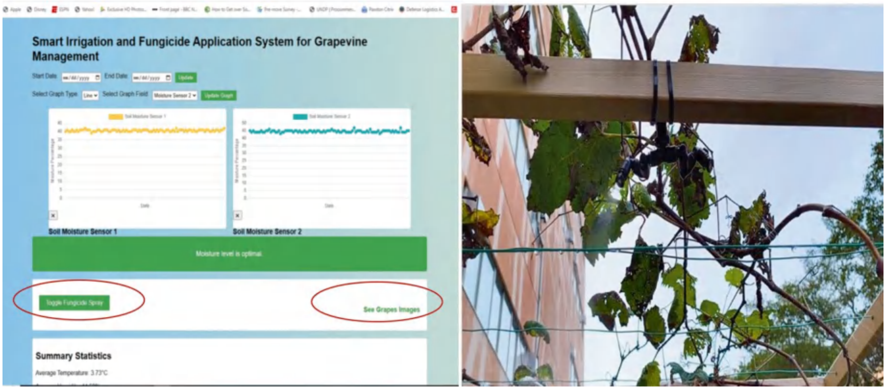

Fig. 3.12 Dashboard fungicide control feature

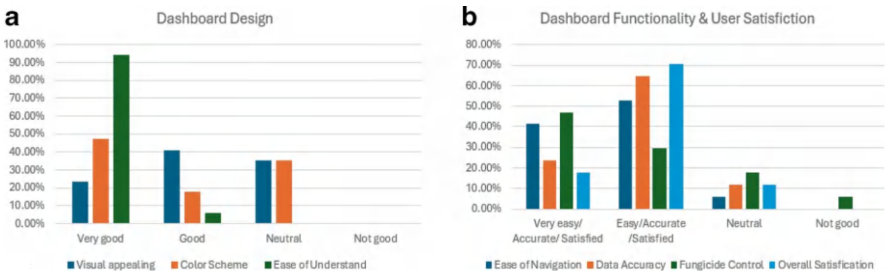

Fig. 3.13 User feedback results for the (**a**) dashboard design and (**b**) dashboard functionality and user satisfaction

R4 and ESP8266 microcontrollers. This system allows real-time monitoring, remote control, and a user-friendly dashboard that consolidates essential data and control options within one interface.

The irrigation system is managed via an Arduino microcontroller R4, to which various irrigation management sensors, such as soil moisture, temperature, and humidity sensors, were connected. Data was logged on the ThingSpeak platform. Soil moisture sensors were calibrated, showing a high correlation of over 96%. A threshold level is set for the soil moisture content at MAD (34%) and FC (56%). Using a YOLO-based detection model, the fungicide application system was controlled via ESP8266 microcontroller in conjunction with the Blynk app to provide remote control over the spraying system, where YOLO11n proved quite effective and accurate.

The cloud-based dashboard enabled the visualization of real-time data, control functions, and threshold alerts for timely intervention. It further integrates well with ThingSpeak and Blynk for unified monitoring and control. Unlike in the traditional method, farmers at remote locations can manage irrigation and fungicide application decisions based on real-time data on this system. Overall, the dashboard's usability and intuitive design made it effective and within the grasp of any user, from those with a low technical background to highly informed ones.

Further research should be carried out to determine the long-term impact of the system on grape yields, quality, and overall health in the vineyard ecosystem. All these metrics would have to be monitored across several years of growth to provide the necessary insights into how to derive the benefits and disadvantages of such systems for long-term sustainability in viticulture. In addition, further studies might look at integrating the dual functionality of irrigation and fungicide applications into a single centrally controlled microcontroller. One central controller could streamline this by combining these systems for fewer devices. This allows irrigation and chemical application coordination, with controls based on the actual moisture and disease-risk input in real time. This integrates operations better, optimizes resources, and reduces overhead costs.

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Chapter 4
Challenge and Opportunities for Developing a Mini-Plant Factory for Vegetable Cultivation in Household Urban Farming

Parwit Chutichaimaytar, Nelundeniyage Sumuduni L. Senevirathne, and Tofael Ahamed

Abstract Mini-plant factories are controlled environment agriculture (CEA) systems for small-scale indoor crop production. This chapter will critically review the existing literature on mini-plant factories for homegrown vegetables, herbs, and spices, covering the challenges of design, implementation, and technology integration, as well as the benefits. This chapter will also focus on developing a conceptual model to improve the boundary conditions and achieve more benefits with suitable crops well suited to mini-plant factory cultivation. Future trends in mini-plant factory design, as well as the application of modern technologies, including AI, the Internet of Things (IoT), and automatic control, are reviewed in this chapter. These systems typically utilize hydroponics or aeroponics to cultivate plants without soil, often incorporating artificial lighting, microclimate controllers, and nutrient management systems. Mini-plant factories can offer several benefits to the home consumer, including the ability to produce consistent and high-quality vegetables within a small space, reduced dependency on external suppliers, and the potential for generating supplemental income. Fogponics is a new method of soilless plant production, in which plant roots are suspended in a chamber, and nutrient-mixed fog is used. This method has shown promising results in increasing crop yields and reducing water usage, making it a sustainable solution for agriculture. Fogponics represents a significant leap in the evolution of hydroponic growing systems. These advantages make fogponics a compelling option for sustainable agriculture, aligning with the global push for more efficient and environmentally friendly farming practices. The potential of fogponics extends beyond traditional agriculture, as it can be implemented in urban farming and indoor gardening, offering a viable

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solution for maximizing plant growth in limited spaces. Urban agriculture in densely populated areas can greatly benefit from integrating modern technologies into mini-plant factories. The automation of tasks through the utilization of agricultural robots and IoT facilitates a reduction in the necessity for manual labor and enables the continuous monitoring and adjustment of growing conditions. Several factors, including financial considerations, maintenance requirements, and the necessary technical expertise, impede the acceptance of miniature plant factories in households. This chapter will critically review these factors to provide a macro view of the technology to be adopted by any interested party.

Keywords Mini-plant factory · Controlled environment agriculture (CEA) · Internet of Things (IoT) · Urban agriculture

4.1 Introduction

4.1.1 Household Urban Farming and Indoor Farming

There has been a growing trend toward household urban farming in recent years, particularly in densely populated areas (Kubota et al., 2019). This trend can be attributed to several factors, including the desire for fresh and organic produce, limited access to land for traditional farming, and growing awareness of the environmental impacts of conventional agriculture (Gao, 2019). Controlled environment agriculture (CEA) represents methods of agriculture that utilize technology to grow plants indoors in a managed environment (light conditions, atmospheric conditions, etc.) to increase productivity. Mini-plant factories are controlled environmental agriculture (CEA) systems for small-scale indoor crop production. By utilizing mini-plant factories, households can create a controlled environment that optimizes plant growth and minimizes resource usage (Huang et al., 2018). By implementing mini-plant factories, households can have greater assurance of the quality and safety of their produce, as they have complete control over the inputs, such as nutrients, water, and pesticides. Moreover, mini-plant factories can also serve as educational tools, allowing households to learn about the science and technology behind plant cultivation. Overall, mini-plant factories offer a sustainable and efficient method for vegetable cultivation in urban areas. By utilizing mini-plant factories, households can overcome challenges such as limited space and a lack of specialized knowledge, while also enjoying the benefits of consistent and high-quality vegetable production, reduced dependency on external suppliers, and the potential for generating supplemental income (Kozai & Niu, 2020). By implementing mini-plant factories, households can have greater assurance of the quality and safety of their produce (Kubota et al., 2019). Furthermore, with the rising demand for fresh and locally grown food in urban areas, mini-plant factories can provide a valuable opportunity for households to contribute to the local food supply chain and promote food security. Additionally, the integration of mini-plant factories in urban household farming can also contribute to a more sustainable future.

4.1.2 Evolution of Indoor Agriculture

There are several types of indoor cultivation, each with its advantages and disadvantages. Soil-based cultivation (Fig. 4.1) is the most traditional method of growing plants, commonly practiced indoors in pots, planters, or raised beds. It may be messy and require more maintenance while also being susceptible to pest infestations (Smirnova, 2020).

Hydroponics (Fig. 4.2) involves cultivating plants without soil using a nutrient-rich water solution. Although hydroponic systems can be highly efficient and productive, they can be costlier and more complex to establish (Verdoliva et al., 2021).

Aquaponics (Fig. 4.3) combines hydroponics with aquaculture (fish farming), where fish waste provides nutrients for the plants, and the plants assist in purifying the water for the fish. While aquaponics systems are known for their sustainability, they require thorough planning and maintenance (Rizal et al., 2017).

Aeroponics (Fig. 4.4) grows plants in a mist environment with roots suspended mid-air. Aeroponic systems can produce high-quality crops efficiently; however, they represent the most complex and expensive indoor cultivation method (Lakhiar et al., 2018).

Vertical farming (Fig. 4.5) entails growing plants in vertically stacked layers. This method is beneficial for enhancing crop productivity within urban areas where limited land availability is a problem (Orsini et al., 2013).

Fogponics (Fig. 4.6) is a novel method of soilless plant production, where plant roots are suspended in a chamber filled with a nutrient-rich fog. This system

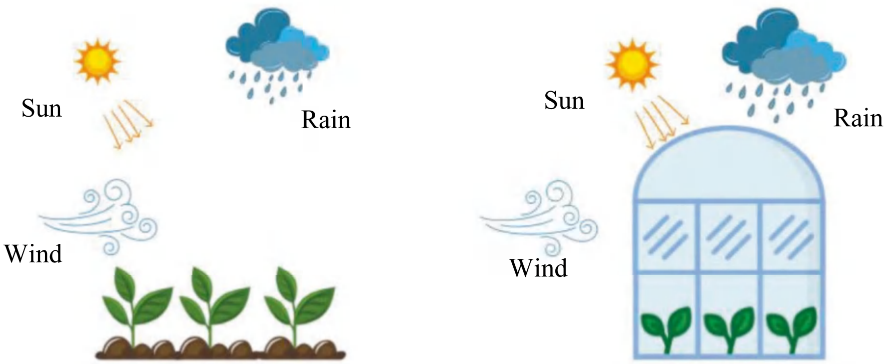

Fig. 4.1 Outdoor and indoor soil-based cultivation concept

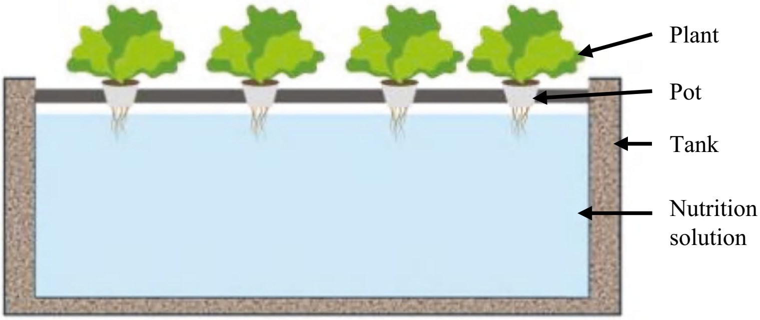

Fig. 4.2 Components of a hydroponics system

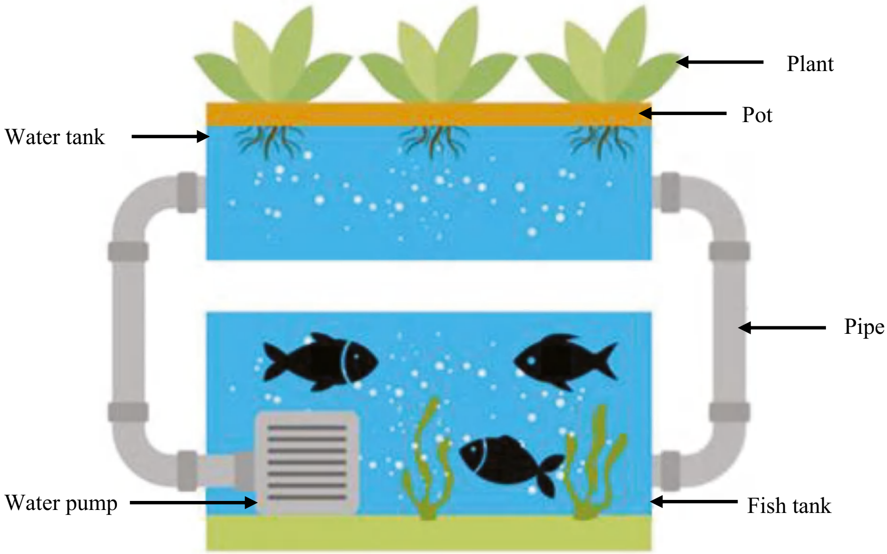

Fig. 4.3 Components of an aquaponic system

enhances irrigation efficiency by minimizing water waste and offers a highly efficient controlled environment (Kukal et al., 2020; Devade & Jain, 2023; Eldridge et al., 2020). Fogponics has several advantages over traditional watering methods. First, fogponics allows for precise and targeted nutrient delivery directly to the roots, ensuring that plants receive the optimal amount of nutrients without waste. Second, the fogponics system is highly water-efficient, reducing water consumption by minimizing runoff and evaporation.

Additionally, fogponics helps to regulate humidity levels, preventing overwatering and reducing the risk of plant diseases, which can harm crop yields. Furthermore, fogponics can promote faster and healthier plant growth by providing a consistent and oxygen-rich moisture supply. This method has shown promising results in

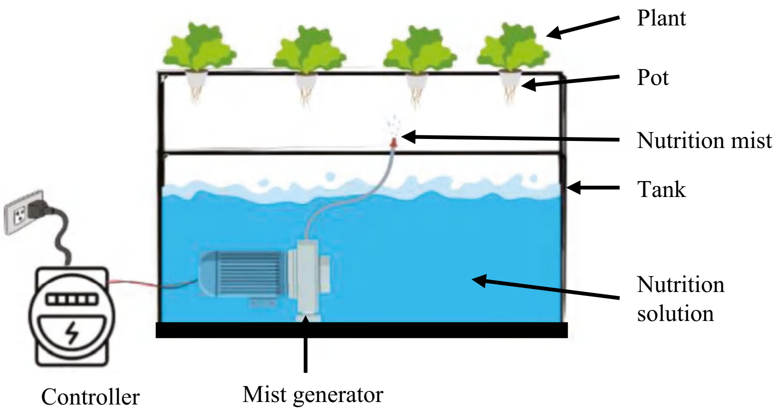

Fig. 4.4 Components of the aeroponic system

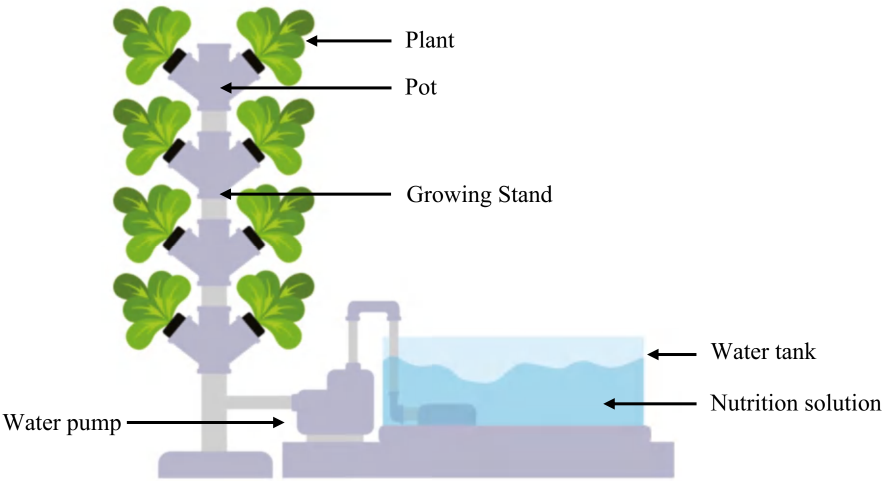

Fig. 4.5 Components of a vertical farming system

increasing crop yields and reducing water usage, making it a sustainable solution for agriculture. Fogponics represents a significant leap in the evolution of hydroponic growing systems. These advantages make fogponics a compelling option for sustainable agriculture, aligning with the global push for more efficient and environmentally friendly farming practices.

The potential of fogponics extends beyond traditional agriculture, as it can be implemented in urban farming and indoor gardening, offering a viable solution for maximizing plant growth in limited spaces. As further research and development continue, fogponics is poised to play a pivotal role in the future of agriculture, offering a promising method for optimizing water usage and crop production. Fogponics

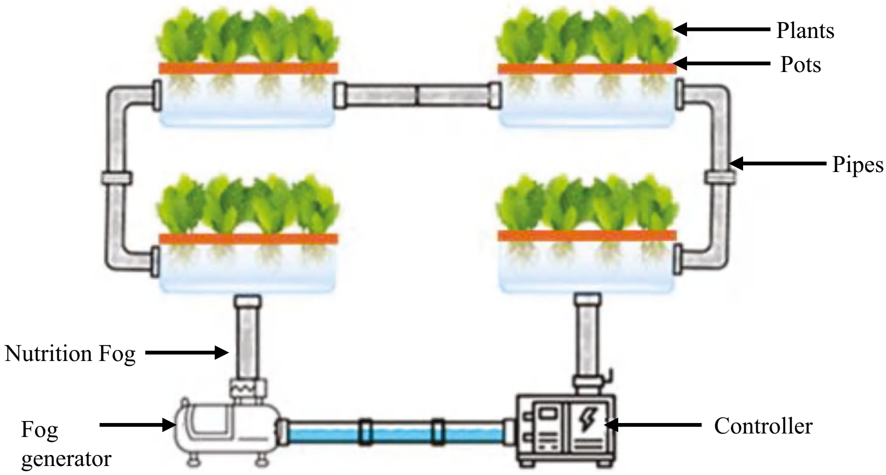

Fig. 4.6 Components of the fogponics system

has the potential to revolutionize the way we water and nurture plants, offering precise nutrient delivery, water efficiency, and humidity regulation. Numerous opportunities arise from developing mini-plant factories for vegetable cultivation in urban household farming. These opportunities include the ability to produce consistent and high-quality vegetables within a small space, reduced dependency on external suppliers, and the potential for supplemental income generation (Huang et al., 2018). By harnessing the principles and practices of plant factories, household urban farming can overcome many of the challenges associated with traditional vegetable cultivation (Gao, 2019). This allows for year-round vegetable production, regardless of external weather conditions or limited outdoor space. Furthermore, mini-plant factories provide households with direct control over the entire cultivation process, from seed to harvest (Kubota et al., 2019).

Despite the potential advancements of mini-plant factory technology, several obstacles and limitations must be addressed. One major obstacle is the high initial investment cost required to set up mini-plant factories. This includes not only the installation of advanced technological systems and infrastructure but also addressing additional expenses, such as increased energy costs from the energy demand of these systems. Furthermore, ongoing maintenance costs can pose a significant financial burden for operators. To address these challenges, it will be crucial to develop cost-effective and energy-efficient technologies for mini-plant factories (Huang et al., 2018) (Table 4.1).

Table 4.1 The advantages and limitations of the different indoor farming systems

Cultivation system	Advantages	Limitations
Soil-based cultivation	Comparatively less initial cost, easy to manage.	Need more space, as soil-borne pathogens can be difficult to manage, and automation is challenging. Low-cost system.
Hydroponics	Easy to manage pests and diseases, high rate of returns, higher productivity, and automation is possible.	Lower costs compared to other soilless systems but require extensive management. Additionally, waterborne pathogens and diseases can spread rapidly.
Aeroponics	Easy to manage pests and diseases, with high rates of return, higher productivity, and automation are possible.	High cost, needs extensive management, and diseases can spread fast.
Aquaponics	With a high rate of returns, higher productivity, and a sustainable system, automation can be integrated with aquaculture systems.	High cost and require extensive management and care. Diseases can spread quickly among plants and fish.
Vertical farming	Easy to manage pests and diseases, high rate of returns, higher productivity, and automation are possible.	High cost, needs extensive management, and diseases can spread fast.
Fogponics	Easy to manage pests and diseases, high rate of returns, higher productivity, water efficiency, and automation are possible.	High-cost and needs extensive management, and diseases can spread quickly.

Sources: Lakhiar et al. (2018), Kozai and Niu, (2020), Sambo et al. (2019), and Sharma et al. (2018)

4.2 Exploration of Design Challenges Focuses on Household Cultivation

Compared to commercial-level plant factories, mini-plant factories that can be used at the household level, we need to consider present challenges under two main categories: design challenges and the integration of modern technologies.

4.2.1 *Design and Logistical Challenges*

Despite mini-plant factory technology's many advantages and potential advancements, several obstacles and limitations must be addressed. One major obstacle is the high initial investment cost required to set up mini-plant factories. This includes not only installing advanced technology systems and infrastructure but also addressing additional expenses such as increased energy costs from the high energy demand of these systems. Furthermore, ongoing maintenance costs can pose a significant financial burden for operators. In addition, scalability may be limited by space constraints in urban areas.

To overcome these challenges and make mini-plant factory technology more accessible, increasing collaboration and knowledge sharing among industry stakeholders, researchers, and practitioners is important. Success relies heavily on developing optimization for crop cultivation technologies like artificial lighting systems, automated cultivation systems, and precise nutrient delivery. Overall progress will depend on overcoming these challenges through technological innovations, cost reductions, and greater industry collaboration. These technologies should reduce overall investment and maintenance costs and minimize energy consumption to ensure long-term sustainability (Kubota et al., 2019). Additionally, educational programs and training initiatives should be implemented to enhance technical skills and knowledge among potential users and operators of mini-plant factories. By addressing these obstacles and limitations, mini-plant factory technology can become more accessible and practical for a broader range of individuals and communities.

4.2.2 Integration of Modern Technologies to Overcome Limitations

With the integration of modern technologies into indoor farming and mini-plant factories, advancements have been made to enhance productivity, sustainability, and efficiency (Kubota et al., 2019). These technologies include automated systems for monitoring and controlling environmental factors such as temperature, humidity, and lighting. Additionally, implementing artificial intelligence and machine learning algorithms can optimize plant growth through data-driven decision-making. Furthermore, IoT devices and sensors enable real-time monitoring of plant health and nutrient levels, allowing for timely adjustments to optimize growing conditions. Moreover, the introduction of agricultural robots has revolutionized indoor farming by automating tasks such as planting, harvesting, and pest control. This integration of modern technologies has led to increased yields, reduced resource consumption, and improved crop quality in indoor farming and mini-plant factories (Idris Muhammad et al., 2021). Overall, modern technologies in indoor farming and mini-plant factories can revolutionize the agriculture industry by increasing productivity, sustainability, and efficiency while reducing resource consumption and environmental impact. Integrating modern technologies into indoor farming and mini-plant factories has revolutionized the agriculture industry by enhancing productivity, sustainability, and efficiency while reducing resource consumption and environmental impact (Huang et al., 2018). Furthermore, these technological advancements have also contributed to the development of sophisticated control systems that can precisely regulate temperature, humidity, and nutrient levels to create optimal growing conditions for plants (Idris Muhammad et al., 2021). These advancements have enabled a high degree of precision and control in indoor cultivation, leading to enhanced crop yields and quality.

Urban agriculture in densely populated areas can greatly benefit from integrating modern technologies into mini-plant factories (Kubota et al., 2019). These technologies enable the efficient use of limited space by maximizing crop production within urban environments. In addition, the automation of tasks through agricultural robots and IoT devices reduces the need for manual labor and allows for continuous monitoring and adjustment of growing conditions.

4.3 Suitable Crops for the Mini-Plant Factories

Even for commercial farming, crop selection is based on several factors. For the mini-plant factory selection, we focus on crop selection based on consumption behaviors (potential harvest), crop cycle length (days required to harvest), cost, and maintenance within the system. Table 4.2 provides the details of mostly used crops for indoor soilless farming.

4.4 Review of Small Mini-Plant Factories for Household Use

This review compares multiple studies addressing small and mini-plant factories intended for household applications, evaluating various cultivation technologies such as hydroponics, aeroponics, fogponics, and IoT-integrated systems. Each research effort identifies distinct advantages, including enhancing urban quality of life, sustainable resource utilization, integrating renewable energy solutions, and deploying cost-effective environmental control systems. Although these studies reveal differences regarding energy consumption, water efficiency, and the

Table 4.2 Some of the potential crops for mini-plant factories with their details

Crop	Length of crop cycle (days)	Average yield (conventional)	Average yield (hydroponics)
Anise	100–130	0.54 kg m^{-1} $year^{-1}$	1.42 kg m^{-1} $year^{-1}$
Fennel	100–120	0.54 kg m^{-1} $year^{-1}$	1.42 kg m^{-1} $year^{-1}$
Coriander	40–50	0.54 kg m^{-1} $year^{-1}$	1.42 kg m^{-1} $year^{-1}$
Chilies and peppers	60–80	8.92 kg m^{-1} $year^{-1}$	15.36 kg m^{-1} $year^{-1}$
Cucumber, gherkins	45–65	24.53 kg m^{-1} $year^{-1}$	20.50 kg m^{-1} $year^{-1}$
Lettuce	45–60	7.12 kg m^{-1} $year^{-1}$	11.03 kg m^{-1} $year^{-1}$
Chicory	50–60	7.12 kg m^{-1} $year^{-1}$	11.03 g m^{-1} $year^{-1}$

Sources: Goh et al. (2023), PimaLib (2024), Storey (2016), Jim (2025), Negi (2024), McCandless (2023), Nesi et al. (2013), and Martin (2023)

Table 4.3 A comparative analysis of different mini-plant factory models

System type	Focus areas	Energy consumption	Water usage	Innovations and benefits	Reference
PFALs	Urban quality of life, indoor green spaces	Optimized (moderate)	Highly efficient	Compactness, year-round indoor production	Kozai et al. (2020)
CPPS	Resource use efficiency, sustainable agriculture	Low to moderate	Extremely efficient	Enhanced sustainability, resource optimization	Kozai (2013a, b)
PFAL + wind energy	Sustainable agriculture, cost-effective solutions	Low (renewable energy)	Efficient	Renewable energy integration	Xydis et al. (2020)
Plant factory (CEA)	Crop production efficiency, sustainability	Moderate	Highly efficient	Controlled environments, increased yields	Takagaki et al. (2016)
CEA	Year-round production, local food access	Variable	Generally efficient	Improved food access, optimal conditions	UNDP (2025)
Mini-PFAL	Environmental control, low-cost sensors	Low	Efficient	Open-source, cost-effective control systems	Çaylı and Kaya (2019)
IoT & Cloud PFAL	Automation, monitoring, and control systems	Optimized	Highly efficient	IoT integration, autonomous data management	Dzaky et al. (2022)
Small-scale urban	Community engagement, food security	Variable	Efficient	Enhancing social capital, urban resilience	Grebitus (2021)
Small-scale farming	Food security, sustainable water use	Variable	Efficient	Sustainable water management, small-scale focus	Su (2021)

implementation of innovative solutions such as autonomous management systems, collectively, they underscore the substantial potential of mini-plant factories to significantly improve household food security, promote environmental sustainability, and strengthen urban resilience (Table 4.3).

4.5 Feasible and Conceptual Models with Prospects of Further Development

With the available commercial-level models and research, we can develop mini-plant factory models to be adopted inside the houses. Further, we can provide guidelines and training for maintenance and automated plant factories with AI technologies that can provide data to the service provider's API, so system owners can directly get the recommendations.

Table 4.4 Cost estimation for the developed mini-plant factory model (Japanese Yen)

Component	Cost (¥)
Fixed costs	
Structure	16,750
Light	8000
Irrigation system	6500
Total fixed cost	31,250
Operation cost (per crop cycle)	
Water 0.10Yen per Liter (160 liters)	6
Electricity ¥35/kWh (43.2 kWh)	1512
Seeds	22.5
Nutrient solution	81.9
Total operational cost	1622.4
Cost per 1 kg.	**5136.944**

If a single household needs to design its own system, AI and IoT can be incorporated with an alert system to receive text messages on their smartphones, helping them find solutions for diseases or nutrient deficiencies. Table 4.4 presents the model's average costs and components, as illustrated in Fig. 4.7.

Figure 4.8 illustrates several conceptual models for low-cost hydroponic systems, designed for adaptability based on user requirements. The system's framework and water distribution network are constructed from standard polyvinyl chloride (PVC) piping, readily available at local hardware retailers. The photo period and the nutrient solution circulation are automated using a conventional electrical timer to regulate the lighting and a small submersible pump, typically sold in local aquarium supply stores.

The primary advantage of this design philosophy is its remarkable accessibility and affordability. By leveraging standard, off-the-shelf components, the system significantly lowers the financial barrier to entry, making soilless cultivation a feasible option for households, educational institutions, and community projects. This approach promotes food security by enabling year-round, localized production of fresh produce and serves as a practical educational tool for demonstrating principles in biology, engineering, and sustainable agriculture. Consequently, these models offer a practical and scalable solution for decentralized food production.

Figure 4.9 presents a conceptual model for a cost-effective, Internet of Things (IoT)-based hydroponics system, designed with significant potential for customization. The system's architecture is built around a central processing unit, a Raspberry Pi 4B, which interfaces with environmental sensors. These components include a DHT22 sensor to monitor ambient temperature and humidity, a light sensor to quantify illuminance (measured in lux), and specialized probes to measure water temperature and pH levels. Furthermore, a Pi Camera module is integrated for periodic image acquisition, enabling visual monitoring of plant health and growth. All system parameters and visual data are aggregated and displayed on a real-time, interactive dashboard presented on a 10-inch screen.

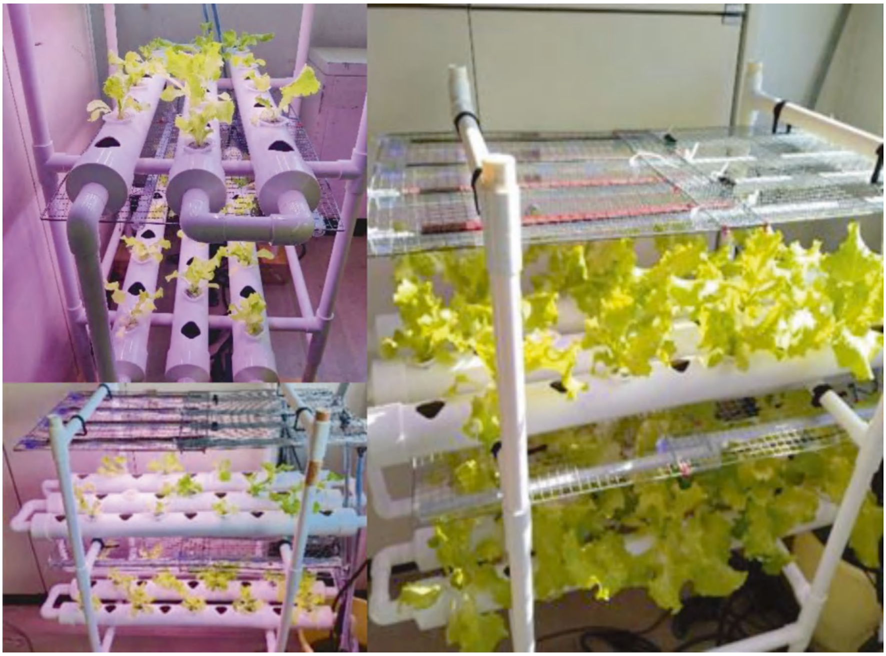

Fig. 4.7 A feasible model was developed to demonstrate the low-cost home-scale mini-plant factory

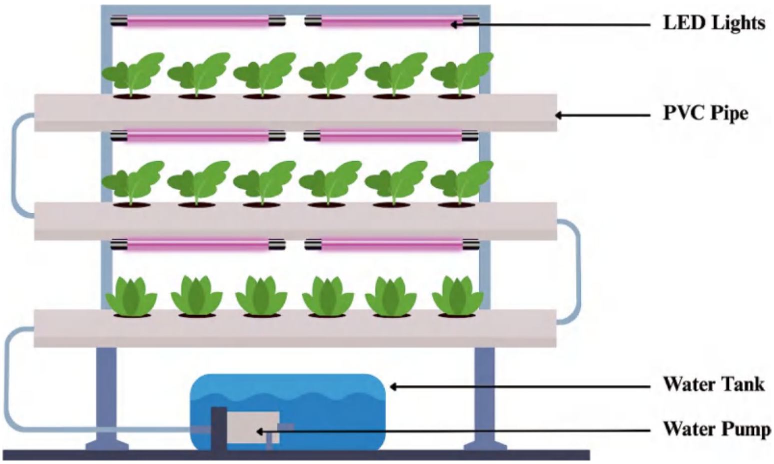

Fig. 4.8 Low-budget hydroponic model for a household

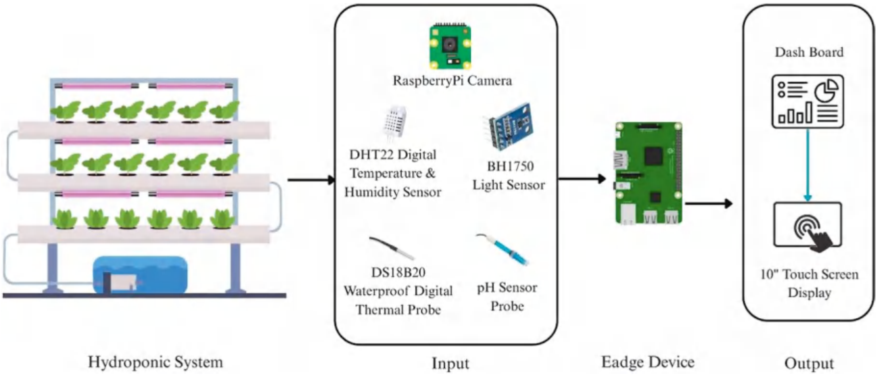

Fig. 4.9 Conceptual hydroponics model with IoT application

4.5.1 Future and Technological Advancement

Deploying cutting-edge tech like automation and robotics into decision-making is crucial for enhancing the system's productivity. Adopting alternative energy solutions ensures the system's sustainability (Idris Muhammad et al., 2021). Moreover, applying artificial intelligence and machine learning algorithms holds great potential in optimizing crop production and resource management within mini-plant factories (Huang et al., 2018). These technological advancements will likely drive the growth and adoption of mini-plant factories, as they offer a viable solution to the challenges of traditional agriculture and provide a sustainable approach to food production in the future (Kubota et al., 2019). Integrating modern technologies into indoor farming and mini-plant factories has revolutionized the agriculture industry by enhancing productivity, sustainability, and efficiency while reducing resource consumption and environmental impact.

Integrating advanced data analytics tools enables farmers to gather valuable insights from the vast data collected by sensors and monitoring systems. This data-driven approach can lead to informed decision-making, predictive modeling, continuous crop cultivation, and improvement in resource management. By harnessing the power of modern technologies and incorporating these advanced features, mini-plant factories have the potential to revolutionize the agriculture industry by maximizing productivity and sustainability while minimizing resource consumption and environmental impact (Tong et al., 2023).

The ability to remotely monitor and control mini-plant factories through connected devices and applications provides farmers with flexibility and convenience. This feature enables real-time adjustments to environmental conditions, ensuring continuous plant health monitoring even when farmers are not physically present at the facility, thereby reducing the need for manual labor (Khattab et al., 2019; Kubota et al., 2019).

Further advancements in sustainable energy solutions, such as advanced solar technologies, efficient energy storage systems, and renewable energy integration, can help mini-plant factories reduce reliance on traditional power sources and minimize their carbon footprint (Kumar & Kumar, 2017). These solutions can make mini-plant factories more environmentally friendly and economically viable in the long run (Kubota et al., 2019).

Advancements in genetic engineering and crop modification technology may lead to the development of plants specifically tailored for indoor cultivation, with traits optimized for space efficiency, nutrient uptake, and resistance to environmental factors (Hiwasa-Tanase & Ezura, 2016; Kubota et al., 2019). These genetically modified crops could significantly enhance the productivity and profitability of mini-plant factories, reducing crop production cost and environmental impact (Huang et al., 2018).

The integration of mini-plant factories into urban infrastructure, such as incorporating them into building designs and utilizing vertical spaces for cultivation, can further enhance the efficiency and sustainability of urban agriculture (Orsini et al., 2013). By integrating mini-plant factories into urban areas, the distances between food production and consumption can be significantly reduced, reducing transportation costs and carbon emissions (Huang et al., 2018).

As mini-plant factory technology becomes more accessible and scalable, there is potential for increased consumer adoption, leading to a shift toward decentralized and localized food production (Kozai, 2013a, b). This shift would empower individuals to have more control over their food sources and reduce the carbon footprint associated with long-distance transportation of food (Kubota et al., 2019). Additionally, the availability of fresh and high-quality produce year-round from mini-plant factories can enhance nutrition and food security in urban areas (Huang et al., 2018) and promote sustainable resource consumption, thereby reducing environmental impact (Kozai & Niu, 2020).

The future of mini-plant factories may involve increased collaboration and knowledge sharing among industry stakeholders, researchers, and technology developers to accelerate innovation and address global food security challenges (Smart Agri Tech, 2020). By pooling resources, expertise, and data, stakeholders can work together to develop more efficient and sustainable practices for the mini-plant factory.

4.6 Conclusion

In conclusion, developing mini-plant factories for vegetable cultivation in household urban farming presents a promising solution to the challenges faced in traditional vegetable production. By embracing this innovative approach, households can overcome barriers such as limited space and a lack of specialized knowledge, while also enjoying the benefits of consistent and high-quality vegetable production, reduced dependency on external suppliers, and the potential for generating supplemental income.

Since the structure can develop in a limited space without any seasonal variation, the mini-plant factory has the potential to improve agricultural productivity. Additionally, they can be situated in urban areas, reducing transportation time to market and enhancing the availability of fresh food.

People living far away from farmlands can use these small demonstrations of the farming system to learn more about agriculture. Mini-plant factories can encourage the adoption of technologies in the sector. To minimize energy expenditures, it is essential to integrate sustainable energy sources. These structures can be placed in urban areas to blend in with existing structures and improve vertical space management in landscape design, while also contributing to food production.

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Chapter 5
Computational Intelligence in Climate-Adaptive Agriculture: Pathways to Resilient Food Systems

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Abstract Climate change is fundamentally reshaping global agricultural dynamics, threatening food security through rising temperatures, erratic precipitation, extreme weather events, and shifting ecological zones. This chapter provides a comprehensive analysis of how integrating Artificial Intelligence (AI) with climate-adaptive agricultural strategies can revolutionize food production, resource management, and resilience building in the face of climate variability. This chapter begins by examining the diverse and intensifying impacts of climate change on agriculture, with a particular focus on yield instability and increased vulnerability to pests and diseases. It then introduces the foundational principles of climate-adaptive agriculture, emphasizing risk assessment, ecological resilience, and resource efficiency. Established adaptation practices such as crop diversification, efficient water management, agroforestry, conservation agriculture, climate-resilient crop varieties, and early warning systems are explored as essential responses. The transformative potential of AI is then analyzed in depth, highlighting its role in enabling, enhancing, and scaling these climate-adaptive strategies. Key applications include precision agriculture for input optimization, remote sensing and analytics for yield forecasting, and predictive models for early warning systems. Furthermore, this chapter demonstrates how AI can be synergistically integrated with adaptive practices, including selecting optimal crop combinations, improving irrigation scheduling, crop diversification, designing agroforestry systems, and accelerating climate-resilient breeding programs. Critical challenges, including limited data availability, digital infrastructure gaps, algorithmic fairness, ethical concerns, and farmer adoption, are critically analyzed. Looking forward, this chapter explores

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emerging innovations, including edge computing, quantum computing, predictive breeding, explainable AI (XAI), blockchain-based supply chain traceability, and AI-driven policy modeling. Together, these insights offer a strategic roadmap for policymakers, researchers, industry leaders, and farming communities to collaboratively build climate-resilient, intelligent, and future-ready agricultural systems.

Keywords Climate change · Artificial Intelligence · Digital infrastructure

5.1 Introduction

The Earth's agricultural landscapes, the very foundations upon which human civilization has flourished, are now facing an unprecedented trial. A gathering storm of climate-induced disruptions is sweeping across the globe, leaving farmers and food systems vulnerable and exposed. Climate change, once a distant threat relegated to scientific reports, has become an undeniable reality, actively reshaping the patterns of agricultural production with each passing season. The warnings from the scientific community, most notably the Intergovernmental Panel on Climate Change (IPCC), are becoming increasingly dire, underscoring that continued reliance on unsustainable practices will lead to irreversible changes, jeopardizing our ability to feed a growing planet (IPCC, 2023). It is within this context of looming crisis that a fundamental transformation of agricultural practices is not merely desirable but an absolute necessity.

The escalating temperatures, for example, are no longer simply a matter of incremental increases. They represent a tangible threat, shrinking growing seasons, pushing crops beyond their physiological limits, and demanding unsustainable levels of irrigation in already arid regions (Ortiz-Bobea et al., 2021). Equally disruptive are the shifting precipitation patterns, which bring prolonged droughts to some areas, turning fertile lands into dust bowls, while unleashing devastating floods on others, washing away topsoil and obliterating entire harvests (IPCC, 2023). The rise in extreme weather events, too, has been impossible to ignore. Unprecedented heat waves sear crops in the fields, while increasingly powerful cyclones and hurricanes flatten entire agricultural regions, leaving communities devastated and food supplies severely disrupted (Mehrabi et al., 2021). As sea levels rise, coastal agricultural zones are becoming increasingly vulnerable to saltwater intrusion, rendering vast tracts of land infertile and displacing generations of farming families (Nicholls et al., 2021). Climate change also is creating a more conducive environment for pests and diseases, disrupting delicate ecological balances and escalating the need for synthetic pesticides that can further harm the environment. Furthermore, these stresses are occurring against a backdrop of declining biodiversity, where the reliance on monoculture farming practices and homogenization reduces the resilience of agricultural ecosystems to climatic shocks (Khoury et al., 2016).

The challenges are immense, but not insurmountable. Amidst the rising tide of climate uncertainty, a powerful convergence of technological innovation and ecological wisdom offers a path toward a more secure and sustainable future for agriculture. To address these challenges, agriculture must adopt a diverse portfolio of climate-adaptive strategies that build resilience, enhance resource efficiency, and support sustainability. Crop diversification remains a cornerstone approach reducing risk, improving soil biodiversity, and stabilizing yields under climatic uncertainty. In tandem, precision water management practices such as drip irrigation, soil moisture monitoring, and rainwater harvesting are vital for reducing water waste and improving productivity in water-scarce regions (Pereira et al., 2020). Agroforestry systems, which integrate trees with crops or livestock, offer significant climate buffers, improve microclimates, and enhance carbon sequestration (Mbow et al., 2014). Conservation agriculture featuring minimum tillage, permanent soil cover, and crop rotation protects soil structure, boosts water retention, and reduces greenhouse gas emissions (FAO, 2021). Climate-resilient crop varieties, developed through advanced breeding and biotechnology, are increasingly important in enabling production under drought, salinity, and temperature extremes (Tester & Langridge, 2010). Furthermore, postharvest adaptation strategies such as improved storage facilities, cold chains, and solar drying technologies help reduce losses exacerbated by climate variability (FAO, 2019). Finally, early warning systems (EWS) provide timely alerts on extreme weather, pests, and diseases, enhancing preparedness and decision-making at the farm level (WMO, 2023). Together, these strategies provide a robust foundation for climate resilience. When combined with AI, they become more dynamic, data-driven, and scalable empowering next-generation agriculture to thrive under a changing climate.

AI, with its unparalleled ability to analyze complex data, recognize intricate patterns, and generate accurate predictions, has emerged as a game-changing tool with the potential to revolutionize agricultural practices (Kamilaris & Prenafeta-Boldú, 2018). AI's capacity for precise optimization, proactive risk management, and personalized decision support can empower farmers to navigate the challenges of a changing climate and enhance the sustainability of agricultural production. Complementing AI's technological prowess is a wealth of established climate-adaptive agricultural strategies, practices honed over decades of research and practical implementation (FAO, 2018). These strategies, rooted in ecological principles and a deep understanding of agricultural systems, offer a pathway toward enhancing resilience, mitigating environmental impacts, and securing food production in the face of climatic uncertainty.

The synergy between AI and climate-adaptive strategies holds the key to unlocking a new era of sustainable and resilient agriculture. By harnessing AI's analytical power, we can optimize the implementation of these strategies, tailoring them to specific environmental conditions and farming contexts. Consider, for instance, the potential of AI to analyze real-time weather data, soil moisture sensors, and plant health indicators to create customized irrigation schedules that minimize water consumption while maximizing crop yields. In the realm of pest management, AI-powered systems can analyze imagery from drones and satellites to detect early signs of pest infestations, enabling farmers to implement targeted interventions that reduce reliance on broad-spectrum pesticides and promote biodiversity. Furthermore, AI can drive the development of sophisticated early warning systems that forecast the likelihood of droughts, floods, and other extreme weather events, giving farmers, policymakers, and communities' valuable time to prepare and mitigate potential damage. The potential to tailor climate-adaptive strategies with the aid of AI through the creation AI-enhanced decision-making tools allows governments and communities develop effective plans (Jain et al., 2023).

This chapter will explore this transformative intersection, investigating how the strategic integration of AI with established climate-adaptive strategies can reshape agricultural practices and build resilience into our food systems. We will examine specific examples of how AI can enhance crop diversification, optimize water resource management, support agroforestry initiatives, accelerate the development of climate-resilient crop varieties, and improve pest and disease control. We also address the ethical challenges and practical obstacles that must be overcome to ensure equitable access and responsible deployment of AI in agriculture, including considerations related to data governance, algorithmic bias, and the need for capacity building. Ultimately, this chapter aims to provide a roadmap for harnessing the power of AI to build climate-resilient and sustainable food systems that can nourish a growing global population while protecting the planet for future generations.

5.2 The Role of AI in Climate-Adaptive Agriculture

The intersection of AI and climate-adaptive agricultural strategies offers transformative potential for building resilient and productive farming systems. While traditional adaptation practices such as crop diversification, water conservation, agroforestry, and soil stewardship have long been employed to buffer against climate variability, their effectiveness can be significantly enhanced when integrated with AI-driven tools. This synergistic approach enables site-specific, data-informed, and dynamically adaptive decisions, allowing farmers and policymakers to respond proactively to the ever-changing climate landscape. Figure 5.1 illustrates how five key domains where AI is augmenting traditional climate adaptation strategies are accelerating the shift toward sustainable and climate-smart agriculture.

Climate change is rapidly altering agricultural landscapes worldwide. From unpredictable rainfall patterns and rising temperatures to the increasing frequency of extreme weather events, the agricultural sector faces unprecedented challenges in ensuring food security and environmental sustainability. In response, the concept of climate-adaptive agriculture has emerged as a strategic framework for building resilience, reducing vulnerability, and maintaining productivity under changing climatic conditions. At the heart of this transformation is AI—a powerful set of technologies that enable smarter, faster, and more data-driven decisions (Fig. 5.1). AI is now a key enabler in making agriculture not only climate resilient but also efficient and sustainable. AI is being applied in various domains of climate-adaptive agriculture, from resource optimization, predictive modeling to early warning systems and supply chain.

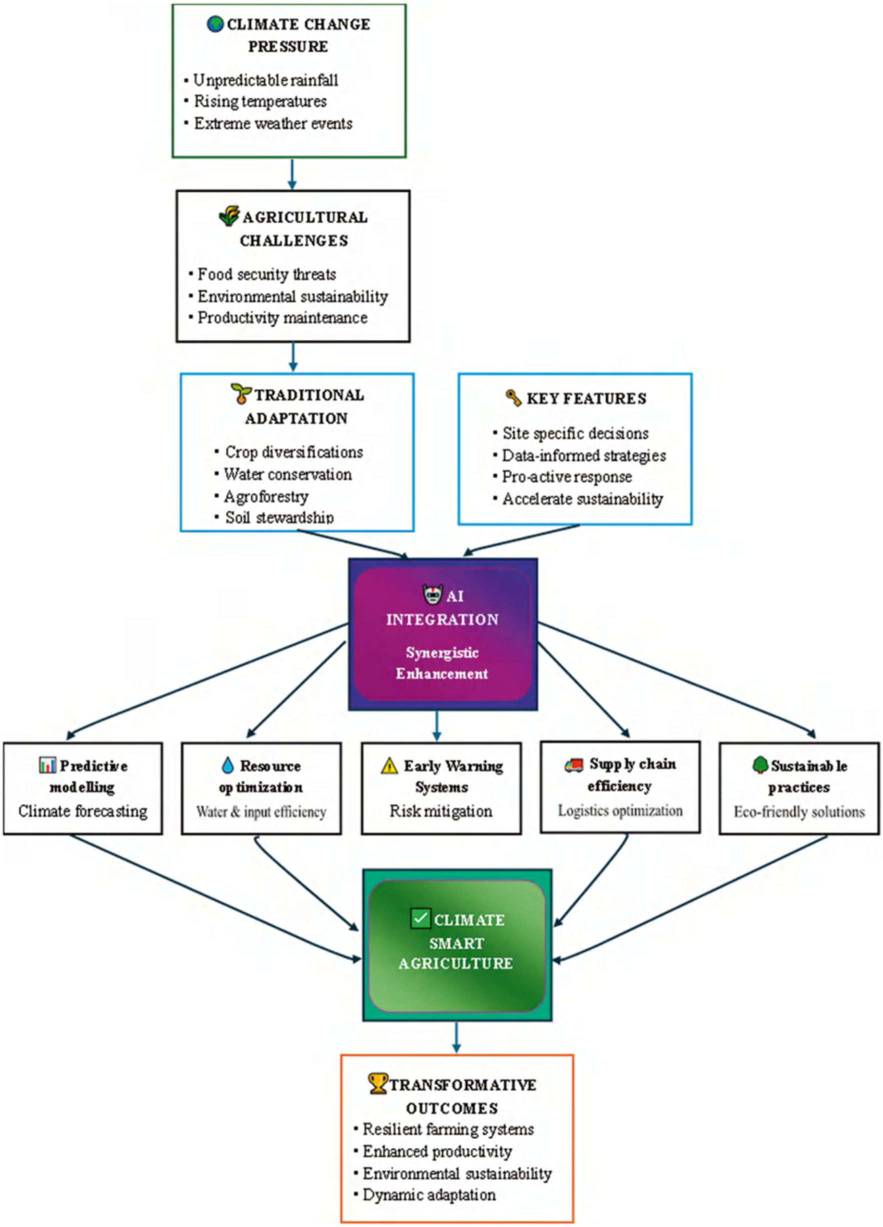

Fig. 5.1 Synergistic integration of climate change adaptation and Artificial Intelligence

5.2.1 Climate Parameter Simulation and Forecasting Using AI

As climate variability intensifies, precision in simulating and forecasting key climate parameters such as temperature, rainfall, evapotranspiration, and drought indices is critical for climate-smart agriculture. Traditional tools, such as Global Climate Models (GCMs) and Regional Climate Models (RCMs), offer macro-scale insights but often lack the spatial resolution and adaptability required for site-specific agricultural planning. Artificial Intelligence, particularly Deep Learning (DL) models, has emerged as a transformative solution by enabling high-resolution, localized climate forecasts derived from historical datasets, satellite observations, and reanalysis products. DL architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and transformers can efficiently capture complex spatiotemporal dependencies in climate data. These models are highly effective in downscaling coarse-resolution outputs from systems like CMIP6, producing granular, farm-level insights. For example, Ma et al. (2022) demonstrated that a CNN-based approach successfully downscaled monsoonal precipitation over South Asia from 100 km to 5 km resolution, significantly improving the prediction of extreme events. Moreover, AI facilitates dynamic scenario modeling by integrating socio-environmental variables to simulate the long-term impacts of climate adaptation strategies. This enables researchers and policymakers to assess how shifts in cropping patterns, irrigation methods, and land use could influence yield resilience, soil carbon dynamics, and water availability under different climate trajectories (Wu et al., 2023). As digital infrastructure expands across rural regions, AI-based forecasting tools are increasingly accessible to farmers and extension systems. These tools empower users to make informed, adaptive decisions enhancing climate resilience across scales, from individual farms to national adaptation strategies.

5.2.2 AI-Based Crop Growth Modeling and Simulation

As climate variability intensifies bringing erratic rainfall, rising temperatures, and extreme weather, AI-based crop modeling offers a powerful tool for predicting how crop varieties will perform under future scenarios. Traditional crop growth models like DSSAT, APSIM, and WOFOST are widely used to simulate crop performance under diverse environmental and management scenarios. However, these models often struggle to account for complex genotype × environment × management (G × E × M) interactions and require extensive calibration (Jones et al., 2003). AI offers a paradigm shift in crop simulation by enabling dynamic, data-driven modeling using large-scale environmental, agronomic, and remote sensing datasets. Machine learning (ML) and Deep Learning (DL) algorithms such as Random Forests, Support Vector Machines, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have demonstrated strong predictive capabilities in simulating biomass, phenology, and yield outcomes. For example, You et al. (2017) applied a CNN-LSTM model to predict maize yields across the US Corn Belt with improved spatial accuracy compared to traditional models. AI-based models also support adaptive planning under climate uncertainty by simulating how changes in sowing dates, irrigation schedules, or crop varieties influence productivity under different climate scenarios (Zhao et al., 2022). By integrating sensors, UAV, and satellite data, these models are transitioning toward real-time, prescriptive analytics for precision farming. As digital agriculture expands, AI-enabled crop modeling is becoming essential for scalable, climate-smart decision-making empowering breeders, farmers, and policymakers to develop resilient cropping systems suited to evolving agro-climatic realities (FAO, 2023).

5.2.3 AI-Assisted Breeding Programs for Climate-Resilient Crops

The accelerating impacts of climate change, rising temperatures, erratic rainfall, and emerging pest pressures necessitate the rapid development of climate-resilient crop varieties. Conventional breeding methods, though foundational, are time-intensive and often unable to match the pace of environmental change. AI, particularly ML and DL, is revolutionizing crop breeding by enabling predictive, data-driven selection of traits linked to stress tolerance, yield stability, and resource-use efficiency (Kushwaha et al., 2021). AI models can analyze high-throughput phenotyping data, genomic sequences, and environmental variables to identify complex genotype-phenotype-environment relationships (Crossa et al., 2017). Techniques such as Random Forests, Gradient Boosting Machines, Support Vector Machines, and Deep Neural Networks have been successfully applied in genomic selection, accelerating the identification of candidate genes for drought tolerance, heat resilience, and nutrient efficiency (Montesinos-López et al., 2018). For instance, AI-assisted genomic selection has reduced breeding cycles in maize and wheat by enabling early prediction of performance across environments (Gillberg et al., 2019). Integration with fCRISPR-based gene editing and multi-environment trials further enhances precision breeding (Chaudhary et al., 2022). Moreover, digital twin models powered by AI allow virtual testing of genotypes under simulated climate futures, optimizing selection strategies. As genomic datasets and AI platforms become more accessible, breeding programs worldwide are leveraging these tools to develop next-generation, climate-resilient cultivars at unprecedented speed and scale.

5.2.4 AI in Conservation Agriculture: Enhancing Soil and Ecosystem Resilience

AI is transforming soil management within conservation agriculture by delivering real-time, data-driven insights that enhance soil health and agricultural resilience. Traditional soil assessment methods reliant on periodic, labor-intensive sampling offer limited spatial and temporal resolution. In contrast, AI-powered platforms integrate data from soil sensors, remote sensing technologies, and historical land-use records to monitor key soil parameters such as moisture, nutrient levels, organic carbon, and compaction in real time. ML algorithms analyze these datasets to detect degradation patterns and forecast soil fertility trends under different conservation strategies (Hengl et al., 2017), enabling timely, targeted interventions. Core practice in conservation agriculture cover cropping also benefits significantly from AI. Selecting optimal cover crop species is complex, as it requires accounting for climate, soil conditions, and crop rotation goals. AI tools synthesize weather data, soil profiles, and historical performance records to recommend region-specific cover crops mixes that optimize nutrient cycling and soil protection. Advanced models using satellite data and computer vision can even estimate biomass and carbon inputs (Crane-Droesch et al., 2020). AI is also reshaping no-till planting practices. Vision-guided autonomous tractors and GPS-enabled precision seeders dynamically adjust depth, spacing, and rate based on real-time field data, improving germination rates and minimizing soil disturbance.

5.2.5 AI-Driven Crop Diversification

Crop diversification is a cornerstone of climate-resilient agriculture, reducing dependence on monocultures, enhancing ecological balance, and buffering against climatic shocks. However, selecting the optimal combination of crops under uncertain climate scenarios and shifting agroecological zones remains a complex task. Artificial Intelligence (AI) provides a transformative solution by integrating large datasets such as soil profiles, historical yields, market trends, and climate forecasts to support intelligent decision-making in crop diversification. Machine learning algorithms can identify optimal crop combinations tailored to specific regions, while predictive models assess climate risks and recommend adaptive crop rotations, intercropping patterns, or varietal mixes (Reynolds 2021). Remote sensing and AI-powered geospatial analysis can further map crop suitability under current and projected climate conditions (Tripathi et al., 2023). These tools not only reduce production risk but also support economic resilience by aligning diversification with market demands and agroecological suitability. Moreover, AI-enabled platforms can offer real-time advisories to smallholder farmers, integrating localized data with national or global trends. By guiding context-specific, dynamic, and climate-smart diversification choices, AI strengthens farm resilience, enhances food security, and promotes sustainable land use in the face of accelerating climate change.

5.2.6 AI Applications in Agroforestry Optimization

Agroforestry integrating trees with crops and/or livestock represents a sustainable land-use strategy that enhances biodiversity, sequesters carbon, and improves soil and water conservation. Optimizing such complex systems requires dynamic, multi-variable analysis, where AI has emerged as a transformative enabler. AI-driven models, including ML, fuzzy logic, and multi-agent systems, are increasingly employed to simulate agroecological interactions, evaluate trade-offs, and design spatially efficient agroforestry layouts (Rahman et al., 2021). These tools support species selection by analyzing climate suitability, soil profiles, pest resistance, and productivity metrics facilitating context-specific decisions that maximize both ecological and economic outcomes (Ojha et al., 2020). Remote sensing combined with AI-based image analysis enables continuous monitoring of tree growth, biomass accumulation, and inter-species competition within agroforestry plots (Kamilaris & Prenafeta-Boldú, 2018). AI-powered decision support systems can forecast long-term performance of tree-crop combinations under projected climate scenarios, thereby aiding in risk mitigation and adaptive planning (Zomer et al., 2022). DL models have also been applied to quantify carbon sequestration potential, enabling agroforestry's integration into carbon markets (Asaduzzaman et al., 2025). Furthermore, AI facilitates landscape-scale agroforestry planning by identifying degraded lands suitable for restoration and optimizing tree placement to reduce shading and water stress (Nguyen et al., 2021). To fully leverage AI's potential in agroforestry, interdisciplinary collaboration, farmer-accessible platforms, and robust, localized datasets are essential. AI offers unprecedented opportunities to scale agroforestry as a climate-smart, productive, and regenerative land-use paradigm.

5.2.7 AI in Farm Mechanization and Autonomous Operations

AI is transforming farm mechanization by enabling intelligent, autonomous operations that improve efficiency, precision, and sustainability. Traditional mechanization systems—tractors, harvesters, planters—are evolving into smart machines integrated with sensors, robotics, and AI algorithms capable of real-time decision-making and adaptive control (Bechar & Vigneault, 2016). This evolution is essential for addressing labor shortages, increasing operational accuracy, and reducing environmental footprints under climate stress. AI-driven perception systems, utilizing computer vision, LiDAR, and multispectral imaging, enable autonomous navigation, object recognition, and precise field operations such as weeding, spraying, and harvesting (Kamilaris & Prenafeta-Boldú, 2018). ML models improve implement control systems, allowing machines to dynamically adjust to soil variability, crop health, or topography (Shah & Sharifi, 2022). DL enhances object detection for fruit harvesting robots, reducing damage and improving yield recovery (Koirala et al., 2019). Examples include autonomous tractors (John Deere), robotic weeders (Naïo Technologies), and AI-controlled drones for crop monitoring and spraying (Tsouros et al., 2019). : Swarm robotics, consisting of multiple small autonomous units, is also emerging as a scalable and low-impact operational approach (Delaney et al., 2021). AI-enabled farm equipment contributes to climate-smart agriculture by optimizing input use, minimizing fuel and chemical applications, and supporting conservation tillage practices (Yahya et al., 2023). As edge computing and IoT connectivity improves, smallholder-accessible autonomous systems are becoming feasible, accelerating inclusive agricultural mechanization (World Bank, 2021). The convergence of AI, robotics, and automation marks a pivotal shift toward next-generation, climate-adaptive farming systems.

5.2.8 AI in Precision Resource Management

Precision resource management represents a transformative frontier in agriculture, aiming to optimize the use of inputs such as water, fertilizers, pesticides, and energy while enhancing productivity and environmental sustainability. AI facilitates this paradigm by integrating diverse datasets ranging from weather forecasts, remote sensing, soil sensors, and crop models to generate site-specific, real-time recommendations. ML algorithms enable variable rate application of resources, minimizing waste and maximizing yield through decision support systems and autonomous machinery (Kamilaris & Prenafeta-Boldú, 2018). AI models have proven effective in optimizing irrigation schedules by predicting evapotranspiration and soil moisture dynamics. DL techniques are also applied for nutrient management, allowing precise timing and dosage of fertilizer applications. Similarly, pest and disease detection via AI-powered image recognition reduces indiscriminate pesticide usage, enhancing ecosystem health. Moreover, AI-enabled drones and autonomous tractors execute precision farming operations with high spatial accuracy, guided by reinforcement learning and computer vision. Integrating AI with GIS platforms supports spatial variability analysis, aiding resource mapping and planning (Gebbers & Adamchuk, 2010). As climate stress intensifies, AI-powered precision management will be central to achieving adaptive, input-efficient agriculture particularly in resource-scarce, smallholder contexts. Equitable access to these tools, however, remains a critical challenge requiring investment in digital infrastructure and inclusive innovation ecosystems.

5.2.9 Smart Irrigation and Water Resource Management

Water scarcity, exacerbated by climate change, is one of the most critical constraints facing global agriculture. Smart irrigation systems, powered by AI, are redefining water resource management by enabling site-specific, data-driven decision-making to optimize water use efficiency and crop productivity. These systems integrate weather forecasts, soil moisture sensors, evapotranspiration models, and crop growth data to apply the right amount of water, at the right time, and in the right place. AI techniques such as ML, fuzzy logic, Artificial Neural Networks (ANN), and reinforcement learning (RL) are increasingly applied in real-time irrigation scheduling and adaptive control. DL models can predict soil moisture dynamics and crop water demand under variable climatic conditions, improving precision and reducing over-irrigation. Internet of Things (IoT)-enabled platforms with AI-based analytics allow for continuous monitoring and autonomous irrigation, enhancing water savings by up to 30–50% compared to conventional methods (Li et al., 2021). These tools are particularly impactful in arid and semi-arid regions where water is a limiting factor for food security. As digital agriculture evolves, AI-driven smart irrigation systems are becoming essential components of climate-smart farming supporting both productivity and sustainability at scale.

5.2.10 Forecasting Pest Outbreaks and Yield Loss Using Predictive Analytics

The increasing frequency and severity of pest outbreaks exacerbated by climate change and global trade pose major threats to agricultural productivity. Predictive analytics, powered by AI, offers transformative potential to forecast pest emergence and associated yield losses before critical damage occurs. By integrating historical pest incidence, weather patterns, crop phenology, and remote sensing data, ML models can identify early warning signals and generate spatially explicit risk maps. Time-series forecasting, Bayesian networks, and Recurrent Neural Networks (RNNs) are now employed to predict outbreak probabilities and pest life cycle stages with high accuracy (Pinter et al., 2020). Coupled with drone-based surveillance and Internet of Things (IoT) sensors, real-time pest detection systems enable timely interventions (Liu et al., 2020). AI also aids in estimating potential yield loss due to pests, weeds, and pathogens, using hyperspectral imaging and data fusion techniques (Gao et al., 2020). For example, India's "FAW Monitor" uses AI to track fall armyworm spread, while NASA's Crop-CASMA integrates satellite data for early stress detection. These tools empower decision-makers with dynamic forecasting for integrated pest management (IPM), minimizing pesticide overuse and enhancing resilience (Kamilaris & Prenafeta-Boldú, 2018). Wider adoption of predictive systems will require investment in high-resolution datasets, farmer-friendly interfaces, and cross-border data sharing frameworks.

5.2.11 AI for Crop Monitoring and Yield Prediction

AI has emerged as a cornerstone of precision agriculture, transforming crop monitoring and yield prediction by leveraging large-scale, multi-source data for real-time insights. The integration of satellite remote sensing, Unmanned Aerial Vehicles (UAVs), Geographic Information Systems (GIS), and in situ sensors facilitates accurate assessment of plant health, crop stress, and productivity forecasts (Kamilaris & Prenafeta-Boldú, 2018). Satellite platforms such as Sentinel-2, MODIS, and Landsat generate multispectral imagery used to compute vegetation indices (e.g., NDVI, EVI), which are critical for identifying canopy vigor and chlorophyll content (You et al., 2017). UAVs equipped with RGB, thermal, and hyperspectral cameras offer high-resolution imagery to detect early signs of water stress, pest outbreaks, and nutrient deficiencies (Zhang et al., 2019). Advanced AI models, including CNNs and LSTM networks, can classify phenological stages, segment crop types, and forecast yield by learning from historical weather, soil, and crop growth patterns (Ferentinos, 2018). GIS further enhances spatial analytics by integrating topography, soil maps, and climate layers for zone-specific yield prediction and decision support (Tripathy et al., 2022). These AI-enabled systems not only inform timely interventions but also support adaptive planning under climate variability. As AI tools become more accessible and interpretable, they are poised to improve productivity, reduce risk, and build resilience in next-generation agriculture.

5.2.12 AI-Driven Early Warning Systems for Risk Forecasting

AI-driven early warning systems (EWS) are transforming agricultural risk forecasting by enabling the timely identification of threats such as droughts, floods, pest outbreaks, and disease epidemics. These systems integrate real-time data from meteorological stations, satellite sensors, UAVs, and IoT-enabled field devices with advanced ML and DL models to predict hazards and their potential impacts on agriculture. Techniques such as Artificial Neural Networks (ANNs), Random Forests, and LSTM networks are widely applied to model temporal-spatial patterns of climate anomalies, crop health deterioration, and pest migration (Chen et al., 2022). Satellite data from Sentinel, MODIS, and TRMM, combined with ML classifiers, enable the detection of early biophysical stress and rainfall deficits that precede drought or crop failure (You et al., 2017). AI-enhanced EWS support decision-makers with probabilistic forecasts, scenario modeling, and risk mapping for specific agro-ecological zones. For example, the FAO's Agricultural Stress Index System (ASIS) and India's FASAL system leverage remote sensing and predictive analytics to issue alerts on droughts or locust threats. By providing timely, localized, and actionable information, AI-enabled EWS enhance adaptive capacity, reduce vulnerability, and build climate resilience across the food system (Tripathy et al., 2022). Their integration into national agricultural monitoring platforms is essential for anticipatory governance and sustainable agricultural transformation.

5.2.13 AI in Carbon Sequestration and Emission Reduction

As agriculture accounts for over 20% of global greenhouse gas (GHG) emissions, integrating AI into emission monitoring and carbon sequestration strategies is vital for achieving climate-smart agricultural transformation. AI-driven tools can quantify, forecast, and optimize both carbon emissions and carbon sinks across agroecosystems with unprecedented precision and scalability. ML and DL algorithms are being applied to estimate emissions from fertilizer use, livestock, tillage, and energy consumption by analyzing complex, multi-source datasets including remote sensing, soil data, farm management practices, and weather patterns (Qiu et al., 2022). For instance, ML models have outperformed conventional methods in predicting nitrous oxide and methane emissions under varying climatic and soil conditions. In carbon sequestration, AI assists in identifying high-potential zones for afforestation, cover cropping, and conservation tillage using spatial analytics, satellite imagery, and AI-based carbon models (Bai et al., 2020). Tools like COMET-Farm and AI-enhanced DNDC are now supporting farmers in estimating carbon credits and guiding carbon farming decisions (USDA NRCS, 2023). AI also powers real-time monitoring of soil organic carbon changes and supports precision nutrient management to enhance sequestration while reducing emissions. As carbon markets expand, AI is becoming a cornerstone in measuring, reporting, and verifying (MRV) systems for climate finance eligibility (Verra, 2023). Through robust quantification and optimization, AI facilitates science-based pathways to low-emission, regenerative agriculture.

5.2.14 AI for Supply Chain Optimization and Post-harvest Management

Inefficiencies in post-harvest handling and supply chain logistics lead to the loss of over one-third of global agricultural production, undermining food security and climate resilience. AI offers transformative solutions by enhancing visibility, traceability, and efficiency across the agricultural supply chain from farm gates to markets. AI algorithms powered by ML, DL, and reinforcement learning are being deployed to forecast demand, optimize transportation routes, and manage inventory in real time. These tools help reduce food waste, minimize energy use in cold chains, and improve shelf life through predictive quality control and condition-based storage (Shukla et al., 2022). Computer vision systems combined with AI can detect spoilage, grade produce, and automate sorting based on ripeness, size, or surface defects. Blockchain integrated with AI further strengthens supply chain transparency and product provenance, enabling secure and tamper-proof records of production, transport, and storage conditions. AI-driven platforms like IBM Food Trust and SAP's Agricultural Supply Chain solutions illustrate real-world implementations of predictive logistics and farm-to-fork traceability (Ellahi et al., 2023). For smallholders, mobile AI apps support harvest scheduling, market matching, and post-harvest decision-making. By reducing losses, enhancing logistics, and ensuring quality control, AI plays a critical role in building sustainable, resilient, and inclusive agricultural supply chains in the face of climate and market uncertainties.

5.2.15 AI for Circular Agriculture and Waste Management

Circular agriculture emphasizes closed-loop systems that minimize waste, recycle nutrients, and optimize resource use to create sustainable, climate-resilient food systems. AI plays a critical role in enabling circularity by detecting inefficiencies, optimizing by-product utilization, and supporting data-driven waste reduction strategies throughout the agri-food value chain (FAO, 2021). AI-driven sensors, image recognition, and ML algorithms can identify and classify agricultural waste streams such as crop residues, food loss, livestock manure, and agro-industrial by-products for targeted valorization. These tools support real-time monitoring of decomposition rates, nutrient content, and environmental risks, facilitating efficient composting, bioenergy generation, or biofertilizer production (Peng & Sadaghiani, 2023). Predictive analytics assist in modeling nutrient recovery from organic waste, enabling precision application of compost or digestate based on crop demand and soil status. AI-integrated waste management platforms also optimize logistics for waste collection, treatment, and redistribution minimizing emissions and maximizing circular value. Additionally, AI supports supply chain circularity by forecasting demand, preventing overproduction, and enhancing food recovery systems. Digital twins and blockchain-integrated AI systems ensure traceability and compliance in organic waste-to-resource pathways (Liu et al., 2023). Through data-informed, intelligent decision-making, AI accelerates the transition to regenerative circular agriculture addressing both environmental degradation and food system inefficiencies.

5.2.16 AI-Driven Renewable Energy in Farming

The convergence of AI and renewable energy presents a transformative climate-adaptive pathway for agriculture. AI algorithms optimize the deployment and management of solar, wind, and bioenergy systems, enabling precise energy forecasting, autonomous irrigation scheduling, and demand-responsive power use in farms (Gupta & Pal, 2022). AI-driven control systems can improve the efficiency of solar-powered pumps, cold storage units, and climate-smart greenhouses, even in remote off-grid areas. Moreover, ML models enhance predictive maintenance and operational efficiency of decentralized renewable energy systems, reducing downtime and cost (UNEP, 2023). This synergy supports low-emission, adaptive agriculture by stabilizing productivity amid climate variability, improving water-energy use efficiency, and empowering smallholders through localized, intelligent solutions. Integrating AI with renewables thus advances both mitigation and adaptation goals, positioning agriculture to thrive in a digitally connected, climate-uncertain future.

5.2.17 AI in Climate Risk Insurance and Financial Services

Climate variability and extreme weather pose significant risks to agricultural productivity and farmer livelihoods. AI is transforming climate risk insurance and financial services by enhancing risk assessment, enabling dynamic pricing, and facilitating rapid claims processing thereby improving resilience and financial inclusion for farmers globally. AI-driven models integrate satellite data, weather forecasts, and historical loss records to quantify climate risk with high spatial and temporal resolution. ML algorithms enhance parametric insurance by accurately predicting yield losses due to droughts, floods, or pest outbreaks, reducing basis risk and encouraging uptake (Qi et al., 2022). Natural language processing (NLP) and computer vision facilitate automated damage assessments through drone imagery and farmer reports, accelerating claims settlement and reducing fraud (Khandelwal et al., 2022). AI also supports financial product innovation, such as index insurance bundled with digital credit and climate advisory services, enabling integrated risk management for smallholders (Amarnath et al., 2023). Moreover, AI-driven credit scoring leverages alternative data to extend affordable finance to underserved farmers, fostering climate-smart investments (Guzman et al., 2021). Platforms like IBM Watson and Microsoft Azure offer AI-powered risk analytics tailored for agricultural finance. By improving risk transparency, lowering transaction costs, and personalizing financial products, AI is accelerating inclusive climate resilience finance critical for sustainable agriculture in a warming world.

5.3 Challenges and Opportunities

Climate change is placing unprecedented stress on global agriculture through erratic weather, rising temperatures, and frequent extreme events, posing serious risks to food security and sustainability. In this context, Artificial Intelligence (AI) offers transformative potential to build adaptive and resilient food systems. From precision farming and climate modeling to logistics optimization, AI can boost yields, improve resource efficiency, and help farmers navigate growing uncertainty. Yet, adoption in low- and middle-income countries (LMICs) faces significant technical, social, and institutional challenges.

A major barrier is the widespread "data drought." Reliable datasets on weather, soils, yields, and pests are often scarce, fragmented, or outdated. Much data also remains proprietary or inaccessible, limiting the development of robust AI models. Algorithmic bias compounds this issue: tools trained on data from large-scale farms in high-income regions often fail to meet the needs of smallholder farmers, risking exclusion of vulnerable groups such as women and indigenous communities. Inclusive data practices and stakeholder engagement are therefore essential. Technical and infrastructure constraints also hinder progress. Many LMICs face poor internet connectivity, limited mobile access, and insufficient computing hardware, particularly in rural areas where only a fraction of households have reliable digital access. Advanced techniques like multi-source data fusion or synthetic data generation could help, but they demand expertise and infrastructure often lacking in resource-constrained settings. Human capacity remains another critical challenge. Farmers, extension workers, and researchers frequently lack the digital literacy and technical skills needed to deploy AI tools effectively. Without targeted training and capacity-building, sophisticated solutions risk remaining underused. Ethical concerns around data ownership, privacy, and the opacity of AI decision-making further complicate adoption, particularly where livelihoods depend on trust in crop insurance, subsidies, and advisory systems. Institutional and policy gaps add systemic obstacles. Fragmented efforts across ministries, donors, and private actors often lead to duplication and inefficiency, while many national agricultural strategies lack explicit support for AI-enabled climate adaptation. Coherent policy frameworks and public-private partnerships are needed to scale AI innovations sustainably. Finally, farmer trust and adoption remain uncertain. Low digital literacy, skepticism of automation, and cultural barriers limit uptake. Developing accessible, culturally relevant, and multilingual tools that complement traditional knowledge is essential to bridge this divide (Fig. 5.2).

Despite these formidable challenges, significant opportunities exist to overcome barriers and scale AI solutions in inclusive and sustainable ways. Strategic interventions include developing open-data platforms, implementing inclusive design processes, establishing comprehensive capacity-building programs, fostering public-private partnerships for infrastructure development, creating ethical frameworks, promoting policy alignment, and adopting participatory approaches that engage farmers as co-creators. Through deliberate, coordinated efforts addressing these interconnected challenges, AI can fulfill its potential as a cornerstone of climate-resilient agricultural systems that are productive, sustainable, and equitable.

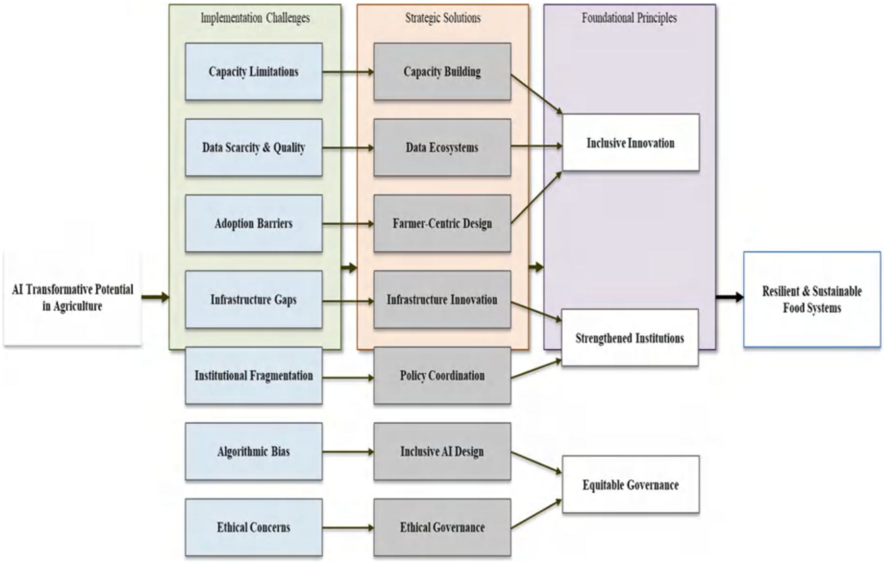

Fig. 5.2 Pathway to AI-enabled climate-resilient agriculture: challenges and opportunities

5.4 Future Outlook in AI-Driven Climate-Adaptive Agriculture

As climate variability intensifies, AI is evolving from a supportive tool to a transformative force in climate-adaptive agriculture, poised to manage entire agricultural value chains through integrated, autonomous systems. Emerging technologies will redefine climate-smart agriculture through several key advancements. Hyperlocal climate intelligence will revolutionize forecasting by integrating AI models with satellite data, IoT sensors, and farmer-reported information. These systems will deliver field-specific predictions for extreme weather, pests, and irrigation needs, enabled by edge computing that ensures functionality in connectivity-poor regions crucial for smallholder farmers. The convergence of AI with robotics will create autonomous farming systems where drone fleets and smart machinery perform precision tasks while adapting dynamically to environmental changes. Simultaneously, AI-powered genomics will accelerate climate-resilient crop development by simulating genotype-environment interactions under future climate scenarios, drastically shortening breeding cycles for drought, heat, and flood-tolerant varieties. Digital twin technology will enable virtual testing of farming strategies through AI-driven replicas of agroecosystems, allowing farmers to simulate "what-if" scenarios under projected climate conditions. This will be complemented by AI-orchestrated circular systems that optimize nutrient cycling, convert waste to bioenergy, and facilitate smallholder participation in carbon markets through automated monitoring and verification. Ethical considerations will become paramount, with explainable AI,

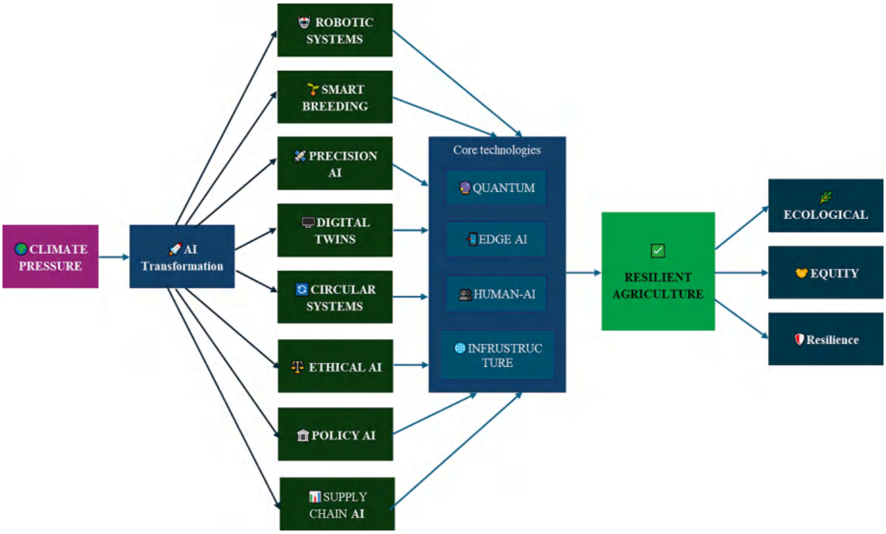

Fig. 5.3 Pathways for AI-driven climate-adaptive agriculture: emerging technologies and systemic outcomes

privacy-aware models, and inclusive design ensuring tools remain accessible to women, indigenous communities, and underserved farmers. AI will also transform policy and finance through impact simulations, dynamic climate insurance, and evidence-based governance that prioritizes vulnerable populations. Looking ahead, quantum computing integration will solve complex agroecological models, while edge AI will enable decentralized decision-making. Supply chain resilience will be enhanced through predictive analytics that minimize disruptions and food waste. Ultimately, human-AI collaboration will be central, augmenting farmer knowledge rather than replacing it, with training programs bridging technical and ecological expertise (Fig. 5.3).

In summary, the future of AI-driven climate-adaptive agriculture is expansive, multidisciplinary, and deeply human-centered. It offers a pathway not only to increased productivity and sustainability but also to ecological renewal, social equity, and systemic resilience amid unprecedented climate challenges. Realizing this vision requires continued investment in digital infrastructure, ethical frameworks, inclusive innovation, and cross-sector collaboration, ensuring that AI empowers farmers and supports a regenerative, climate-resilient food system for generations to come.

5.5 Conclusion

Integrating AI with climate-adaptive strategies represents a paradigm shift in agricultural science and practice, enabling unprecedented precision and resilience amid accelerating climate variability. AI's capacity for processing massive multisource datasets including remote sensing, genomics, soil microbiome profiles, and real-time environmental sensors facilitates the development of predictive, autonomous, and adaptive systems that dynamically optimize resource allocation, crop management, and ecosystem services. Advanced ML models, such as Deep Neural Networks and reinforcement learning, enable nuanced simulation of crop-climate interactions and stress responses, supporting accelerated breeding of climate-resilient cultivars and precision input management. Quantum computing, edge computing, and explainable AI (XAI) ensure decision-support tools are accessible and interpretable even in low-connectivity regions, democratizing innovation and fostering inclusive adoption. Moreover, AI-enabled digital twins of agroecosystems integrate spatial, temporal, and ecological variables to simulate scenarios and inform policy interventions with a high degree of granularity and foresight. Coupled with robust climate models and blockchain-based traceability, these systems support transparent, accountable, and adaptive governance frameworks critical for sustainable intensification and carbon sequestration. However, the successful operationalization of AI-driven climate adaptation requires multidisciplinary collaboration, ethical governance, and capacity-building to address technological inequities and socioecological complexities. This integrative approach not only enhances productivity and food security but catalyzes the transition toward regenerative, climate-smart agriculture that aligns with global sustainability goals. Ultimately, integrating AI with climate-adaptive strategies holds the promise of securing food sovereignty, enhancing livelihoods, and safeguarding ecosystems thereby shaping a resilient agricultural future for generations to come.

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Chapter 6
Agronomic Performance and Physiological Responses of Inbred Rice (Rc 512) Using Drone Seeding Technology

Randy T. Soriano, Esther Josephine D. Sagalla, and Janet P. Pablo

Abstract The study was conducted at Apita's Integrated Farm School at Appas, Tabuk City, Kalinga, from August 2024 to December 2024. A Randomized Complete Blocked Design (RCBD) with a two-factorial structure was employed. The study aimed to evaluate the agronomic and physiological response of inbred rice under different drone seeding parameters through two experiments. The study investigated the effects of drone speed (5, 6, and 7 m/s) and seeding rate (40, 60, and 80 kg/ha). Results showed that drone speed significantly influenced plant density, with 6 m/s producing the highest density. However, seeding rate alone did not significantly affect plant density, panicle number, spikelet count, or yield. No significant interaction effects were observed between drone speed and seeding rate, indicating that these factors function independently. Physiological traits, such as harvest index (HI), leaf area index (LAI), crop growth rate (CGR), and net assimilation rate (NAR), were not significantly affected by either factor. Correlation analysis showed that early vegetative traits (e.g., plant density and tiller number) were positively interrelated, while grain yield was more strongly associated with reproductive traits, particularly 1000-grain weight. Economic analysis identified the most profitable treatment as a drone speed of 7 m/s with a seeding rate of 60 kg/ha, yielding a net income of PhP 26,166 and a benefit-cost ratio (BCR) of 1.51. Drone seeding also proved financially viable at scale, with estimated annual returns of PhP 1.26 million over 1000 hectares, a breakeven price of PhP 720.70/ha, payback period of 1.58 years, NPV of PhP 2.39 million, and BCR of 1.40. The study concludes that

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drone seeding is a promising and cost-effective approach for rice cultivation. It recommends using a 60 kg/ha seeding rate and mid-range drone speed or altitude for optimal performance. Further research is suggested across multiple cropping seasons and rice varieties to validate and refine these findings.

Keywords Drone · Speed · Altitude · Seeding rate · Rice · Agronomic · Physiological

6.1 Introduction

As one of the world's largest rice-consuming countries, the Philippines faces the significant challenge of ensuring sustainable rice production to meet the demands of its growing population. In response to this challenge, the Philippine government has crafted Ambisyon 2040, which envisions a prosperous and inclusive Philippines where all Filipinos enjoy a high standard of living. Aligned with Ambisyon 2040, the Philippine Rice Roadmap charts a strategic course for the rice industry, emphasizing the need to enhance productivity, competitiveness, and resilience. However, implementing these plans faces hurdles, particularly with the recent enactment of the Rice Tariffication Law, which has resulted in increased competition, fluctuating prices, and heightened pressure on local rice producers. Moreover, the high cost of inputs such as seeds, fertilizers, and labor further exacerbates rice farmers' challenges, affecting their profitability and livelihoods. For instance, a study by Balderas et al. (2025) found that the high cost of inputs, such as seeds, fertilizers, and labor, significantly affects the profitability of rice farming in the Philippines. A comparative study conducted in major rice-growing regions in six countries in Asia in 2013 and 2014 shows that the average cost of producing one kilo of unmilled rice in the Philippines was P12.41, compared to only P6.53 in Vietnam and P8.85 in Thailand (Moya et al., 2016). More recent data for the Philippines show that the production cost for rice is P12.02/kg of paddy produced, which is still much higher than that of rice exporters, Vietnam and Thailand (PSA, 2021).

A dominant difference in rice production costs between the Philippines and major rice-importing countries is the high labor cost, which accounts for nearly half of the total rice production costs in the Philippines. One of the biggest labor costs in rice cultivation is crop establishment due to rice farmers' dominant practice of manual transplanting (Bordey et al., 2016). Manual transplanting accounts for 21–24 labor-days per ha, over 30% of the total labor use in the country. On the other hand, Thailand and Vietnam extensively use direct seeding, which uses only about 1–2 labor-days per ha (Bautista et al., 2023). Considering the current labor cost in the Philippines and the prevailing peso-dollar exchange rate, this results in an additional cost of approximately USD 156.17 to USD 171.78 per ha compared to the crop establishment methods used in Thailand and Vietnam.

Production costs can be significantly reduced through mechanization and a shift in crop establishment methods from transplanting to direct seeding (Pagaduan, 2025). Additionally, efficient seeding practices can lead to higher yields and reduced costs. One such technology is drone seeding, which can enhance agronomic performance, optimize resource use, and improve profitability in rice cultivation. By precisely and efficiently sowing seeds, drones have the potential to improve crop establishment, reduce seed wastage, and ultimately increase yields (FAO, 2018).

In a study conducted by Capistrano et al. (2022), using drones in the seed spreading and fertilizer application operations in rice production resulted in relatively higher grain yield and positive financial benefits. However, there are still areas that need in-depth research to make drone technology more efficient and applicable to the operations in rice production, such as making seed spreading more evenly distributed (i.e., along the flight path and periphery), calibrating the spreader, traveling speed, and flying height. Understanding how these factors interact is crucial for maximizing the benefits of drone technology in rice farming. Thus, there is a need for empirical research that evaluates the efficacy of drone seeding under different operational conditions specific to rice cultivation, ultimately resulting in evidence-based recommendations for optimizing seeding practices and enhancing the sustainability and profitability of rice production systems.

These drones are now available for commercial use in our country, offering custom servicing to rice farmers. Assistance is provided in the various aspects of rice farm management, including seeding, fertilizing, applying pesticides, and monitoring.

6.1.1 Importance of the Study

With the global demand for rice rising and challenges such as labor shortages, escalating input costs, and the imperative for sustainable production methods, exploring innovative technologies like drone seeding becomes paramount. Agricultural drone technology involves using unmanned aerial vehicles (UAVs) or drones equipped with various sensors and imaging devices to collect data and perform agricultural management, monitoring, and decision-making (Hunt & Rondon, 2019).

By determining the most effective drone seeding parameters, this study can help promote higher yields and better grain quality in rice farming (Adithya et al., 2024). Moreover, understanding the cost-effectiveness of drone seeding can inform investment decisions and support the adoption of innovative farming practices that enhance farm profitability (Rejeb et al., 2022).

6.1.2 Time and Place of the Study

The study was conducted at Apita's Integrated Farm School in Provincial Road, Appas, Tabuk City, Kalinga (Fig. 6.1), from August 2024 to December 2024.

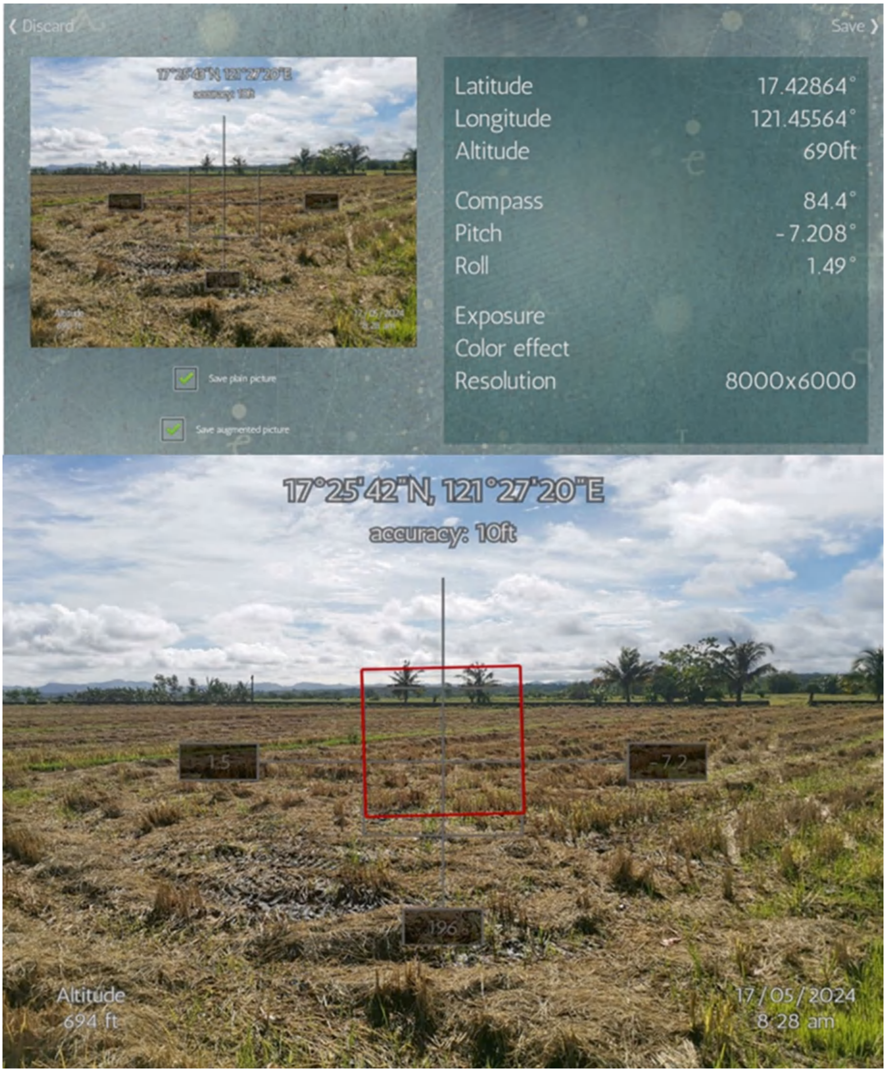


Fig. 6.1 Production site location

6.1.3 *Objectives of the Study*

There are four main objectives for this research:

(i) Evaluate the effect of the different levels of drone traveling speed and seeding rate on the agronomic performance and physiological response of inbred rice.

(ii) Analyze the interaction effects between the agronomic performance and physiological responses of inbred rice as influenced by drone traveling speed and seeding rate.
(iii) Examine the correlation between drone traveling speed and seeding rate in relation to the agronomic and physiological responses of direct-seeded rice; and
(iv) Determine the profitability of drone seeding on rice production.

6.2 Materials and Methods

6.2.1 Materials

The study used drones equipped with precision seeding equipment, which was outsourced to AGRIDOM, Inc., based in Nueva Ecija, Philippines. These drones (Fig. 6.2), essential for carrying out the drone seeding process in the rice field, utilized Terra Software to prepare the flight plan.

Additionally, certified high-quality inbred rice seeds from the variety Rc 512 sourced at PhilRice-Isabela were used. RC 512 is a high-yielding inbred rice variety with a growth duration of 111–125 days and a potential yield of up to 8.5 tons per hectare. Standard agricultural equipment, including spades, measuring tapes, and markers, was utilized for plot delineation and data collection. Data collection tools such as notebooks, pens, and data sheets were employed to record observations and measurements throughout the study period. Personal protective equipment (PPE) such as gloves, goggles, and boots was used for the safety of the researcher and

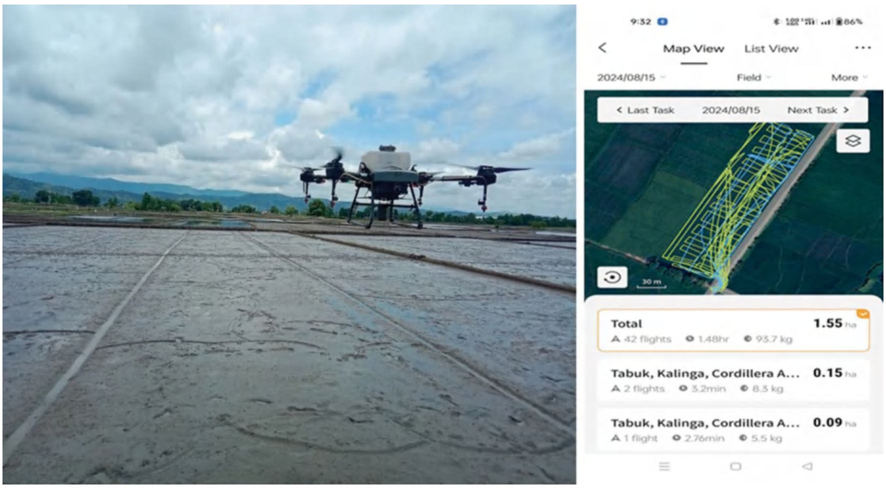
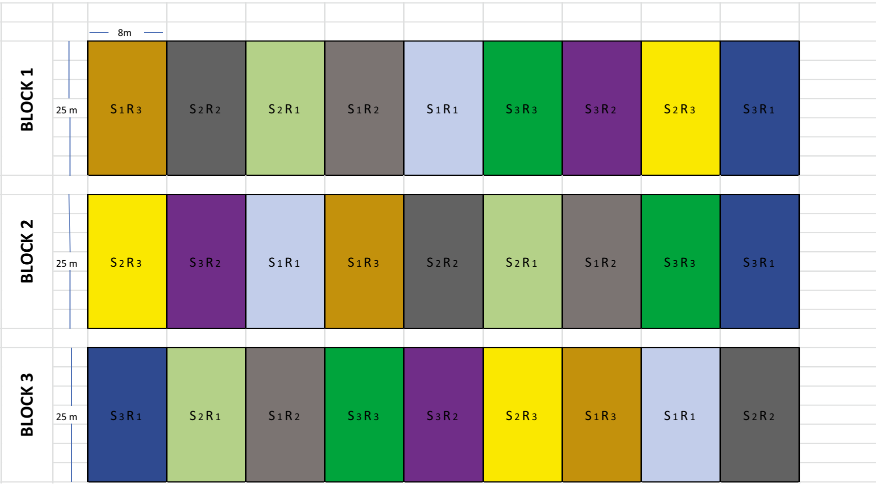


Fig. 6.2 DJI Agras T-30 Drone used in the study



	Drone speed at 5 m/s @ 40 kg/ha seeding rate		Speed at 7 m/s @ 40 kg/ha seeding rate
	Drone speed at 6 m/s @ 60 kg/ha seeding rate		Speed at 7 m/s @ 60 kg/ha seeding rate
	Drone speed at 6 m/s @ 80 kg/ha seeding rate		Speed at 6 m/s @ 40 kg/ha seeding rate
	Drone speed at 5 m/s @ 60 kg/ha seeding rate		Speed at 7 m/s @ 80 kg/ha seeding rate
	Drone speed at 5 m/s @ 80 kg/ha seeding rate	Drone flight altitude @ 2.5 m	

Fig. 6.3 Layout design of the plot

personnel involved in fieldwork. Statistical software programs such as SAS were utilized for data analysis and statistical interpretation of the results.

This study explored how drone traveling speed and seeding rate collectively influence rice agronomic performance and profitability. Twenty-seven plots, each spanning 8 m by 25 m, were established for the experimentation (Fig. 6.3). A Randomized Complete Blocked Design (RCBD) with a two-factorial structure was employed, where Factor A denotes different levels of traveling speeds (5.0 m/s, 6.0 m/s, and 7.0 m/s). At the same time, Factor B represents the different levels of seeding rates (40 kgs/ha, 60 kgs/ha, and 80 kgs/ha). The drone flight altitude was 2.5 m. Each treatment combination was replicated three times to ensure statistical validity and reliability of results.

The maximum 7.0 m/s traveling speed was based on the maximum speed limit of AGRAS T-30. In comparison, 5.0 m/s and 6.0 m/s speeds were based on the recommendation of Rice Today (2022) as speeds that are slower than the maximum drone capabilities to prioritize seeding accuracy over sheer speed. The 40 kg to 60 kg seeding rates were based on the recommended application of the PalayCheck System for manual direct-seeded rice (Philippine Rice Research Institute, 2020).

6.2.2 Data Gathered

Agronomic performance

(i) *Leaf area index (LAI).* Petiole Pro application was used to measure the leaf area, while LAI was computed using the formula:

$$\text{Leaf area index}\left(\text{LAI}\right)=\frac{\text{Total leaf area}}{\text{Ground area}} \tag{6.1}$$

(ii) *Crop growth rate (CGR(g m^{-2} d $^{-1}$)).* Biomass accumulation from panicle initiation to booting was computed using a one-square-foot sampling per plot. Fresh samples were weighed and then oven-dried at the BPI-NSQC laboratory for 72 h at 70–80 °C. The final dry weight was recorded after drying. Below are the formulas used in computing CGR:

$$\text{CGR}=\frac{\text{Biomass accumulation @ PI}\left(\text{g}\right)-\text{Biomass accumulation @ booting}\left(\text{g}\right)}{\text{Number of days from PI to booting}\left(\text{days}\right)} \tag{6.2}$$

(iii) *Net Assimilation rate (NAR*(g m^{-2} d $^{-1}$)). Net assimilation rate (NAR) measures the efficiency with which a plant converts absorbed carbon dioxide (CO_2) into dry matter during photosynthesis, minus the respiratory loss. A dense and healthy canopy enhances light interception and assimilate production, positively influencing NAR. NAR was computed using the formula:

$$\text{NAR}=\frac{[\left(\ln\left(\text{LAI at PI}\right)-\ln\left(\text{LAI at booting}\right)\right]\times\text{CGR}}{\left[\left(\text{LAI at PI}\right)-\left(\text{LAI at booting}\right)\right]} \tag{6.3}$$

Yield components

(i) *Number of panicles.* The number of panicles per square meter was counted to assess the reproductive performance of rice plants.
(ii) *Number of grains per panicle*. The average number of grains per panicle was determined by counting the grains from ten sample panicles from a one-square-meter quadrat plot.
(iii) *Grain weight.* The weight of grains harvested in a one square meter quadrat from each plot was measured to determine the average weight.
(iv) *Spikelet sterility.* The sterile spikelets were identified by pressing the grains with the fingers and counting those that did not have endosperm at the mature grain stage. The percentage of spikelet sterility was computed as follows:

$$\%\text{Spikelet sterility}=\frac{\text{Number of unfilled grains per panicle}}{\text{Total number of grains per panicle}}\times 100 \tag{6.4}$$

(v) *1000-grain weight.* A random sample of 1000 well-developed, whole grains dried to 14% moisture content was weighed using a digital weighing scale.

(vi) *Aboveground biomass weight.* Fresh and oven-dried weight of aboveground biomass was taken from a one-square-meter quadrat.

(vii) *Harvest index (HI).* Harvest index (HI) was calculated using the formula: HI = [total ODW of filled grains (g) + total ODW of unfilled grains (g)] per square meter/[total ODW of filled grains (g) + total ODW of unfilled grains (g) + total ODW of rice straw (g)] per square meter. Oven-dry weight or ODW was the final weight of the filled, unfilled grains, or rice straw after all the moisture or water evaporated in the oven. The ODW was established as the constant weight obtained after the subsequent oven drying and weighing of the plant samples (Mondejar & Bello, 2023).

Harvest index = wt. of harvested grains + wt. of unfilled grains

wt. of harvested grains + wt. of unfilled grains + wt. of total aboveground biomass

(iv) *Computed yield.* The primary outcome variable measured was rice yield, which was quantified in kg/ha at harvest. This involved harvesting rice from each experimental plot and weighing the harvested grain, which was computed on a hectare basis.

$$\text{Yield}\left(\text{tons / ha}\right) = \frac{\text{Total yield per plot}\left(\text{kg}\right)}{\text{Plot size}\left(\text{m}^2\right)} \times \frac{10{,}000\text{m}^2}{1\text{ha}} \times \frac{1\text{ton}}{1000\text{kg}} \tag{6.5}$$

Pearson correlation coefficient (r) was utilized to analyze the correlation between grain yield and various yield component characteristics. This statistical method measures the strength and direction of the linear relationship between two variables. The formula used for calculating the Pearson correlation coefficient (r) is as follows:

$$r = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[\sum x^2 - \left(\Sigma x\right)^2\right]}[n\Sigma y^2 - \Sigma\left(\sum y\right)\wedge 2]} \tag{6.6}$$

Where n is the number of observation, x represents the values of one variable (e.g., grain yield), y represents the values of another variable (e.g., yield component characteristics, Σxy is the sum of the products of paired values, Σx is the sum of the values of variable x, Σy is the sum of the values of variable y, Σx^2 is the sum of the squares of the values of variable x, and Σy^2 is the sum of the squares of the values of variable y.

The correlation coefficient (r) for each pair of variables (e.g., grain yield vs. panicle number, grain yield vs. spikelet number per panicle) was calculated. The resulting correlation coefficient ranged from −1 to 1, where R = 1: Perfect positive correlation, R = −1: Perfect negative correlation, and R = 0: No correlation. A positive correlation indicates that the other variable also tends to increase as one variable increases. A negative correlation indicates that the other variable tends to decrease as one variable increases. A correlation value closer to 1 or −1 suggests a stronger linear relationship between the variables.

6.2.3 Profitability Using Cost and Return Analysis per Hectare of Drone Seeding Operation

The study conducted a comprehensive cost and return analysis of drone seeding, manual seeding, and manual transplanting, considering a service area of 1000 hectares per year and a service fee of P2,000 per hectare for drone seeding. This analysis aimed to evaluate the economic viability of drone seeding compared to traditional methods by assessing operational costs, profitability, and overall efficiency.

Key financial metrics for drone seeding operations. The study conducted a financial analysis of drone seeding operations using key financial metrics, including breakeven price, breakeven volume, payback period, net present value (NPV), and benefit-cost ratio (BCR), to evaluate the economic viability of the technology (PCCAARRD, 2008).

(i) *Breakeven price (BEP).* This was determined as the minimum service fee (P/ha) required for drone seeding to cover its total operating costs without incurring a loss. This helped assess the feasibility of the P2,000/ha service fee.

$$\text{BEP}\left(\text{Pha}\wedge-1\right) = \frac{\text{Total fixed cost}}{\text{Total hectares}} + \text{Variable cost per hectare} \tag{6.7}$$

(ii) *Breakeven area (BEA).* This was calculated as the minimum number of hectares that needed to be serviced annually for the operation to recover its total costs. Given the assumption of 1000 hectares per year, this metric identified whether the operation could sustain profitability at the projected scale.

$$\text{BEA}\left(\text{has}\right) = \frac{\text{Fixed cost}}{\left(\text{Price / Unit}\right) - \text{Variable Cost per Unit}} \tag{6.8}$$

(iii) *Payback period (PBP).* This was estimated to determine the time required to recover the initial investment in drone seeding equipment and infrastructure through operational earnings. A shorter payback period indicated faster capital recovery and lower financial risk.

$$\text{PBP}\left(\text{yr}\right) = \frac{\text{Initial investment}}{\text{Net annual cash floe}\left(\text{net revenue}\right)} \tag{6.9}$$

(iv) *Net present value (NPV).* This was computed to assess the total value of projected future cash flows from drone seeding operations, discounted at 10%. A positive NPV signified that the investment generated more revenue than its costs over time, confirming its financial viability.

$$\sum_{t=1}^{n} \frac{\text{Net cash flow}}{\left(1+r\right)^{t}} - \text{Initial investment} \tag{6.10}$$

(v) Benefit-cost ratio (BCR). This was analyzed to compare total benefits and costs, determining whether drone seeding was cost-effective. A BCR greater than 1.0 indicated that the benefits outweighed the costs, justifying the investment in drone technology.

$$\text{BCR} = \frac{\text{Present value of benefit}\left(\text{PVB}\right)}{\text{Present value cost}\left(\text{PVC}\right)} \tag{6.11}$$

By analyzing these financial indicators, the study provided a comprehensive assessment of drone seeding operations' profitability, sustainability, and investment feasibility compared to traditional rice establishment methods.

Treatment of Data

Data were analyzed using the Statistical Analysis System (SAS) software. The analysis of variance (ANOVA) for RCBD with two factors was considered. The Duncan's Multiple Range at 5% significance level was used to determine significant differences among treatment means.

6.3 Results and Discussions

6.3.1 Effect of the Different Levels of Drone Traveling Speed and Seeding Rate on the Agronomic Performance of Inbred Rice

The study revealed that drone traveling speed markedly affected the agronomic performance of inbred rice, particularly on plant density (Table 6.1). Moderate speeds of 5–6 m/s produced higher plant densities (88.33–90.66 plants/m^2), while 7 m/s reduced density to 81.00 plants/m^2. This may be attributed to more uniform seed distribution at moderate speeds, which supported better stand establishment, while faster speeds caused scattering and irregular stands. The best density (90.66 plants/m^2) was obtained at 6 m/s with a 60 kg/ha seeding rate, underscoring the importance of optimizing speed and rate. These findings are consistent with Jat et al. (2022), who emphasized that proper drone speed enhances seeding uniformity. IRRI and PhilRice (2024), who reported erratic seed placement at higher speeds, increasing

Table 6.1 Growth parameters of inbred rice using different levels of drone speed and seeding rate treatments

Plant height							
Treatment	Plant density	Plant spacing	No. of tillers	Max tillering	PI to booting	Heading	Maturity
				40 days after	60 days after	80 days after	110 days after
				Sowing (DAS)	Sowing (DAS)	Sowing (DAS)	Sowing (DAS)
	(m^2)	(cm × cm)		(cm)	(cm)	(cm)	(cm)
Drone speed							
5 m/s	88.33[ab]	19 × 19	13.44	61.58	83.02	98.27	101.76
6 m/s	90.66[a]	18 × 18	14.71	61.75	86.00	100.27	104.93
7 m/s	81.00	18 × 19	11.33	58.75	80.47	96.8	104.64
Seeding rate							
40 kgs/ha	87.00	19 × 18	12.71	60.04	81.31	98.24	104.42
60 kgs/ha	85.00	20 × 19	12.02	60.42	82.84	97.51	102.29
80 kgs/ha	88.11	10 × 19	14.75	61.62	85.34	99.58	104.62
S × R	*	_	ns	ns	ns	ns	ns
CV	8.99	_	24.25	7.8	6.19	4.95	4.15

A mean labeled "ab" shows that its plant density falls in between the two groups, and the statistical test found no significant difference between it and either group A or group B

seeding rates from 40 to 80 kg/ha produced only slight and non-significant density improvements, supporting Wu et al. (2024), who noted that higher seeding rates may enhance early vigor but risk crowding and yield loss.

Plant spacing was also influenced, with more consistent spacing at 5 and 6 m/s (19 × 19 cm and 18 × 18 cm) than at 7 m/s (18 × 19 cm), where irregularity occurred due to reduced drop accuracy. This aligns with IRRI (2024), which observed that higher speeds compromise spacing. Higher seeding rates reduce spacing variability by filling potential gaps, thus improving stand uniformity. Seedling vigor showed no significant differences, with ratings averaging 4 (vigorous to normal), indicating minimal influence of speed and seeding rate. However, earlier studies by Liu et al. (2022) and Worakuldumrongdej et al. (2019) observed that faster drone speeds can reduce uniform emergence, a tendency also noted here, though not statistically significant. The number of tillers was influenced by drone speed, with lower speeds encouraging more tillering. At 5 m/s, plants produced 13.44 tillers, compared with 11.33 at 7 m/s. This highlights the benefit of better seed placement at slower speeds, consistent with Liu et al. (2022). Seeding rate also contributed, with 80 kg/ha producing the most tillers (14.75), likely due to denser stands, though the effect was insignificant.

Plant height followed a similar pattern, with 6 m/s producing the tallest plants (104.93 cm), closely followed by 80 kg/ha (104.62 cm). This suggests that denser, uniform stands promote vertical growth through light competition, consistent with Han et al. (2024). While the speed–rate interaction was not statistically significant for height, the results indicate that optimal speed combined with moderate-to-high seeding rates enhances overall crop performance.

6.3.2 Effect of the Different Levels of Drone Traveling Speed and Seeding Rate on the Agronomic (Yield and Yield Components) Performance of Inbred Rice

The study examined the effect of drone traveling speed and seeding rate on the yield and yield components of inbred rice. Although most results were not statistically significant, the observed trends provide important agronomic insights that can guide drone-based seeding practices (Table 6.2).

Panicle number ranged from 364.67 to 383.45 per m^2 across treatments, which is within the optimal range for wet season cropping as IRRI (2007) recommended. Neither drone speed nor seeding rate significantly influenced panicle number, although the 60 kg/ha seeding rate recorded the highest mean. This finding supports the study of Bueno et al. (2023), who reported that panicle numbers often remain stable across similar seeding rates. Likewise, the absence of an interaction effect between speed and rate is consistent with Xu et al. (2019), who observed that drone speed and seeding density typically influence plant establishment independently rather than interactively in direct-seeded rice.

Spikelet number per panicle showed a slight upward trend with increasing drone speed, ranging from 103.33 at 5 m/s to 109.67 at 7 m/s. While the differences were insignificant, this pattern suggests that lower plant density at higher speeds may allow individual plants to produce larger panicles, as Zhu et al. (2023) reported. The seeding rate also had no significant effect on spikelet numbers, a finding consistent

Table 6.2 Yield and yield components of inbred rice using different levels of drone speed and seeding rate treatments

Treatment	Panicle no.	Spikelet no. per	Percent filled	Wt. of 1000	Yield @
	Per sq. m	Panicle	Grains	Grains	14% mc
				(g)	(kg/ha)
Drone speed					
5 m/s	383.11	103.33	52.57	28.93	3434.78
6 m/s	364.67	108.00	52.88	28.82	3299.33
7 m/s	376.89	109.67	56.13	28.94	3845.35
Seeding rate					
40 kgs/ha	372.67	112.67	50.95	29.05	3466.24
60 kgs/ha	383.45	102.67	55.97	28.86	3766.58
80 kgs/ha	368.55	105.67	58.08	28.99	3346.64
S × R	ns	ns	ns	ns	ns
CV	11.03	12.29	15.51	4.09	16.30

with those of Li et al. (2020). However, Mai et al. (2021) cautioned that excessively high seeding rates could negatively influence spikelet formation due to increased plant competition and limited assimilation of reproductive structures.

The number of filled spikelets and fertility also showed no significant treatment effects, but higher values were generally observed at the moderate drone speed of 6 m/s. This outcome may be explained by better stand uniformity and reduced inter-plant competition, which promotes more balanced reproductive growth. Similar observations were reported by Parida et al. (2022), who noted that more uniform panicle structures and balanced resource allocation among spikelets improve grain filling and fertility. Meanwhile, the seeding rate did not show any consistent effect on spikelet fertility, supporting the findings of Bueno et al. (2023) that fertility is largely influenced by climatic and physiological conditions rather than seeding density alone.

Grain weight, measured as 1000-grain weight, remained relatively stable across all treatments, with no significant differences observed. This indicates that grain size is largely genetically determined and less affected by drone operational factors, as also emphasized by Li et al. (2020). While lower seeding rates showed slightly higher grain weights, the differences were minimal and not agronomically meaningful.

Grain yield followed the overall trends of the yield components. Although no statistically significant differences were detected, higher yields were generally associated with a drone speed of 6 m/s combined with a seeding rate of 60 kg/ha. This combination appeared to strike the best balance between adequate stand density and uniform crop establishment, leading to improved yield performance. Similar results were reported by Dong et al. (2024), who highlighted that optimizing both drone speed and seeding rate in precision agriculture enhances crop uniformity and productivity. While reducing plant density, higher drone speeds tended to favor larger panicles, partially compensating for the lower standing population. Conversely, higher seeding rates increased tiller numbers but did not improve yield, likely due to competition effects, which aligns with the findings of Wu et al. (2024).

6.3.3 Effect of the Different Levels of Drone Traveling Speed (m/s) and Seeding Rate (kg/ha) on the Physiological Responses of Inbred Rice

Inbred rice's harvest index (HI) was not significantly influenced by drone speed, with values ranging from 20.45 at 5 m/s to 22.56 at 7 m/s (Table 6.3). Although statistically insignificant, a trend toward increased HI was observed at higher speeds, suggesting improved allocation of assimilates toward grain production under faster drone operations. The seeding rate also showed no significant effect on HI, but the highest value was recorded at 60 kg/ha, coinciding with a higher panicle number and grain yield. This observation supports Li et al. (2021), who emphasized that

Table 6.3 Physiological response of inbred rice using different levels of drone speed and seeding rate treatments

Treatment	Harvest	Leaf area	Leaf area	Crop growth	Net assimilation
	Index	Index (LAI)	Index (LAI) @	Rate (CGR)	Rate (NAR)
		@ Booting	Panicle initiation	@ Booting	(g m^{-2} day^{-1})
				(g m^{-2} day^{-1})	
Drone speed					
5 m/s	20.45	7.60	2.89	10.38	2.09
6 m/s	20.84	7.44	2.90	11.11	1.89
7 m/s	22.56	7.44	3.18	9.51	1.93
Seeding rate					
40 kgs/ha	20.69	7.38	3.04	9.67	2.12
60 kgs/ha	22.29	7.01	2.95	9.71	1.83
80 kgs/ha	20.87	8.08	2.99	11.62	2.11
S × R	ns	ns	ns	ns	ns
CV	11.61	23.78	3	28.48	26.16

optimal plant density enhances reproductive efficiency by promoting better assimilating partitioning to grain development.

Leaf area index (LAI) was likewise unaffected by drone speed or seeding rate at both the panicle initiation and booting stages. At booting, LAI ranged from 7.01 to 8.08, with the highest value recorded at 5 m/s, while values at panicle initiation ranged from 2.89 to 3.18. The relative stability of LAI across treatments suggests that environmental and nutritional factors more influence leaf expansion than drone-related parameters. Hashimoto et al. (2019) similarly observed minimal differences in canopy reflectance under different sowing methods, while Jin et al. (2025) and Prabhakar et al. (2024) noted that LAI tends to remain consistent across different planting densities due to rice's compensatory tillering ability.

Crop growth rate (CGR) between panicle initiation and booting did not differ significantly among treatments. Values ranged from 9.51 to 11.11 g m^{-2} day^{-1}, with the highest observed at 6 m/s. This suggests that while drone speed may influence seed distribution, its impact on crop growth under favorable conditions is minimal unless precision variables such as seeding depth or flight altitude are adjusted. These findings are consistent with Liu and Li (2023) and García-Munguía et al. (2024), who reported that seeding methods seldom influence CGR when optimal environmental conditions are met. Similarly, the seeding rate (40–80 kg/ha) showed no significant effect on CGR. Although higher rates increase plant population, they do not necessarily accelerate growth when water and nutrients are not limiting, which agrees with the findings of Han et al. (2024) and Ahmed et al. (2016).

Net assimilation rate (NAR) was likewise unaffected by either drone speed or seeding rate. Values ranged from 1.89 to 2.09 g m^{-2} day^{-1}, showing only a slight, statistically insignificant decline as drone speed increased. Syaifudin et al. (2018)

emphasized that NAR is more strongly influenced by factors such as LAI, nitrogen availability, and environmental conditions than planting methods. Seeding rates also showed no significant effect, although values ranged from 1.83 g m^{-2} day^{-1} at 60 kg/ha to 2.12 g m^{-2} day^{-1} at 40 kg/ha. This variation may be attributed to differences in plant competition and resource use efficiency. This supports Rajput (2017), who explained that higher plant density can cause mutual shading, while lower densities may lead to underutilization of space and nutrients.

Across all physiological parameters studied, HI, LAI, CGR, and NAR, no significant interaction was observed between drone speed and seeding rate, indicating that their effects were independent. Although no interaction effects were detected in this study, the literature still highlights the potential benefits of optimizing both factors in combination. Dhakad et al. (2025) stressed that fine-tuning drone operations and seeding practices together can improve crop performance, while Guebsi et al. (2024) similarly noted that while factors such as flight speed and altitude affect seed distribution, interaction effects are often absent.

These findings reinforce the conclusion that drone speed and seeding rate independently influence crop physiology. However, their integration under precision management may provide a pathway toward improved resource use efficiency and productivity.

6.3.3.1 Correlation Between Drone Traveling Speed and Seeding Rate in Relation to the Agronomic and Physiological Responses of Inbred Rice

Pearson Correlation

The correlation matrix (Fig. 6.4) reveals several important relationships among agronomic and tillers (A2), plant height at maximum tillering (A3), and plant height from panicle initiation to booting (A4), indicating that higher plant density tends to promote vegetative growth. The number of tillers (A2) is also highly and positively correlated with plant height at both the maximum tillering (A3) and booting stages (A4), suggesting that taller plants tend to produce more tillers.

Plant height traits are generally interrelated, particularly A3, A4, and A5 (plant height at heading). However, plant height at maturity (A6) and seedling vigor (A7) do not correlate significantly with other traits, indicating a degree of independence in later developmental stages and early vigor from other measured parameters.

Yield (B5) is most strongly and positively correlated with the weight of 1000 grains (B4), highlighting the critical role of grain size in yield determination. Conversely, yield shows negative correlations with plant density (A4), plant height (A2 (PI to booting)), and other plant height traits, suggesting that increased vegetative growth may not always translate into higher grain yield. Spikelet number per panicle (B2) also exhibits strong positive correlations with both plant height (A5) and panicle number (B1), emphasizing the importance of reproductive structure development in yield components.

Correlations (Study 1 - SxR)

Traits	A1	A2	A3	A4	A5	A6	A7	B1	B2	B3	B4	B5	C1	C2	C3	C4	C5	C6	Legend	
A1	1																		A1	Plant density
A2	.615**	1																	A2	Number of tillers
A3	.442*	.708**	1																A3	Plant height (max tillering)
A4	.703**	.827**	.603**	1															A4	Plant height (PI to booting)
A5	0.3058	.523**	.577**	.684**	1														A5	Plant height (heading)
A6	-0.126	-0.126	0.0007	0.0103	0.0869	1													A6	Plant height (maturity)
A7	-0.286	0.0448	-0.037	-0.237	-0.276	-0.169	1												A7	Seedling vigor
B1	-0.104	0.1562	0.0327	0.0514	0.2558	-0.04	-0.264	1											B1	Panicle number
B2	0.1603	.444*	.424*	.430*	.576**	-0.165	-0.154	.568**	1										B2	Spikelet number per panicle
B3	0.2309	.433*	.592**	0.3176	0.2809	-0.075	0.0926	-0.01	0.3083	1									B3	Percent filled grains
B4	-0.232	0.1222	0.0441	-0.151	-0.146	-0.341	.659**	0.047	0.2876	0.2631	1								B4	Wt. of 1000 grains
B5	-.434*	-0.272	-0.318	-.423*	-0.326	-0.309	.469*	-0.071	-0.122	-0.19	.660**	1							B5	Yield
C1	0.0568	-0.235	-0.33	-0.239	-0.363	0.0204	0.0955	-0.318	-.534**	-0.284	-0.25	-0.106	1						C1	Harvest index
C2	-0.22	-0.229	0.034	-0.171	-0.028	-0.063	-0.056	-0.112	-0.27	-0.368	-0.245	0.0757	-0.003	1					C2	LAI (heading)
C3	-0.181	-0.214	0.0021	-0.156	-0.014	-0.07	-0.124	-0.049	-0.241	-.425*	-0.313	0.0337	0.0862	.976**	1				C3	LAI (maturity)
C4	-0.176	-0.222	-0.191	-0.123	0.0972	-0.112	-0.084	0.3285	0.0715	-0.104	-0.158	0.0341	-0.249	.562**	.585**	1			C4	CGR (PI to booting)
C5	-0.153	-0.264	-0.353	-.387*	-.440*	0.2955	0.2394	-0.081	-0.302	-0.349	-0.035	0.1026	.425*	-0.006	0.0262	0.132	1		C5	Net assimilation rate

Legend
- Highly significant correlation
- Significant correlation
- No significant correlation

Fig. 6.4 Pearson correlation of agronomic performance and physiological responses of inbred rice as influenced by drone speed and seeding rate

Although weakly correlated with most traits, the net assimilation rate (C5) shows a significant positive relationship with harvest index (C1), implying that efficient assimilate partitioning contributes to better yield efficiency.

The study underscores the complex interplay between growth, yield components, and physiological traits. It highlights that while early vegetative vigor and taller plant stature may promote reproductive development, they do not always yield higher grain. Strategic trait selection focusing on reproductive efficiency and grain characteristics appears more beneficial for yield improvement in this context.

6.3.4 *Profitability of Drone Seeding in Rice Production*

Table 6.4 presents a detailed cost and return analysis for drone seeding at three speeds (5 m/s, 6 m/s, and 7 m/s) and three seeding rates (40, 60, and 80 kg/ha) in an irrigated rice ecosystem. The analysis includes gross sales, production costs, net income, and the benefit-cost ratio (BCR), allowing for a comprehensive evaluation of the profitability of each treatment combination. Gross sales were computed based on the prevailing farmgate price of palay, set at PhP 18.50 per kilogram. Across all drone speeds, the 60 kg/ha seeding rate consistently yields the highest net income and BCR, reinforcing its status as the most economically efficient rate. At 5 m/s, net

Table 6.4 Profitability of drone seeding in rice production

Particulars	5 m/s			5 m/s			5 m/s		
	40 kg/ha	60 kg/ha	80 kg/ha	40 kg/ha	60 kg/ha	80 kg/ha	40 kg/ha	60 kg/ha	80 kg/ha
I. Gross sale (PhP)	61,746	70,099	58,784	61,411	62,323	59,377	69,212	76,627	67,576
II. Production cost (PhP)									
1. Material input									
(a) Seeds	1650	2475	3300	1650	2475	3300	1650	2475	3300
(b) Fertilizer									
Urea	6120	6120	6120	6120	6120	6120	6120	6120	6120
Complete	5920	5920	5920	5920	5920	5920	5920	5920	5920
Muriate of potash	1500	1500	1500	1500	1500	1500	1500	1500	1500
(c) Pesticides	6550	6550	6550	6550	6550	6550	6550	6550	6550
2. Labor									
(a) Land preparation	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
(b) Crop establishment	2000	2000	2000	2000	2000	2000	2000	2000	2000
(c) Fertilizer and pesticide application	7000	7000	7000	7000	7000	7000	7000	7000	7000
(d) Harvesting	5527	6309	5291	5527	5609	5344	6229	6896	6082
(e) Drone service fee	2000	2000	2000	2000	2000	2000	2000	2000	2000
III. Total cost (PhP)	48,267	49,874	49,681	48,267	49,174	49,734	48,969	50,461	50,472
IV. Net income	13,479	20,225	9103	13,144	13,149	9643	20,243	26,166	17,104
V. BCR	1.28	1.41	1.18	1.27	1.27	1.19	1.41	1.51	1.30

income peaks at PhP 20,225 with a BCR of 1.41 when using 60 kg/ha. Similarly, at 6 m/s, 60 kg/ha again leads with a BCR of 1.27, although the net income (PhP 13,149) is noticeably lower than the same rate at 5 m/s. The trend is even more pronounced at 7 m/s, where the combination of 7 m/s speed and 60 kg/ha seeding rate results in the highest net income of PhP 26,166 and the highest BCR of 1.51, suggesting this is the most profitable and efficient treatment among all tested.

In contrast, the 80 kg/ha seeding rate consistently shows the lowest BCRs and net incomes across all drone speeds. The lowest BCR of 1.18 and net income of PhP 9103 were observed at 5 m/s and 80 kg/ha, highlighting the inefficiency of using excess seeds without a proportional increase in yield. Although gross sales may appear high at times with 80 kg/ha, the increased seed costs and relatively similar yields dilute the net income. Interestingly, the gross sale values are highest at 7 m/s,

Table 6.5 Comparison of key financial metrics based on service area and service fees/hectare

Particulars	Service area and service fee 1000 HA @ PhP 2000/HA	500 HA @ PhP 2000/HA	500 HA @ PhP 2500/HA
Breakeven price (BEP)	PhP 720.70/ha	PhP 990.70/ha	PhP 1180.70/ha
Breakeven area (BEA)	207.52 has	199.49 has	168.40 has
Payback period (PBP)	1.58 years	3.99 years	3.05 years
Net present value (NPV)	PhP 2393, 685.01	PhP 182,882.31	PhP 857,947.73
Benefit-cost ratio (BCR)	1.40	1.02	1.12

particularly with 60 kg/ha (PhP 76,627), aligning with the notion that optimal drone speed may contribute to better seed distribution and stand establishment, resulting in higher yields and better returns. On the other hand, production costs remain relatively stable across treatments, primarily driven by fixed costs in fertilizer, pesticides, and labor, with only minor variations in seed cost and harvesting expenses.

6.3.5 Comparison of Key Financial Metrics Based on Service Area and Service Fees

Table 6.5 shows the comparison metrics of drone seeding operations based on service area and service fee. The analysis assumes that operating below 500 hectares is not financially viable, as it would likely result in losses. At 500 hectares per year with a service fee of P2,000 per hectare, the benefit-cost ratio (BCR) is 1.02, indicating marginal profitability. Any further reduction in the service area would push the BCR below 1.0, meaning the enterprise would operate at a loss. However, increasing the service fee to PhP 2500 per hectare improves financial performance, reducing the breakeven area to 168.40 hectares and shortening the payback period from 3.99 years to 3.05 years.

Expanding to 1000 hectares at P2,000 per hectare provides the most financially viable scenario, with the lowest breakeven price (PhP 720.70/ha), shortest payback period (1.58 years), highest net present value (NPV) of PhP 2393,685.01, and strongest BCR of 1.40. This suggests that economies of scale significantly improve profitability, lower per-hectare costs, and accelerate investment recovery. In contrast, while a 500-hectare operation at PhP 2000/ha is barely profitable, increasing the service fee to PhP 2500/ha significantly improves its financial outlook, raising NPV to PhP 857,947.73 and BCR to 1.12.

The results indicate that investors should not operate below 500 hectares to avoid financial losses. The best strategy for maximizing profitability is expanding to 1000 hectares or increasing service fees if operating on a smaller scale. Drone seeding is designed for large-scale farming, making it essential to maximize operational capacity. Unlike traditional manual or machine seeding, drones offer efficiency and speed, but their high initial investment and operating costs require economies of scale to remain profitable. Operating at a service area below 500 hectares would not generate enough revenue to cover fixed and variable costs, leading to financial strain.

6.4 Summary, Conclusions, and Recommendations

6.4.1 Summary

This study evaluated the agronomic and physiological responses of inbred rice to varying drone seeding parameters. Specifically, it investigated the effects of drone traveling speeds (5, 6, and 7 m/s) and seeding rates (40, 60, and 80 kg/ha) on crop performance under drone-based direct seeding conditions.

Results showed that drone speed significantly influenced key agronomic traits such as plant density, with 6 m/s producing the highest plant density. In contrast, the seeding rate alone had no significant effect on plant density, panicle number, spikelet count, or yield. Moreover, interaction effects between drone speed and seeding rate were generally non-significant across most agronomic and physiological parameters, indicating that these factors function independently. Physiological responses, including harvest index (HI), leaf area index (LAI), crop growth rate (CGR), and net assimilation rate (NAR), were not significantly affected by either factor or their interaction.

Correlation analysis revealed that early vegetative traits like plant density and tiller number were positively interrelated. Grain yield was more strongly correlated with reproductive traits, particularly grain size (1000-grain weight). Additionally, physiological traits such as LAI at maturity, CGR, and NAR showed consistent internal associations.

In terms of profitability, the most advantageous treatment was a drone speed of 7 m/s paired with a seeding rate of 60 kg/ha, which yielded the highest net income (PhP 26,166) and benefit-cost ratio (1.51). At a service scale of 1000 hectares, drone seeding was a financially viable enterprise, with an estimated annual net revenue of PhP 1.26 million, a breakeven price of PhP 720.70/ha, a payback period of 1.58 years, an NPV of PhP 2.39 million, and a BCR of 1.40.

6.4.2 Conclusions

Drone speeds between 5 m/s, 6 m/s, and 7 m/s, and seeding rates of 40 kg/ha, 60 kg/ha, and 80 kg/ha did not significantly influence all the growth and yield parameters except plant density. A drone speed of 6 m/s produced the highest plant density. Yield positively correlated with weight of 1000-grains, panicle number, harvest index, a speed of 7 m/s, and seeding rates 40 kg/ha, 60 kg/ha, implying that increasing grain size, enhancing panicle production, and improving biomass allocation are key strategies for improving rice yield. In terms of profitability, the most advantageous treatment was a drone speed of 7 m/s with a seeding rate of 60 kg/ha, yielding the highest net income (PhP 26,166) and BCR (1.51). Among the altitude treatments, the most cost-effective combination was 3.0 meters at 60 kg/ha, generating a net income of PhP 21,387 and a BCR of 1.43.

At a larger operational scale of 1000 hectares, drone seeding proved to be a financially viable enterprise, with an estimated annual net revenue of PhP 1.26 million, a breakeven price of PhP 720.70/ha, a payback period of 1.46 years, a net present value (NPV) of PhP 2.73 million, and a BCR of 1.75.

Recommendations

Based on agronomic and profitability results, drone speeds between 5 and 7 m/s are recommended for rice seeding. While growth and yield were not significantly affected within this range, 7 m/s combined with a 60 kg/ha seeding rate yielded the highest profitability. Seeding rates from 40 to 80 kg/ha were generally viable, but 60 kg/ha consistently provided favorable outcomes. Since yield was linked to 1000-grain weight, panicle number, and harvest index, management should focus on enhancing grain size, panicle development, and biomass allocation. Drone seeding proved financially viable at a service scale of 1000 hectares with an annual net revenue of PhP 1.36 million, a payback period of 1.46 years, an NPV of PhP 2.73 million, and a BCR of 1.75.

Future studies should cover multiple seasons, different rice varieties, including hybrids, and comparisons with manual seeding under varied conditions. Research integrating fertilization with drone seeding and expanding trials to high-value crops such as vegetables will further establish its potential.

The Department of Agriculture (DA) should promote the economic and environmental benefits of drone seeding for wider adoption. Given the high upfront cost (up to PhP two million), substantial government support and investment are needed. Capacity-building for drone operators and a public–private partnership (PPP) model could help address financial and logistical barriers, linking private service providers with organized farm clusters.

The strong BCR underscores profitability, making drone seeding attractive to private investors. The DA should establish service centers for parts, maintenance, and technical support to sustain operations. The Agricultural Training Institute (ATI) should also integrate drone technology into training programs in partnership with Learning Sites for Agriculture (LSAs) and Local Government Units (LGUs) to accelerate farmer adoption of digital innovations.

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Chapter 7
Deep Learning Strategies for Smart Agricultural Space: Diagnostics, Automation, and Quality Systems

Shih-Fang Chen

Abstract Agricultural transformation demands a fundamental reconceptualization from reactive problem-solving to predictive system integration. This note highlights the strategic convergence of deep learning technologies across three critical domains: multimodal plant health diagnostics, autonomous precision field management, and intelligent product quality optimization. Advances in computer vision, robotics, and spectroscopy are enabling real-time systems that learn and adapt to dynamic field conditions. These technologies are increasingly integrated into platforms that democratize expert-level functions and optimize operations at scale. The next frontier lies in generative AI, which promises to transform analytical systems into conversational advisors, accelerating the adoption of intelligence-augmented agriculture.

Keywords Agricultural intelligence · Predictive systems · Deep learning · Diagnostics · Precision farming · Quality optimization

7.1 Introduction

Agricultural development has long been shaped by technological revolutions—from mechanization to chemical inputs, genetics, and precision tools. Today, deep learning drives a new phase of transformation: enabling systems that interpret complex field data, adapt to evolving conditions, and execute predictive management strategies. This shift moves agriculture beyond isolated innovations into integrated intelligence networks.

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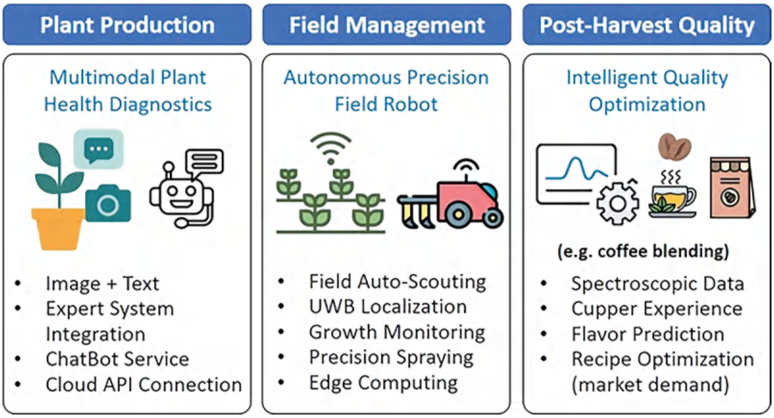

Fig. 7.1 Deep learning applications across the agricultural supply chain stages

The implementation of deep learning in agriculture can be strategically analyzed through three critical stages of the agricultural supply chain, each presenting distinct challenges and opportunities. At the production stage, intelligent diagnostics processes multimodal data for early plant stress and disease detection. Autonomous systems execute precision management with minimal human input during growth and harvest. In post-harvest operations, intelligent quality systems optimize value through predictive assessment and optimization strategies. These three domains (Fig. 7.1) demonstrate how deep learning applications address specific needs at different supply chain stages, creating a comprehensive framework for scalable, adaptive, and expert-augmented agricultural systems.

7.2 Production Intelligence: Multimodal Plant Health Diagnostics

Traditional plant health assessment depends heavily on sequential visual inspections, expert interpretation, and manual decision-making. This process introduces delays and limits scalability in the face of increasing crop diversity and labor shortages. The reliance on specialist knowledge creates accessibility challenges, particularly during critical periods when expert availability is limited or when rapid response is required across multiple locations simultaneously.

Deep learning approaches address these limitations by enabling real-time, multimodal diagnostic systems that integrate image analysis and contextual input such as text or voice. Recent implementations achieve over 95% accuracy in field diagnostics, while multimodal systems outperform image-only models with a precision increase from 0.85 to 0.95 (Hsu et al., 2025). Such systems leverage mobile interfaces and cloud-based processing, allowing deployment even in low-resource environments.

The strategic significance lies in their ability to extend expert knowledge accessibility across geographies and user expertise levels. These tools deliver diagnosis, treatment suggestions, and application timing when connected with treatment databases and advisory platforms. This represents a fundamental shift toward distributed, accessible intelligence for plant health management, enhancing the availability of expert-level diagnostic capabilities while maintaining the critical role of agricultural specialists in complex decision-making scenarios.

7.3 Field Intelligence: Autonomous Precision Management

Monitoring field conditions in greenhouses or open fields has traditionally relied on frequent manual inspections, consuming labor and introducing inconsistency. With increasing production scale and complexity, this method becomes inefficient and unsustainable. Autonomous platforms represent a paradigm shift by delivering continuous, high-resolution monitoring and intervention without human presence. Modern autonomous systems integrate sensing, navigation, and actuation modules. Huang et al. (2024) developed a positioning system in greenhouse asparagus monitoring using ultra-wideband (UWB) signals to achieve sub-30 cm precision, enabling reliable operations even in GPS-limited environments such as dense canopies. Transformer-based computer vision architectures demonstrate average precision above 95% in crop segmentation and asparagus spear detection tasks.

Crucially, these systems support real-time decision-making. For example, crop density classification enables variable-rate interventions such as fertilization or pesticide spraying. Rather than applying treatments uniformly, autonomous systems can adjust actions based on real-time conditions, enhancing both efficiency and environmental sustainability (Huang, 2024). Remote-access interfaces extend managerial reach, transforming farm supervision into a scalable, distributed model.

7.4 Quality Intelligence: Intelligent Post-harvest Optimization

Post-harvest quality control, predominantly sensory quality evaluation in the food and beverage industry, is in high demand due to increasing expectations for product consistency, premium quality, and consumer satisfaction. This process has traditionally relied on trained experts for post-processing flavor assessment. While effective, this approach is inherently subjective, labor-intensive, and difficult to scale. These limitations limit quality consistency and product innovation, especially for high-value processed goods.

Recent advances in spectroscopy and deep learning offer a transformative alternative. Models trained on spectral data can predict sensory attributes such as flavor and aroma with high fidelity (Chang et al., 2021). In coffee applications, near-infrared spectral models have achieved mean absolute errors below 0.125 for cupping score prediction and over 78% accuracy in classifying flavor profiles (Tsai et al., 2025). These systems enable reproducible quality control across batches, reducing variability associated with human assessment while complementing expert evaluation capabilities.

7.5 Toward Integrated Agricultural Intelligence

Achieving fully intelligent agricultural systems requires a multi-layered technology stack. Edge computing enables localized decision-making in the field, reducing latency and minimizing reliance on connectivity. Meanwhile, cloud-based platforms aggregate large-scale data and support the training of sophisticated models across multiple locations and conditions.

The evolution from traditional agricultural practices to AI-enhanced systems follows a progressive integration pathway (Fig. 7.2). This transformation encompasses the convergence of sensing technologies, data analytics, and decision-support systems across all agricultural domains. A transformative advancement lies in applying generative AI to agricultural interfaces. By translating complex analytics into natural-language interactions, generative models allow users to ask practical questions—e.g., "What pest control strategy fits my field conditions and budget?"—and receive actionable responses. This evolution empowers users with varying technical backgrounds to interact meaningfully with advanced agricultural systems.

Such systems can integrate sensor data, visual inputs, historical trends, and real-time constraints to produce contextualized advice. The result is a conversational

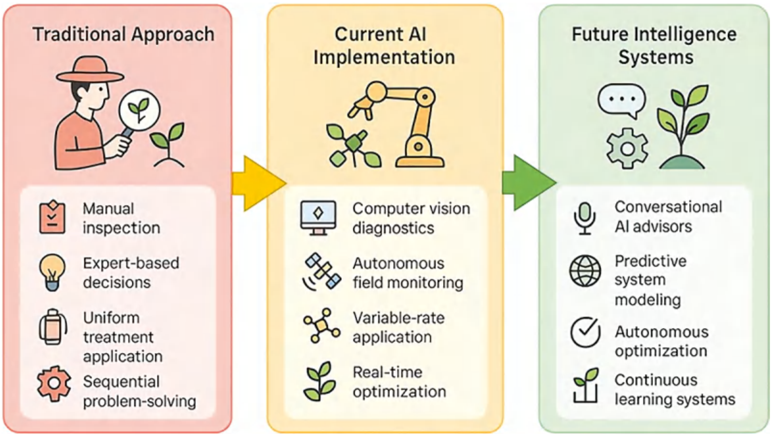

Fig. 7.2 Evolution of agricultural intelligence systems from traditional practices to AI-enhanced integrated platforms

advisor for agriculture that bridges the gap between high-tech capabilities and user-friendly accessibility. This approach enhances decision-making processes, promotes widespread adoption, and supports sustainable practices even in resource-limited regions.

7.6 Strategic Outlook

The convergence of deep learning, robotics, and generative interfaces signals a systemic agricultural shift. Unlike past innovations, which addressed isolated constraints, current developments simultaneously optimize productivity, sustainability, and cost. Standardization of data formats and communication protocols will be essential to ensure interoperability across platforms and technologies.

Education must evolve toward training farmers and technicians to work effectively with intelligence-augmented tools to support adoption. As agriculture becomes more automated and data-driven, ensuring compatibility between technological capabilities and user needs becomes increasingly critical.

The strategic pathway involves coordinated technological advancement alongside integrated education and technical standardization efforts. This comprehensive approach ensures that AI-enhanced agriculture delivers on its transformative potential while addressing technical interoperability and supporting broader access to advanced agricultural technologies.

7.7 Conclusion

Deep learning redefines agriculture across plant diagnostics, field management, and quality optimization domains. Integrating predictive, adaptive, and generative systems enables scalable, accessible agricultural intelligence that augments human expertise rather than replacing it. As generative AI evolves, future systems will offer intuitive, conversational support for complex decisions, empowering broader adoption of sustainable practices. Coordinated development across technical and educational fronts is essential to fully realize this transformation while ensuring effective technology transfer and implementation across diverse agricultural contexts.

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Chapter 8
Feature Selection Technique for Model Development

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Abstract One of the most critical issues in developing the model to analyze real-world problems is the input variable selection problem. Determining how many input variables the model needs to predict the target variable and gain insight into the research question is one of the most important considerations when developing a model, especially for an Edge-AI model. This also relates to justifying the sample size to maximize the research's resources and efficiently test the hypothesis. Thus, the feature selection techniques will be presented as the core of this chapter. Feature selection and input variable selection are used interchangeably. Both refer to the process of choosing a subset of relevant variables (features) from the dataset that will be used to train the model. Both goals usually improve model performance, reduce overfitting, and simplify the model. It is a crucial step in the model development process to assess the significance of each feature in relation to the target variable, ensuring that selected features contribute meaningfully to the model. It facilitates a clearer understanding of the relationships between specific features and the target variable. By selecting only the most relevant features, the model becomes more focused and can lead to a more accurate and efficient model, improving the predictive performance on training and unseen data. Also, feature selection helps prevent overfitting, where a model becomes too complex and fits the noise in the training data, leading to poor generalization on new data.

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8.1 Feature Selection Methods for Model Development

This part introduces three-feature selection approaches to create a prediction model with robust predictive power by using as few features as possible.

1. The Filter method, specifically Correlation-based Feature Selection (CFS), involves selecting features based on their correlation with the target variable while considering inter-correlations. This study utilized Pearson correlation and managed multicollinearity through the variance inflation factor (VIF) to eliminate redundant features and retain the most relevant ones.
2. The Wrapper method consists of forward feature selection (FFS), backward feature elimination (BFE), and recursive feature elimination (RFE). FFS begins with an empty set of features and iteratively adds the most significant feature at each step based on specific criteria, such as improved model performance or reduced error. BFE starts with the entire set of features and iteratively eliminates the least significant feature at each step. The goal is to improve the model's performance by removing features that contribute less to the overall predictive power. RFE systematically eliminated less relevant features by recursively constructing models and evaluating their performance, continuing until the desired number of features was reached.
3. The Embedding method utilizes L1 regularization, or L1 regularisation, as part of the feature selection process to prevent overfitting and encourage sparsity in the model's feature set. In the linear regression equation, the lasso regularization term is added, which is the sum of the absolute values of the coefficients multiplied by a regularization parameter (alpha). The function for lasso regularization is often expressed as:

$$\text{Loss} + \propto * \Sigma \left| \beta i \right| \tag{8.1}$$

where Loss is the traditional loss function, α is the regularization parameter, and $\Sigma|\beta i|$ is the sum of the absolute values of the coefficients.

The lasso regularization term tends to drive some coefficients to exactly zero, effectively excluding certain features from the model. This sparsity-inducing property makes lasso regularization a tool for feature selection, as it automatically selects a subset of the most relevant features (Muthukrishnan & Rohini, 2016).

By the end of this chapter, an example of developing regressor models employing a filter method for feature selection to predict the body weight of Thai cattle is presented. This is to gain insights into determining how many input variables are necessary for accurate estimation.

8.2 Comparison of Feature Selection Techniques: Filter, Wrapper, and Embedded Methods with LASSO Regularization

Feature selection is a pivotal step in developing robust and efficient predictive models. Among the numerous techniques, filter, wrapper, and embedded methods, such as LASSO regularization, stand out for their differing concepts and operational mechanics. This part compares these three methods, emphasizing their implications on model complexity, computational speed, interpretability, and linearity in predictive analytics.

8.2.1 *Model Complexity*

Filter methods operate independently of any machine learning algorithm, selecting features based on their statistical properties relative to the target variable. Standard techniques include Pearson correlation, Chi-squared test, mutual information, and ANOVA F-test. The computational complexity is low because the filter methods evaluate each feature individually or pairwise without building predictive models.

Wrapper methods evaluate subsets of features by training and validating models on them. Techniques such as recursive feature elimination (RFE), sequential forward selection, and genetic algorithms fall into this category. Complexity is relatively high, since models are trained multiple times for different feature subsets, and the computational burden increases exponentially with the number of features.

Embedded methods incorporate feature selection as part of the model training process. LASSO is a prominent example that introduces an L1 penalty term in linear regression, effectively shrinking some coefficients to zero and thus performing feature selection. Since LASSO combines model fitting and feature selection in a single optimization problem, balancing performance and efficiency, its complexity is moderate.

8.2.2 *Computational Speed*

The speed of the filter method is high since the independence of Pearson correlation analysis, Chi-squared test, and ANOVA F-test from model training allows for rapid processing, making them suitable for high-dimensional datasets. The iterative nature of model-building makes wrapper methods time-consuming, especially with complex models or large datasets and low computational speed. The embedded method's speed is moderate to high. It is faster than wrapper methods but slower than simple filter techniques.

Table 8.1 Comparative summary on feature selection techniques

Feature	Filter method	Wrapper method	Embedded method (LASSO)
Model dependency	No	Yes	Yes
Computational cost	Low	High	Medium
Scalability	High	Low	Moderate
Handles collinearity	Yes	Yes	Partially
Detects nonlinear relations	No	Yes (depends on model)	No
Handles feature interaction	No	Yes	Partially
Risk of overfitting	Low	High	Low
Interpretability	High	Model-dependent	High (sparse coefficients)
Typical use case	Initial screening	Small feature sets, performance-focused tasks	High-dimensional data, sparse models

8.2.3 *Linearity in Feature Selection Techniques*

Linearity in feature selection techniques reflects whether the selection method assumes or favors linear dependencies between features and the target variable. Filter methods like Pearson correlation or ANOVA assume linear or monotonic relationships.

Wrapper methods can accommodate linear and nonlinear models depending on the chosen estimator. For example, random forest regression can detect nonlinear relationships. Then, wrapper methods are quite flexible depending on the underlying model.

Embedded methods using LASSO inherently assume a linear model structure, since LASSO is based on linear regression with L1 regularization.

Consequently, filter methods provide a fast and scalable approach for preliminary selection. Wrapper methods, while powerful, may be impractical for large datasets due to their computational demands. Embedded methods, exemplified by LASSO, offer a balanced solution by integrating selection with model training, especially effective in sparse, high-dimensional environments. Understanding the trade-offs between complexity, speed, and modeling assumptions helps practitioners make informed decisions tailored to their specific modeling goals (Table 8.1).

8.3 A Case Study: Developing Regressor Models Employing the Filter Method for Feature Selection to Predict the Body Weight of the Thai Cattle

8.3.1 *Introduction*

This case study focused on developing regressor models employing the filter method for feature selection to predict the body weight of the Thai cattle. The predictor variables should be selected to support developing a model to further implement on a local edge AI to reduce processing time and the possibility of overfitting. Thus, feature selection techniques using the filter method, consisting of low variance removal, VIF, and Pearson correlation, were employed to assess the significance of the body measured variables concerning the body weight of one Thai cattle breed. Three regressor algorithms, including multiple linear regression (MLR), random forest regression (RFR), and artificial neural network (ANN), were employed to assess the predictive ability of regressor algorithms.

8.3.2 Materials and Methods

Developing a regression model involves a series of structured steps to ensure the model is accurate, interpretable, and generalizable. Here is an outline of the typical steps involved.

8.3.2.1 Data Collection

The farm study in the central region of Thailand measured and recorded the lives of 257 cattle. Five linear body measurements, composed of body length, chest width, chest length, shoulder height, hip height, and body weight, were also measured.

8.3.2.2 Features Selection

Filter methods select features based on their statistical properties without involving machine learning models. This study utilized two established statistical techniques—Pearson's correlation coefficient and the Variance Inflation Factor (VIF)—to systematically identify and mitigate multicollinearity among candidate input variables. This preliminary step eliminates redundant or highly correlated predictors before model training.

Pearson's Correlation: This method calculates the Pearson correlation coefficient between features and the target variable. Features with a high correlation with the cattle's body weight are retained, while those with a low correlation are discarded.

Variance Inflation Factor (VIF): This technique measures the collinearity among features. High VIF values indicate that a feature is highly correlated with other features and could be removed to mitigate multicollinearity.

Here are the empirical formulas for Pearson's Correlation Coefficient (r) and Variance Inflation Factor (VIF).

1. *Pearson's Correlation Coefficient (r)*

The Pearson correlation coefficient measures the linear relationship between two continuous variables X and Y. It is defined as:

$$r_{XY} = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \cdot \sqrt{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}}$$

where X_i, Y_i = Individual data points

n = Number of observations
when $r = +1$, it means a perfect positive linear relationship
$r = -1$, which means a perfect negative linear relationship
$r = 0$, which means no linear relationship.

An $r > 0.8$ or $R < -0.8$ threshold is commonly used to indicate strong multicollinearity between predictors (Dormann et al., 2013).

2. *Variance Inflation Factor (VIF)*
The VIF quantifies how much the variance of a regression coefficient is inflated due to multicollinearity. For a predictor X_j, the VIF is computed as:

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2}$$

where R^2_j = Coefficient of determination is obtained by regressing X_j on all other predictors in the model.

when VIF = 1: No multicollinearity.
$1 < \mathrm{VIF} \leq 5$: Moderate correlation (may be acceptable).
VIF > 5: High multicollinearity (variable should be reviewed).

A VIF quantifies the degree to which a predictor's variance is inflated due to its dependence on other variables in the model. Values exceeding five indicate problematic multicollinearity (James et al., 2013).

8.3.2.3 Machine Learning Models

After the feature selection process, three machine learning models of varying complexity were applied to fit the data from the cattle body measurements. Three regressor algorithms, including multiple linear regression (MLR), random forest regression (RFR), and artificial neural network (ANN), were employed for the study.

8.3.2.4 Model Development

A cross-validation approach was used to obtain an unbiased predictive accuracy estimation. Cross-validation is an empirical approach aimed at obtaining an unbiased estimate of predictive accuracy (Ramezan et al., 2019). In this study, models were trained, validated, and hyperparameters tuned using fivefold cross-validation. The dataset was divided into fivefolds. Each fold was used as a validation set once, while the remaining folds were used for training. The model's performance was evaluated on the validation set.

8.3.2.5 Model Performance Testing

The final models obtained from the training dataset were evaluated for their performance using the testing dataset. In this process, we could compare the model performances among models developed by comparing the predicted values from forecast models with actual values from the testing dataset. Error matrices commonly used, including mean absolute error (MAE) and root mean square error (RMSE), were calculated to determine forecast performances among the developed models. It is generally accepted that the lower the measure error metric values, the better the method (Hyndman & Athanasopoulos, 2021).

8.3.3 Results and Discussions

8.3.3.1 Correlation and Multicollinearity Analysis

A multicollinearity assessment used two key metrics: Pearson's correlation coefficient and the Variance Inflation Factor (VIF). High multicollinearity among predictor variables can inflate coefficient variances, leading to unstable model estimates.

1. *Correlation Analysis*: A Pearson correlation analysis was conducted to examine the relationship between five body measurements of cattle, composed of *body length, chest width, chest length, shoulder height, and hip height* (X), with cattle's *body weight* (Y). A correlation matrix was generated to explore relationships, as shown in Fig. 8.1. The correlation of all pairs of variables is statistically significant (at $p < 0.01$), and they are statistically associated. The strongest correlation was between chest length and weight ($r = 0.96$). Pairwise correlation analysis revealed strong linear relationships ($|r| > 0.8$) between the following variables: *chest_length* and *chest_width* ($r = 0.91$) as well as *hip_height* and *shoulder_height* ($r = 0.86$). Such high correlations suggest redundancy, as these variables may capture similar underlying variance in the data.

2. *Variance Inflation Factor (VIF) Assessment*: To assess multicollinearity among predictors, the Variance Inflation Factors (VIFs), which measure how much the variance of an estimated regression coefficient increases due to collinearity with other predictors, are computed, as shown in Fig. 8.2. When a VIF threshold of 5 was adopted, the analysis identified two variables exceeding this threshold. *Chest width* (VIF = 6.48) and *chest length* (VIF = 6.13) indicated substantial overlap.

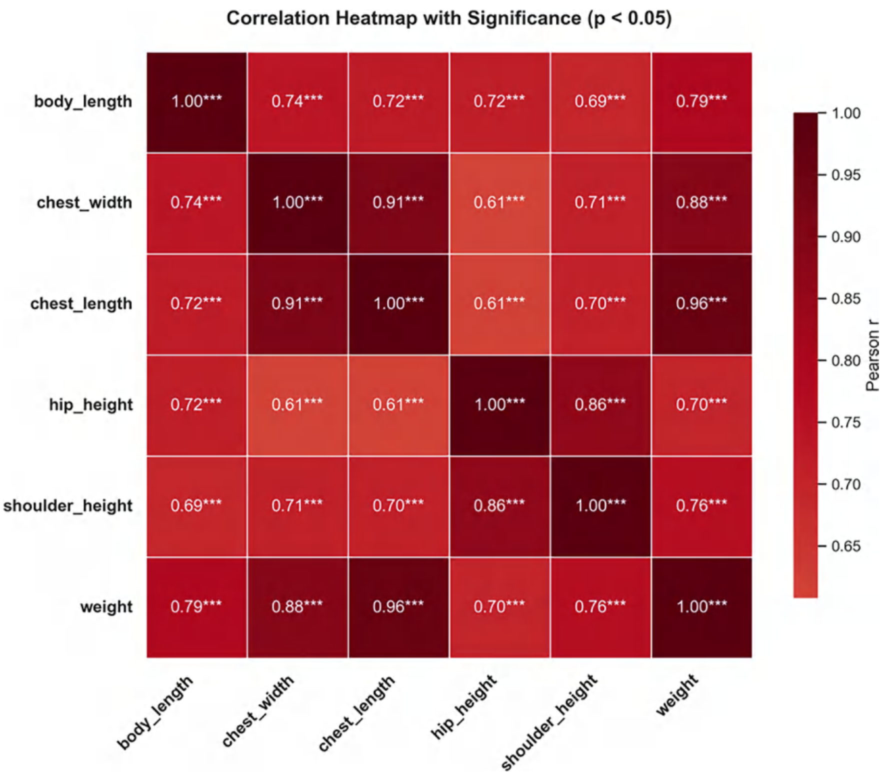

Fig. 8.1 Correlation matrix of cattle body measurements and weight characteristics

8.3.3.2 Feature Selection Prioritization

Since Pearson's r identifies pairwise collinearity but does not account for multivariate dependencies, VIF extends this by evaluating how much a*ll other predictors* in the model explain a variable. To justify the combined use in feature selection, the Composite Score is applied. This is to prioritize variables that are highly correlated with others *and* contribute to variance inflation. A composite score (VIF + HighCorrCount) was computed for each variable by summing its VIF and the number of high correlations ($|r| > 0.8$) it exhibited. The variables were then ranked by severity (Table 8.2).

Based on this scoring system, *chest_width* in our dataset (VIF = 6.48, $r = 0.91$ with *chest_length*) was identified as the most problematic variable, followed by *chest_length* and *shoulder_height*.

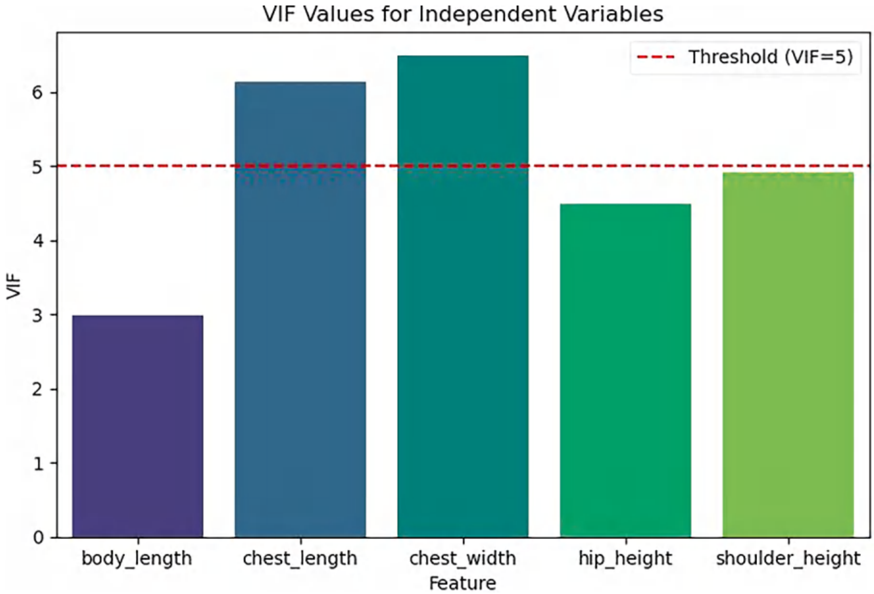

Fig. 8.2 Multicollinearity assessment of cattle body measurements using variance inflation factors (VIF)

Table 8.2 Feature selection prioritization scores combining VIF and correlation metrics

Feature	VIF	HighCorrCount	Composite score
Chest_width	6.48	1	7.48
Chest_length	6.13	1	7.13
Shoulder_height	4.92	1	5.92
Hip_height	4.49	1	5.49
Body_length	3	0	3

8.3.3.3 Model Performance with Iterative Variable Dropping

We aim to enhance model performance by applying the filter-based strategy while adhering to statistical best practices for multicollinearity management. This section details the empirical findings and implications via model performance analysis with iterative variable dropping. This experiment systematically evaluates the impact of removing correlated or less informative independent variables on model performance across three different algorithms: Multiple Linear Regression (MLR), Random Forest Regression (RFR), and Artificial Neural Network (ANN) through R^2 values (Fig. 8.3) and RMSE (Fig. 8.4). The goal is to determine the optimal number of variables to retain while balancing predictive accuracy, interpretability, and computational efficiency.

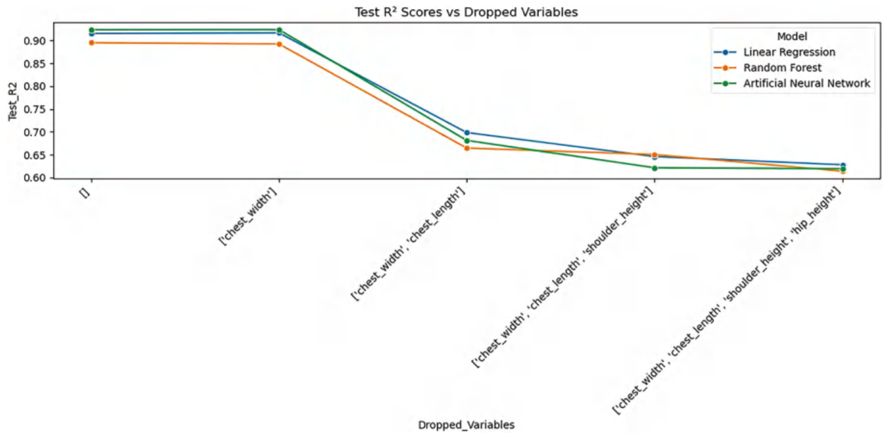

Fig. 8.3 Evolution of predictive performance (R^2) during sequential feature elimination for different regression models

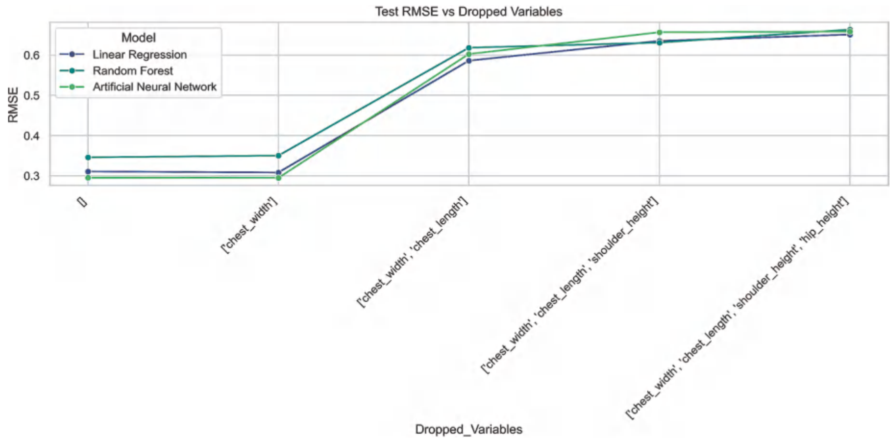

Fig. 8.4 Evolution of test RMSE across sequential feature elimination for different predictive models

1. *Initial Full Model Performance*

When all predictors were included (*body_length, chest_length, chest_width, hip_height, shoulder_height*), the ANN demonstrated superior generalization, achieving a Test R^2 of 0.924 and the lowest Test RMSE of 0.261 standardized units (equivalent to approximately ±0.26 standard deviations from the mean weight). The MLR performed similarly to the ANN, with a Test R^2 of 0.915 and a Test RMSE of 0.281, but the MLR exhibited marginally higher average prediction errors than the ANN.

The RFR, while exhibiting near-perfect training accuracy (Train R^2 = 0.991, Train RMSE = 0.089), showed signs of overfitting, as evidenced by its degraded test performance (Test $R^2 = 0.895$, Test RMSE = 0.321). This divergence between training and test metrics suggests the model memorized noise in the training data, necessitating stricter regularization or feature simplification.

2. *Targeted Removal of chest_width*

The systematic removal of *chest_width*—identified through prior multicollinearity analysis as exhibiting strong collinearity with *chest_length* ($r = 0.91$)—yielded insightful results regarding feature redundancy in the prediction models. This targeted elimination of the *chest_width* variable produced negligible effects on model performance metrics, providing empirical evidence of informational redundancy in our feature set.

The artificial neural network (ANN) demonstrated exceptional robustness, with test R^2 values decreasing only marginally from 0.924 to 0.916 ($\Delta = -0.008$) following *chest_width* removal. Correspondingly, the root mean square error (RMSE) increased by a statistically insignificant 0.002 standardized units (from 0.261 to 0.263). This minimal decline in predictive accuracy suggests that the ANN successfully compensates for the omitted feature through its nonlinear processing architecture, with remaining features sufficiently capturing the relevant variance.

Multiple linear regression (MLR) results proved particularly, as the model maintained nearly identical performance (test R^2: 0.915 → 0.917, RMSE: 0.281 → 0.283). This stability strongly indicates that *chest_length* alone provides the same predictive information as both chest measurements combined, confirming our hypothesis of dimensional redundancy. The 0.002 RMSE increase falls well within expected random variation, suggesting no meaningful degradation in predictive precision.

The random forest regression (RFR) exhibited slightly greater sensitivity to feature removal, showing a modest performance decline (test R^2: 0.895 → 0.892, RMSE: 0.321 → 0.324). This differential response likely stems from the RFR's feature subsampling mechanism, wherein *chest_width* may have contributed to specific tree constructions. However, the minimal magnitude of these changes ($\Delta R^2 = -0.003$, ΔRMSE = +0.003) still supports the conclusion of feature redundancy.

3. *Critical Role of chest_length and shoulder_height*

Further removal of *chest_length* precipitated a sharp decline in all models' performances (e.g., MLR Test R^2 dropped to 0.699). This substantial reduction suggests that *chest_length* captures unique variance in weight prediction that cannot be compensated for by remaining features, establishing its status as a non-redundant predictor. The corresponding RMSE increases (MLR: +0.142 standardized units; ANN: +0.098) further confirm that prediction errors become substantially larger without this *chest_length* measurement. Similarly, retaining *shoulder_height* alongside *body_length* and *hip_height* improved Test R^2 by ≈0.05–0.07 compared to models excluding it, underscoring its predictive relevance. The results strongly support the retention of both *chest_length* and *shoulder_height* in final model specifications, as their removal substantially degrades prediction accuracy.

4. *Limits of Simplification*

The experimental reduction of our feature set to only *body_length* resulted in the poorest performance (Test $R^2 \approx 0.62$), representing a 32–35% reduction in explained variance compared to the full multivariate models. The corresponding RMSE values increased by 0.38–0.42 standardized units, equivalent to nearly doubling prediction errors. This has highlighted the inadequacy of univariate models. The poor performance of univariate modeling confirms that cattle body weight cannot be adequately estimated through any single linear dimension. This reflects animal morphology's complex, multidimensional nature, where weight determination depends on interactions between multiple body segments and volumetric characteristics. The oversimplification sacrifices critical biological interactions.

8.3.4 Discussion and Recommendation

The stability of model performance after removing *chest_width* strongly implies multicollinearity, likely inflating standard errors in the MLR coefficients. This aligns with Variance Inflation Factor (VIF) principles, where VIF > 5–10 signals problematic redundancy. Dropping *chest_width* to mitigate multicollinearity without sacrificing predictive power was recommended. Its exclusion reduced multicollinearity while preserving model R^2 ($\Delta < 0.01$), demonstrating the method's efficacy. Retaining *body_length*, *chest_length*, *hip_height*, and *shoulder_height* to maximize accuracy was also suggested.

From the perspective of cattle's body measurement, these findings suggest that chest circumference (*chest_length*) alone may sufficiently capture volume information relevant to body weight estimation, making the additional width measurement unnecessary. The stability of RMSE across all models following feature removal provides compelling evidence that prediction error distributions remain effectively unchanged, reinforcing the practical viability of simplified measurement protocols.

About algorithm-specific consideration, the ANN was consistently superior in generalization (the highest Test R^2 across trials), supporting its use for complex, high-dimensional relationships. This also indicates its ability to represent nonlinear relationships between independent variables that traditional linear methods cannot adequately describe. The performance degradation (Test R^2 decline from 0.915 to 0.628) with variable removal of the MLR emphasizes its reliance on retaining all linearly informative features. While the RFR algorithms are inherently robust to multicollinearity through their ensemble-based feature randomization, the observed performance gap between training ($R^2 = 0.991$) and testing ($R^2 = 0.895$) metrics indicates persistent overfitting. This divergence suggests that tree depth regularization tuning strategies should be performed to limit model complexity and to prevent individual trees from memorizing noise in the training data rather than generalizing patterns.

8.3.5 Summary

This iterative feature selection analysis demonstrates that optimal model performance requires retaining four of five original predictors, with *chest_width* identified as expendable due to redundancy. Its exclusion reduced multicollinearity while preserving model R^2 ($\Delta < 0.01$), demonstrating the method's efficacy. The ANN emerged as the most robust algorithm, though MLR offers superior interpretability when addressing multicollinearity. While all models showed performance degradation with variable removal, the ANN maintained the smallest relative decline ($\Delta R^2 = -0.303$ from complete to single-variable model vs. -0.327 for linear regression), demonstrating better tolerance to feature reduction. The MLR assumes that each feature contributes independently to explaining variance in the target variable. Removing moderately correlated predictors (like *chest_width)* reduces the model's capacity to capture these additive effects.

Meanwhile, the RFR demonstrates inherent robustness in handling correlated features; our experimental results revealed persistent overfitting. This outcome underscores the necessity for careful hyperparameter optimization. These findings emphasize the importance of systematic feature evaluation in harmonizing statistical and domain-specific criteria in predictive model development.

8.4 Conclusions

This chapter has presented a systematic approach to feature selection that emphasizes computational efficiency and methodological transparency, particularly when working with high-dimensional datasets. Our framework demonstrates that effective predictive modeling requires careful consideration of two interdependent components: (1) an initial filter-based feature selection process and (2) strategic algorithm selection tailored to the characteristics of the resulting feature set.

The importance of this dual approach became evident through our case study, which revealed several key insights. First, we observed that different machine learning algorithms derive predictive value from features through fundamentally distinct mechanisms. While multiple linear regression models showed significant performance degradation when features were removed—decreasing from $R^2 = 0.915$ to $R^2 = 0.628$—artificial neural networks demonstrated greater robustness to feature reduction, maintaining superior performance across all experimental conditions. This suggests that algorithm selection cannot be an afterthought but must be informed by both the feature selection process and the underlying relationships in the data. Second, our results highlight how different algorithms benefit from different feature set characteristics. Linear models, for instance, required complete, non-redundant feature sets to achieve optimal performance, while tree-based methods could tolerate some feature correlation but needed careful regularization to prevent overfitting. These findings align with established machine learning theory, yet provide novel empirical evidence of these relationships in the prediction context.

The practical implications of this work are significant. Researchers working with high-dimensional data should:

1. Begin with conservative filter methods to remove objectively problematic variables
2. Select modeling approaches based on the characteristics of the remaining feature set
3. Employ more computationally intensive wrapper or embedded methods only for final refinement

This staged approach balances computational efficiency with model performance, while maintaining interpretability—a crucial consideration in many scientific applications. Our framework makes two primary contributions to the field of predictive modeling:

1. It demonstrates that feature selection and algorithm selection must be considered as interrelated decisions rather than sequential steps.
2. It provides concrete guidance on matching algorithms to feature set characteristics based on empirical evidence.

Future research could extend this work by examining additional algorithm classes and exploring automated methods for matching algorithms to feature set properties. Nevertheless, the findings provide a robust foundation for building more effective and efficient predictive models across scientific domains.

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Chapter 9
Development of Remote Autonomy of Multi-Cluster Agricultural Machinery Control System Using YOLO Deep Learning Algorithm and WebSocket Protocol

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Abstract In light of addressing the shortage of agricultural workforce and the consequent rise in the need for integrated machinery, this chapter presents a study that endeavored to construct a remote autonomous system for multi-cluster agricultural machinery by implementing an IoT-based and AI-based system using the WebSocket protocol and the YOLO deep learning algorithm. Considering contemporary machinery's difficulties, including substantial operational expenses and arduous learning curves, this research aims to enhance operational efficiency for supporting labor shortages and increasing productivity. Utilizing low-cost hardware, the system facilitated coordinated and autonomous operations by enabling real-time communication between machinery clusters and users via cloud services and the WebSocket protocol. Moreover, the system facilitated cost-effective implementation by migrating the YOLO algorithm from an offline environment to the cloud. The system could transmit real-time data, such as state information, commands, and image frames, which were critical for the operation and control of the machine, while also ensuring stability. In addition, orchard experiments demonstrated that the system employed real-time cloud AI for automated irrigation and reduced the cost of AI processing time. Subsequent developments in agricultural production would be facilitated by the system's establishment of a robust framework for developing autonomy and intelligent machinery.

Keywords Agricultural machinery · Management · Cluster · WebSocket · YOLO

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9.1 Introduction

9.1.1 Background

In recent years, considerable progress has been made in advancing artificial intelligence technology, particularly in natural language processing and image recognition. This has led to the development of various frameworks, including Faster R-CNN, SSD, RetinaNet, and YOLO (You Only Look Once). YOLO (You Only Look Once) has gained prominence among these frameworks due to its exceptional stability and efficiency. As a result, it has found extensive application in the agricultural production sector, specifically in tasks such as cherry fruit recognition (Gai et al., 2023) and disease identification (Morbekar et al., 2020). Furthermore, the advancement of network technologies, particularly the emergence of 5G, has facilitated the utilization of cloud services. The WebSocket protocol is commonly employed for user-to-user communication, such as chat functionalities, as an intermediary between cloud services and clients. Additionally, in Japan, it has been utilized for the real-time dissemination of seismic data through DM-D.S.S (Disaster Mitigation-Data Send Service).

Agricultural machinery can be categorized based on its intelligence levels: traditional agricultural machinery, which replaces manual labor, and computer-driven automated agricultural machinery. Traditional agricultural machinery has been gradually phased out due to its heavy reliance on the operator's characteristics. Despite the continuous iteration of automated agricultural machinery driven by the advancement of artificial intelligence, several issues persist as follows:

I. The cost of hardware highly reliant on arithmetic power is comparatively high, resulting in inevitably increased expenditures.
II. Inconsistent platforms or versions may prevent most agricultural machines from attaining unified control and management after scale formation.

Previous studies have attempted to address the aforementioned issues of management and control by employing the WebSocket protocol in conjunction with IoT technology for data monitoring and analysis (Zhou & Zhang, 2018).

9.1.2 Justification of This Research

Currently, inadequate computational resources resulting from chip scarcity and other factors can be addressed primarily through algorithm optimization or cloud processing. Furthermore, the existing connectivity of agricultural machinery to the Internet of Things (IoT) primarily serves the purpose of remote control and data processing via sensors. This utilization of the server's computational resources is inefficient. Consequently, to simultaneously reduce the hardware cost of computational power and enhance the level of cluster management for agricultural machinery, it is possible to integrate and optimize cloud services to fulfill the aforementioned requirements. Since the WebSocket protocol can transmit larger packets concurrently, it is feasible to incorporate the transmission of image frames alongside the data transmission. In this manner, image recognition capabilities initially implemented offline in the local operation of agricultural machinery could be transferred to the Internet once idle arithmetic power is available. Subsequently, the application can be executed on a server with idle arithmetic power. By adopting this strategy, the system's capability and adaptability are enhanced.

9.1.3 Objectives

The integration of image recognition and IoT technologies has enabled the transfer of the image recognition process from multiple agricultural machines, which previously necessitated powerful computing chips, to a server using the WebSocket protocol. The server would then return the results via its protocol and utilize the information to assist with subsequent automated operations, including pesticide spraying, irrigation, and other tasks. Following the aforementioned methodology, the objectives of this research are as follows:

I. To optimize the transfer process based on the WebSocket protocol for the automated operation of agricultural machinery and achieve the transfer of the image recognition process
II. To attain active control and real-time monitoring of data and screens by utilizing an optimized transfer process
III. To automate agricultural processes by leveraging server-side larger image recognition models, which yield results at a quicker rate

9.2 Materials and Methods

9.2.1 System Architecture

This study was divided mainly into the part of the cloud server and the part of the embedded system, which was mainly offline and relied only on a device that could be connected to the Internet as a bridge between the cloud servers (Fig. 9.1).

Embedded systems are required to incorporate sensors, and to support the machine vision system, an additional camera was also incorporated. To optimize the utilization of the benefits of cost-effectiveness and swift implementation, the primary control center was a microcontroller. An initial laptop was employed for debugging purposes, which was subsequently replaced by a Jetson Nano. Arduino was incorporated to regulate the hardware, and its GPIO interfaces were employed to govern the relay, motor, and servo. Regarding agricultural machinery that is

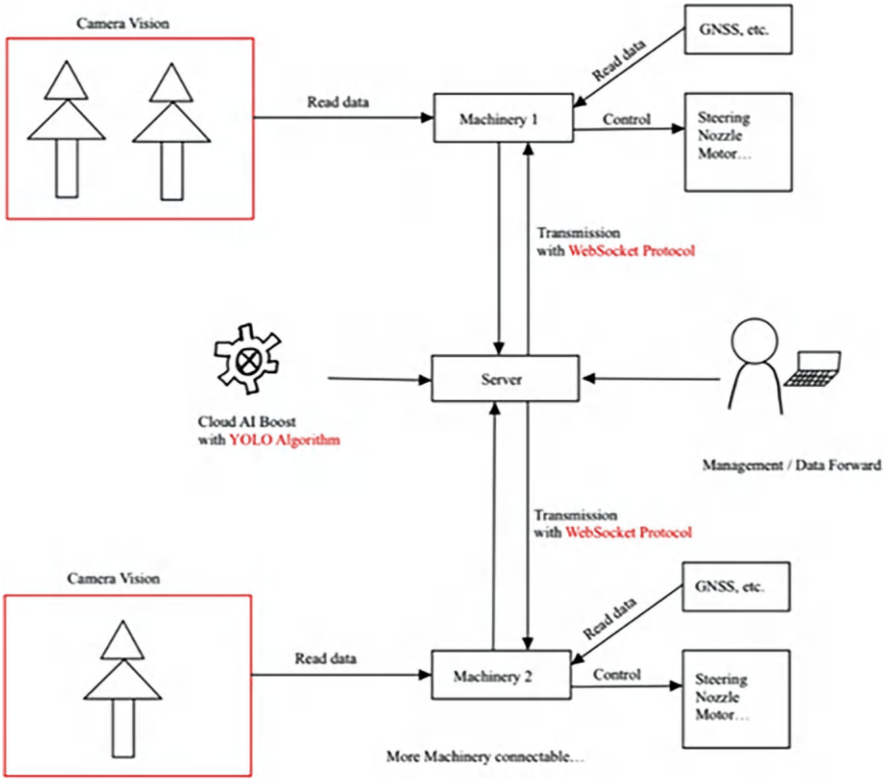

Fig. 9.1 Flowchart of the system for the multi-cluster system to control agricultural machinery

directly controllable via CAN Bus, the Jetson Nano directly manages the movement of the machinery. The cloud server with a mighty graphics card supplies processing power and manages data for the embedded system installed on the agricultural machinery. The backend is implemented in Python and supports bidirectional communication via the WebSocket protocol. Information such as the connected device's UUID and IP address was stored in the SQLite database, which generated the necessary db file upon the initial execution of the Python backend, eliminating the necessity for further deployment. Furthermore, the front-end visualization and control system generated a web page utilizing the WebSocket protocol and JavaScript to ensure comprehensive platform support.

Concurrently, the backend program was integrated with YOLOv5. Once it received the camera images transmitted by the agricultural machinery, it executed a recognition algorithm utilizing the YOLOv5x model in an asynchronous thread. Then, it sent the results back via the same connection, which were then utilized by the agricultural machinery to determine its subsequent course of action, supply processing power, and administer data for the embedded system installed on the agricultural machinery.

9.2.2 Embedded System

This study separated the embedded system into three parts: the central controller, the hardware controller, and the input and output devices. Jetson Nano served as the primary controller, executing program logic and communicating with the server. It was controlled directly if the agricultural machinery could communicate and was controlled using the CAN protocol compatible with the USB interface. For example, a webcam can be managed via the web API interface. It can also be controlled directly via the Jetson Nano's complete web protocol capabilities using web protocol commands. Some devices, like relays and servos, required GPIO interfaces, and an extra Arduino device was utilized to support their control using the original SDK library. The name of the device and its corresponding function in the system are given in Table 9.1.

9.2.2.1 Primary Controller

The primary controller was the NVIDIA Jetson Nano, only 70 × 45 mm. A quad-core ARM Cortex-A57 CPU with 4GB of 64-bit LPDDR4 RAM, a Gigabit Ethernet connection for network access, and USB 3.0 and USB 2.0 connectors for peripheral and accessory connectivity were at the device's core. In addition to these fundamental enhancements, as a "minicomputer," it has GPIO, I2C, I2S, SPI, and UART interfaces for IoT device interaction. Meanwhile, because it supports HDMI, it can be utilized for development, testing, and demonstration. In this study, its low-power properties, combined with its powerful processing capabilities, made it perfect for edge computing applications in terms of energy usage.

9.2.2.2 GNSS System

The acronym GNSS refers to the Global Navigation Satellite System. This system encompasses various satellite-based navigation systems, including the US-led GPS, the European Union's Galileo system, Russia's GLONASS system, and China's

Table 9.1 Name of the device and its corresponding function in the system

Device name	Function
Jetson Nano	Primary controller
Arduino	Sub controller
CAN bus	Communication device
u-blox C94-N8P	GNSS module
Logitech C920	Camera
Ctronics IP Camera	Web camera on the farm
Relay	Motor & Nozzle control actuator
Servo	Steering & Nozzle control actuator

Beidou navigation system, which are now operational. This system's function involved using user equipment that receives signals from a minimum of four satellites. The equipment could determine the precise distance between each satellite and the receiver by accurately determining the flight duration of these signals. Based on the provided distance data, the receiver employed the triangulation technique to determine its geographical coordinates on the Earth's surface precisely. The u-blox C94-M8P RTK application board kit was utilized in this study to locate the system precisely and return data to the server for analysis and statistics. The NEO-M8P module includes the kit and offers the UHF radio link, ports, and SDK to make development easier. The NEO-M8P module introduces the "rover" and "base station" roles. After the base station is put inside the study room, it may communicate a stream of position-corrected data to the "rover," with positioning accuracy reaching centimeters. The u-blox C94-M8P RTK application board kit is available in four distinct variants worldwide, each pre-configured with a different radio link to comply with different radio frequency restrictions in different regions worldwide. The C94-M8P-4, which complies with Japanese frequencies, was used in this investigation.

9.2.2.3 Machine Vision

To integrate machine vision, embedded systems employ two types of cameras. The first was a web camera, which connects to a Jetson Nano via a USB interface; in this study, a Logitech C920, which is often used in PCs, was employed. The Logitech C920 has a full HD glass lens that produces 1080p quality at 30 frames/s with about a 78-degree field of view angle, followed by spray logic based on this field of view angle. In addition, C920 also has automatic HD light correction, which adapts to all lighting situations in the farm.

The second method was to use IP cameras, which will automatically connect to the LAN or even the Internet, eliminating the need to connect via cable and instead immediately accessing their IP address and selecting the necessary protocol to read or control the video screen. The IP camera series from Ctronics was employed in this study. It connects to a Wi-Fi router via a 2.4GHz network. It connects to an official server while establishing a local server, allowing access from many LANs and the Internet. It can read streams with a resolution of up to 4K and gives up to 4K image quality. Furthermore, it has a control API interface that may be used to control its direction via API and authentication.

9.2.2.4 Test Platform for CAN Bus

This study used the Yamaha G30Es, a golf cart, as a test platform for agricultural machinery based on its size, automation, and expansion capabilities, with detailed parameters as shown in Table 9.2.

Table 9.2 Detailed parameters of Yamaha G30Es

Parameter	Value
Total length	3670 mm
Total width	1265 mm
Total height	1860 mm
Weight	485 kg
Distance between axes	2140 mm
Rated voltage	72 V
Rated output	3.5 kW
Manual running speed	0–19 km/h

Table 9.3 Detailed parameters of Canycom EJ20

Parameter	Value
Total length	1040 mm
Total width	610 mm
Total height	940 mm
Weight	62 kg
Maximum load capacity	200 kg
Rated voltage	24 V
Rated output	350 W
Manual running speed	0–4.5 km/h

9.2.2.5 Test Platform for GPIO

There was also a test platform in this study. The prototype was the Canycom EJ20. Originally, it was a motorized cart. After a few modifications to the powertrain, a relay was added to control the motor, so it was possible to use Arduino's native libraries to control the relay and the servo. The detailed parameters are shown in Table 9.3.

9.2.2.6 Program Logic of Primary Controller

The program was programmed in Python. Asynchronous function execution was implemented using the async and thread libraries. WebSocket protocol support was implemented using a library called "websockets," and the images returned by the camera were supported using the OpenCV library. The overall logic can be seen in Fig. 9.2.

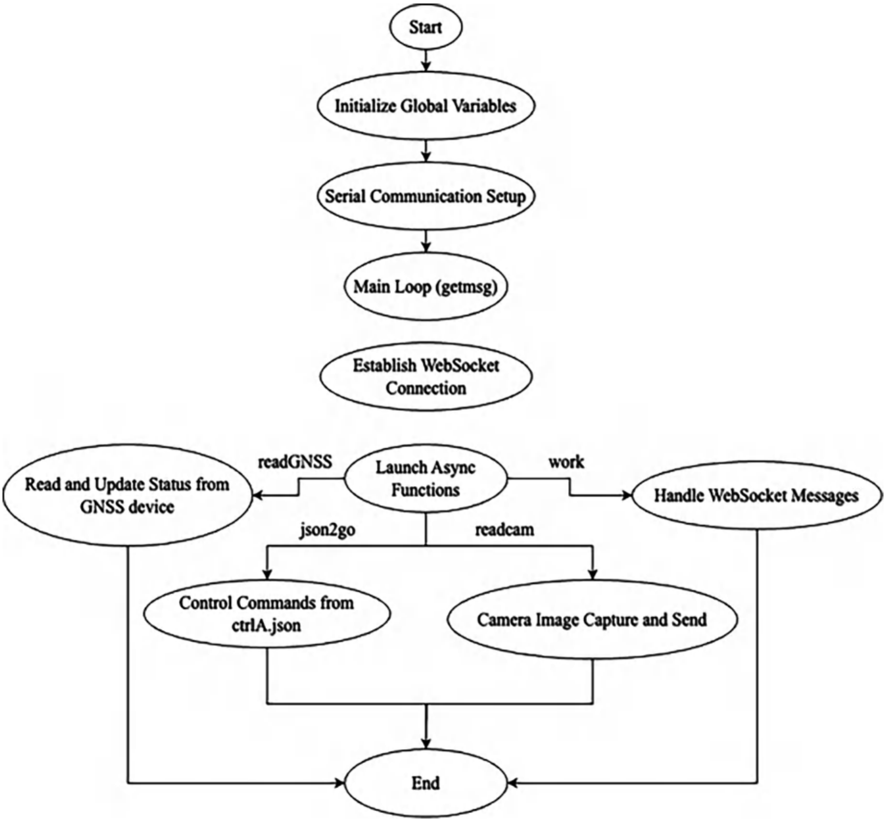

Fig. 9.2 Basic logic of the controller for the upper client (agricultural machinery)

9.2.2.7 Spraying System

In this study, the spraying system could be divided into two parts: equipment and logic. The equipment is the spray nozzle, which was controlled using relays. The first problem to be solved is the spraying range to realize accurate spraying. The study used the plant size result calculation from AI to calculate the spraying range. If the nozzle is considered a point, then only the spraying angle needs to be known to cover the plant without affecting the others. To calculate this angle, this study tried to use Intel RealSense to get the distance from the nozzle to the plant, using a library called pyrealsense2 to call RealSense to get the distance from the point cloud to the nozzle, and after getting the distance, it just needed to use the following Eq. (9.1) to calculate the horizontal spraying angle.

$$\text{Angle} = 2 \times \arctan\left(\frac{\text{size}/2}{\text{distance}}\right) \tag{9.1}$$

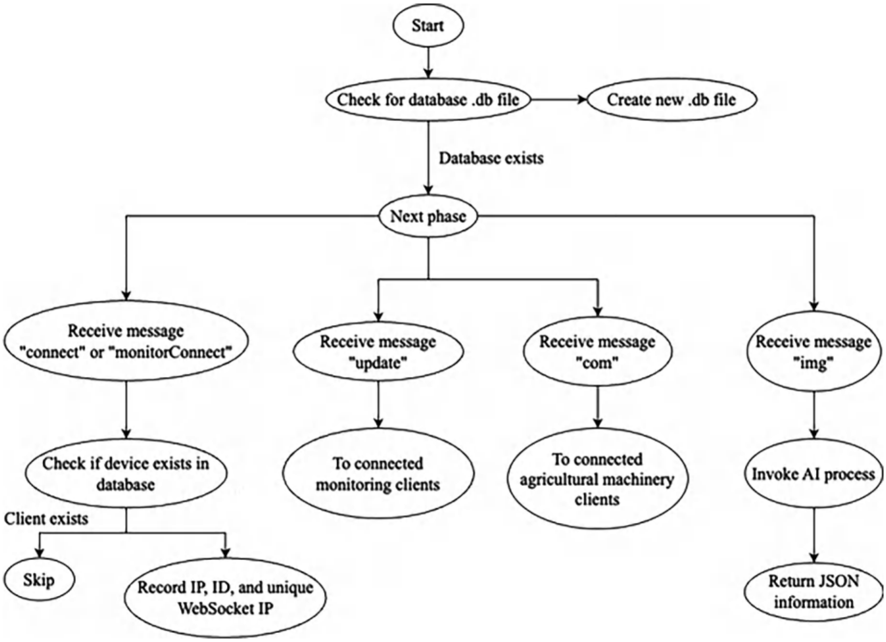

Fig. 9.3 Flowchart of the cloud system, including initialization and process after receiving messages

However, using an additional point cloud camera just to get the distance adds to the cost, so this study used another way to calculate the spray angle without requiring distance: using the camera's field of view angle.

9.2.3 Sensor Module Design

The cloud system was also based on the Python programming language and a "websockets" library to build a server that can load multiple devices. The flowchart is shown in Fig. 9.3.

9.2.3.1 Data Store and Read System

This study used SQLite, which was easy to deploy quickly, for reading and writing data. SQLite had some advantages over MySQL-like databases. The first was its lightweight nature. Instead of being a standalone service process, it can be embedded directly into an application. Due to this feature, SQLite's database is a single file, making it much easier to back up, move, and share the database without spending lots of time installing the service framework.

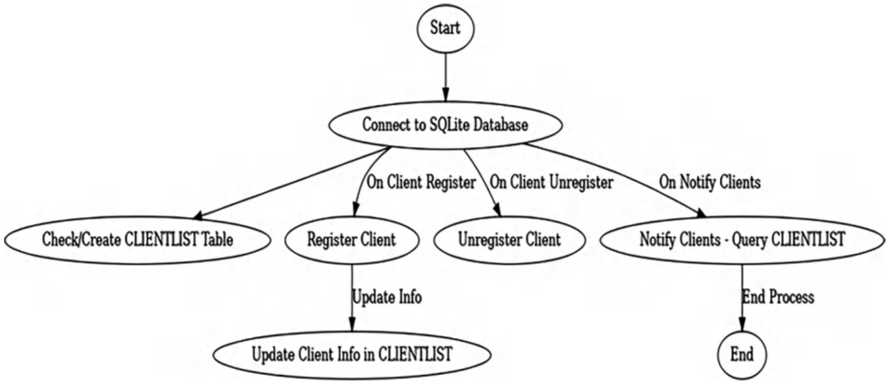

Fig. 9.4 Flowchart of the data storage in the server-side program

Second, SQLite was also much more reliable. Although SQLite uses a single file to store data, in actual use, if the program crashes or there is a problem with the logic, in most cases, it will not affect the regular reading and writing of data. Since we want to realize the back-and-forth communication of WebSocket, the program must know the WebSocket ID of the client to make a precise lookup, so the server-side program would check whether there is already a file called "clients.db" at runtime, and create a new one if there is not. The database stored the WebSocket ID, the device ID, and the IP address (non-essential) information. The process of initializing and the logic of the data store with SQLite after the system is launched are shown in Fig. 9.4.

9.2.3.2 Communication System

On the server side, we also used the library websockets to use the serve function to map port 8765 and open it to the IP address of 0.0.0.0; this means that the port is open to the public network, not only locally. In the main function, the async function establishes an asynchronous process for each message received. As all messages are sent and received in a unified JSON format, the current receive message types are supported in Table 9.4.

A distinct processing logic was implemented for each message type upon receiving a message. When a "connect" type message is received, a new agricultural machinery has connected to the server. If the ID is not found, the function writes the WebSocket ID, the machinery ID from the message, and the IP address (for querying if necessary) to the database. The connected client may be a vehicle machine, a camera, or another machine; the user must determine this and complete the setup. The program has already recorded the ID, allowing the user to set the corresponding relationship later.

Similarly, when a monitor client connected to the server, it would pass the WebSocket connection to the function "register_user" as a parameter. The monitor

Table 9.4 Current support receives message types from clients

Type	Keyword in JSON
Initializing	connect
Updating data	update
Communication with others	com
Image AI processing	img
Monitor initializing	monitorConnect

client did not require and store a unique WebSocket ID, because it received all messages in a unified way. Therefore, the connection was simply added to an unordered, non-repeating set of elements with another name.

If an "update" message was received, the agriculture machinery sent a status update message to the server and monitor clients. In this study, the implemented statuses that could be updated were latitude and longitude, quality of the connection, and the mode being used. Regarding program logic, it was possible to update all text messages, such as sensor-based humidity, temperature, and soil nutrients. After the message was received, the function called "notify_users" would be executed. The logic of this function was that it first tried to send a message synchronously to every monitor client that had ever registered. If the timeout was exceeded, the WebSocket protocol would automatically set a "close_code," and at this point, the program would remove the disconnected monitor client from the set of elements; thus, the program would not make any more useless attempts to send it.

If the message of type called "com" was received, this message could be from the monitor client or the agricultural machinery. Because no matter what, it would add its own ID in the message, at this time, the program for the synthesis of the sender's ID, the receiver's ID, then added the instruction to the JSON message "cmd," and further added the specific content to the JSON message "cnt" in the JSON message. Then, a function called "notify_client" was executed, which was reserved for a notification of all the logic. If the recipient ID is zero, notify or forward the message to all registered clients. If the recipient's ID was specified, an SQL query was executed in client.db to find the WebSocket ID corresponding to this ID, and then a packaged JSON message was sent to it.

Finally, if the type of the message was "img," the message's content was a base64-encoded image, which needed to be recorded as "from which device" for AI recognition, and then two functions needed to be executed. First, the program needed to write down "from which device." Then, the first one was the function called "notify_users," which was the same as updating the status of the device; it told the monitor client that there was a monitoring screen from the agriculture machinery, which would be used as important monitoring data and displayed on the monitor client. Next, a function called "imgprocess" was executed. The primary process of this function was to decode the image file with base64 and store it in the buffer, then read the image data with OpenCV and create a new asynchronous processing thread to pass it to YOLOv5. The AI part would be discussed in detail in the next section. Since the recognition part of YOLOv5 had been adjusted as part of the

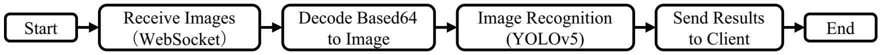

Fig. 9.5 The image processing in a cloud system includes decoding and recognition

code, the result data returned by the AI would also be a JSON message, which would be uniformly formatted and passed back to the device according to the "from which device" ID recorded at the beginning. The details of the image process are in Fig. 9.5.

9.2.3.3 AI Recognition System

The AI recognition was based on YOLOv5, and the plant data was collected independently and trained in YOLOv5x. Although YOLOv5x was highly accurate, it is relatively large in scale, so it was not suitable for a high-performance computing platform specifically for agricultural machinery to run it. Therefore, this study utilized the stability and reliability of WebSocket for large-scale data and the idle computing resources of cloud servers to move AI recognition from offline to the cloud.

Overall, the YOLOv5x is still based on the base structure of the YOLOv5s, which is shown in Fig. 9.6, but it has been significantly improved in depth and width compared to the YOLOv5s.

9.2.3.4 Image Data Collection

The dataset was collected from Tsukuba-Plant Innovation Research Center (T-PIRC) (36°06′56.9″ N, 140°05′36.5″ E) under sunny and cloudy weather.

Then, an iPhone was used to walk around the fruit tree and take two 4K 60-frame videos, and then ffmpeg was used to export each frame as a 1280 pixels × 720 pixels image. To avoid unnecessary labeling caused by the same image in the two frames before and after, the photos were then randomly extracted by using a Python program to disrupt the order of the original and rename the file as a four-digit number in accordance with the sequential filename. After completing the data acquisition, the plants were labeled. In T-PIRC, the plants are mainly classified into four kinds, as shown in Fig. 9.7.

For preparing the training and validation sets, 475 images were labeled and divided into training and validation sets in a ratio of 4 to 1, that is, 380 training set images and 95 validation set images.

9.2.3.5 Model Training

The model was trained using the computer hardware described in Table 9.5.

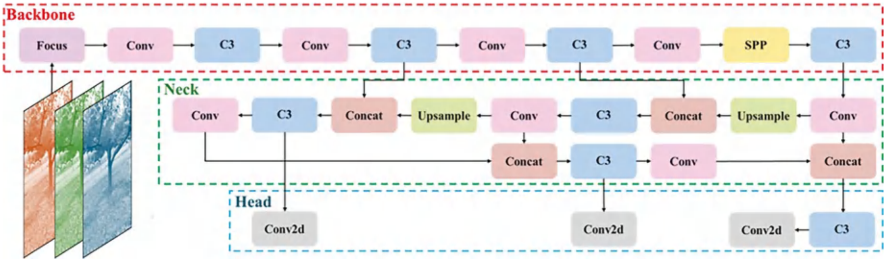

Fig. 9.6 The architecture of the YOLOv5x is used for recognition

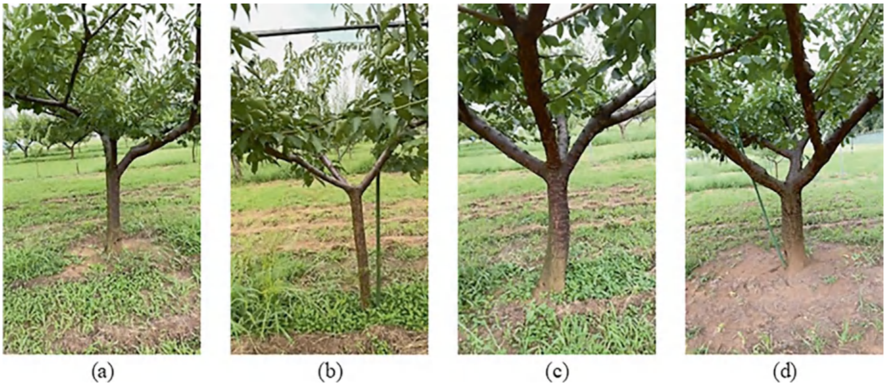

Fig. 9.7 Different types of trees that have been taken for training: (**a**) Thin, but unsupported trunk. (**b**) Thin and braced trunk. (**c**) Stout, but unsupported trunk. (**d**) Stout and braced trunk

Due to the graphics card resources needed to train the model, CUDA 11.8 and cuDNN 8.9.0 were installed and then used to manually specify the graphics card as the computing device in the Python program used for training. The epoch and batch size, which refer to the number of training times and the amount of data in one iteration, must be set for the training of this study. The greater the batch size, the more data is used in one iteration, and if the total amount of data stays the same, the faster the training is at one time, but it will also result in the graphics card being loaded simultaneously. It will, however, also result in an overload on the graphics card. In this study, the epoch was set to 300 and the batch size to 16, considering the size of YOLOv5x, the size of the video memory, and the amount of time needed. There was also an additional test that if the batch size is increased again during the test, the training would crash owing to insufficient graphics card memory; thus, this argument is relatively suitable for the study.

Table 9.5 The hardware details of the computer that was used for training

Hardware	Model
CPU	Intel(R) Core (TM) i7-11700F @ 2.50GHz
Graphic card	NVIDIA GeForce RTX 3060
The graphics card's RAM	12 GB
RAM	16 GB

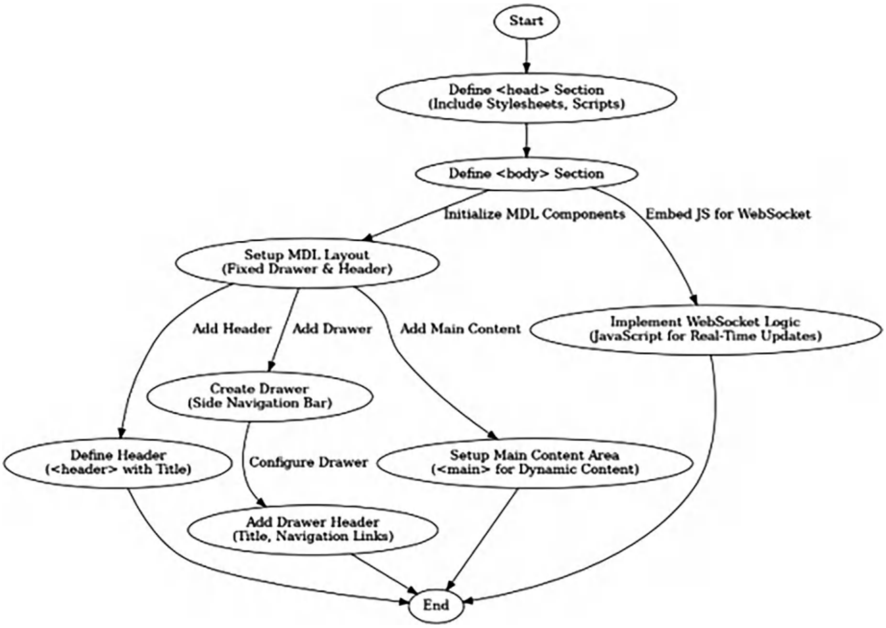

Fig. 9.8 The running process of the user interface and the system

9.2.4 User Monitoring and Controlling System

Considering platform compatibility, this study prioritized using web pages to write the user interface and JavaScript to write the logic. The front-end interface was built using a CSS framework called Material Design Lite, and it defined a left sidebar on the desktop to allow space for displaying the status and information of each connection's agricultural machinery. This space was uniformly placed in a hidden sidebar on the mobile side. The process is shown in Fig. 9.8.

9.2.4.1 System Logic

The JavaScript program used a list map called “idMap” to provide a client ID-to-name mapping to achieve id-to-name and even functional correspondence. It initialized a list called “clientarr” to store the ID information. Before the logic begins, the web page checks to see if the browser supports WebSocket, and then establishes a WebSocket connection to the server using a library called “reconnecting-websocket,” an improved JavaScript library based on the native WebSocket library. The “reconnecting-websocket” was a JavaScript library that improved on the native WebSocket library by working on automatic reconnection of a WebSocket connection after an unexpected disconnection. The program then defined three callback functions to handle WebSocket events as follows in Table 9.6.

In this study, after the connection was established, the monitoring client would send a message whose content is “monitorConnect” to the server, and the server would register it as a monitoring client when it learned about this message. Moreover, since the auto-reconnect logic already existed, the function only displayed a prompt in the user interface when the connection was closed. The monitoring client handled the new client connection message since it was already defined in the programs used in the cloud server and embedded systems. It then added the message to the “clientarr” list for storage. It dynamically updated the interface’s elements to display information and control buttons based on the corresponding names of the “idMap” and the type of agricultural machinery. If a message contained a status update, the client’s display was updated in subsequent messages with the same ID. Moreover, if the message type were “image,” the image on the interface would also be updated.

Furthermore, the program could also send control messages in reverse in addition to the abovementioned logic. For example, the control functions, stop, go (which also represents the head up of the camera), down, left, and right, were defined in the program to control the web camera’s direction and the golf cart’s walking. Each of these functions could be passed a parameter called id, which tells the function which device should be controlled. Considering the user’s intuitive operation, the stop function was not attached to a button. Instead, the program defined the corresponding function in the user interface in response to the pressing of the buttons controlling the forward, left, and right turns, and it immediately executed the stop function upon the release of the button.

Table 9.6 The logic of three callback functions

Function name	Meaning
onopen	Handling when the connection is established
onmessage	Handling when it receives messages from the server
onclose	Handling when the connection is closed

9.2.4.2 User Interface

In the header elements of the page, the Roboto fonts and Material Icons were referenced, and then the arrangement of the interface elements was defined. In particular, the borders of the left sidebar of the page were removed. The layer priority of the background element was lowered to ensure that the information was displayed correctly at the top level. A flex layout allowed the containers for each agricultural machinery information to be aligned vertically. The navigation bar was defined to change the background and the text color when the mouse hovered to provide intuitive feedback. The main section on the right-hand side also used a flex layout to align each container neatly and ensure that the aspect ratio of the containers automatically adjusted to the image size (i.e., the sequence of frames returned by the camera). Since it was necessary to display the title of the image and the control buttons, a border was set for each container to avoid misreading.

9.3 Results and Discussions

9.3.1 AI Training

In this study, we used YOLOv5 to identify fruit tree trunks fast and accurately. The confidence loss and bounding box loss results for the training on the previous training machine are shown in Fig. 9.9a, b. The result shows that the confidence loss and bounding box regression loss gradually stabilize after the 200th epoch and reach their lowest value at the 300th epoch.

Also, as shown in Fig. 9.9c, d, the model performed significantly in terms of precision and recall, reaching 96.58% and 98.03%, respectively. The accuracy of the model measures how many instances of all the instances labeled by the model as positive classes are truly positive classes. The calculation process is as shown in Eq. (9.2).

$$\text{Precision} = \frac{\text{True positives}(\text{TP})}{\text{True positives}(\text{TP}) + \text{False positives}(\text{FP})} \tag{9.2}$$

Model recall refers to the ratio of the number of instances correctly predicted as positive class by the model to the total number of actual positive class instances, which is calculated as shown in Eq. (9.3). This indicates that the model completed in this training produces fewer misclassifications in prediction and can identify most of the positive class instances with fewer omissions.

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \times 100\% \tag{9.3}$$

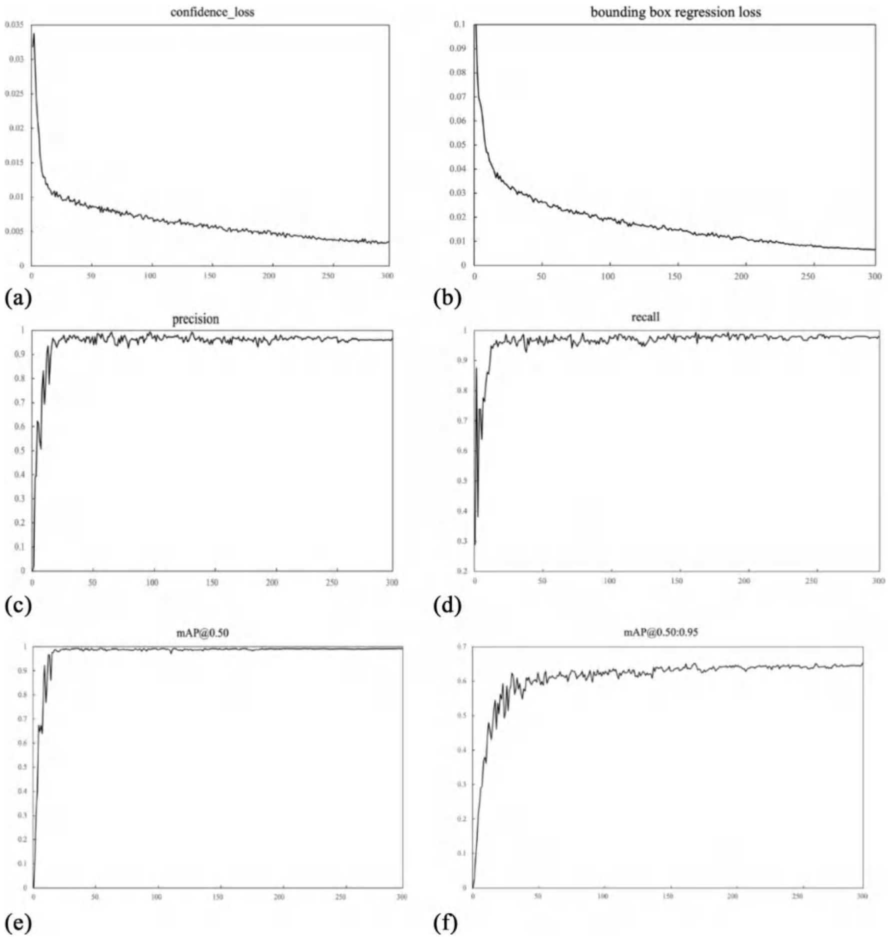

Fig. 9.9 (**a**) Confidence loss of training from the one epoch to the 300 epoch. (**b**) Bounding box regression loss of training from the one epoch to the 300 epoch. (**c**) Precision of the trained model from the one epoch to the 300 epoch. (**d**) Recall of the trained model from the one epoch to the 300 epoch. (**e**) mAP when Intersection over Union threshold was set to 0.50 from the one epoch to the 300 epoch. (**f**) mAP when Intersection over Union threshold under 0.50:0.95 from the one epoch to the 300 epoch

In addition, as a model evaluation metric, mAP stands for mean Average Precision, which focuses on two aspects in object detection tasks: the accuracy of localization and the accuracy of class predictions. To obtain the value of mAP, first, based on the recall, the maximum precision is calculated for distinct levels of recall. Then the average of these maximum precision values is calculated and regarded as AP. Based on AP, the mAP could be calculated as in Eq. (9.3). As shown in Fig. 9.9e, mAP@0.50 reached up to 99.36%, which means the model was accurate enough when the Intersection over Union threshold was set to 0.50.

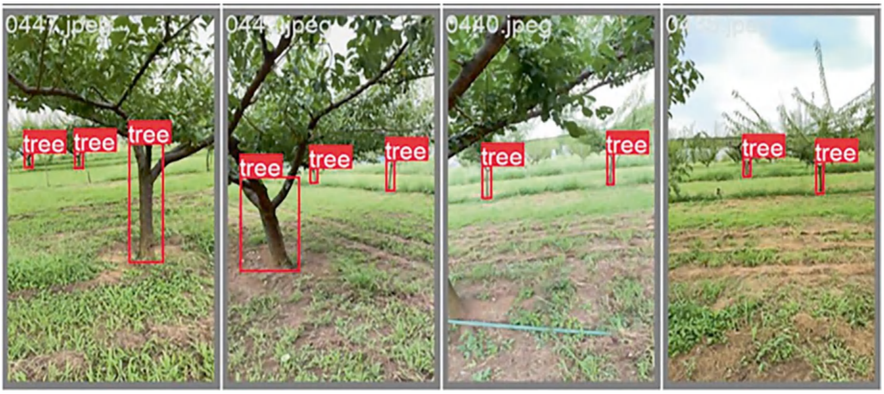

Fig. 9.10 Trunk recognition results under real-world conditions

However, this did not mean that the model had reached a standard that could be practically applied, for scenarios that require higher boundary accuracy, it was necessary to calculate the mAP value of Intersection over Union threshold at 0.50:0.95, which is more responsive to the evaluation metrics of the quality of the model's target detection compared to the mAP@0.50. It had also been used for evaluating the model trained in this study, as shown in Fig. 9.9f, the highest mAP@0.50:0.95 reached 65.25%, which means that the model was not only able to detect the presence of objects well, but also locate the bounding boxes of these objects with relative accuracy. However, this value also implied that the model still had room for improvement.

After quantifying the training results, the model was also tested under real-world conditions, and the results are shown in Fig. 9.10. The model identifies and localizes the position of the trunk very well.

However, the result reflected that the model still had some deficiencies, for example, in Fig. 9.11, there was a probability of not recognizing the tree trunks when they were far away from the camera. Although in the actual spraying application, the more distant trunks could be ignored, the results still show that there was a tree because of the bracket, which also affected the recognition of the results, causing a small amount of accuracy degradation.

9.3.2 Cloud System and Communication System

In this study, the WebSocket protocol shows unprecedented advantages over traditional protocols due to cloud computing concepts. Before the experiment, a transmission performance test was done with the POST protocol at distances of 1 and 5 m. The experiment's procedure is to make a large packet and then use two devices to calculate the total latency of transmission back and forth. The results of the

Fig. 9.11 Trunks that are not recognized in the test because of the bracket

latency of the WebSocket protocol (Solid line) and the POST protocol (Dots line) at 1 m were recorded in Fig. 9.12a.

The result shows that at 1 m, the performance of the WebSocket protocol is not good enough, even worse than the POST protocol. This result is because, in the program under study, the return of a message requires looking up the corresponding ID in the database. This process required additional time. However, if the distance reached 5 m, the advantage of the stability of the WebSocket protocol was shown. The result is shown in Fig. 9.12b, where the solid line represents the WebSocket protocol, and the dotted line represents the POST protocol.

The results show that, especially in the first half, the latency caused by the POST protocol is greater than that of the WebSocket protocol for two-way transfers. The WebSocket protocol is significantly more stable than the POST protocol, which has ultra-high latency that seriously affects the experience in two out of 50 transfer tests.

Then, the system's transmission performance test was also done. Fifty times of transmission of image sequence frames and return of recognized text information were tested, and the average value of image transmission is about 40.5 ms, and the average value of return of text format results is about 13.9 ms. The fluctuation is relatively smooth, as shown in Fig. 9.12c.

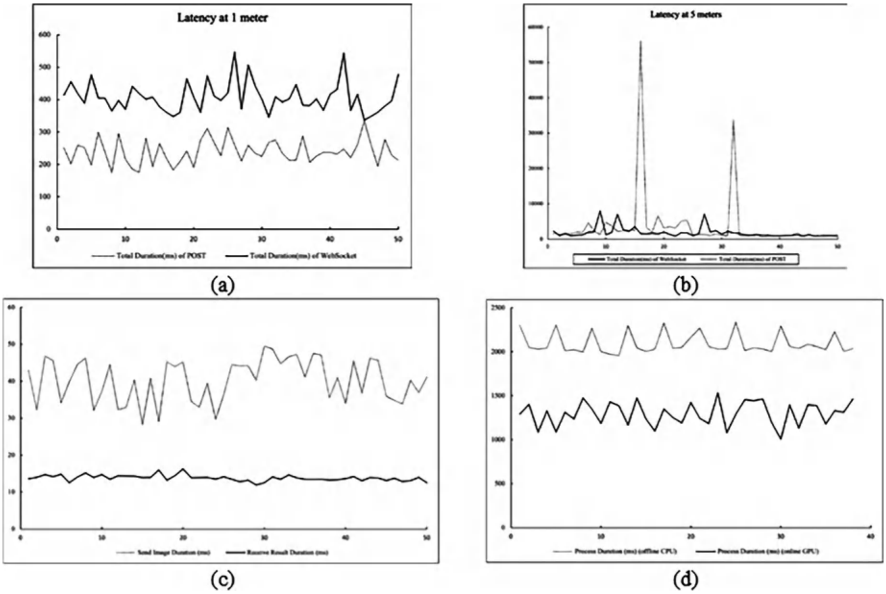

Fig. 9.12 (**a**) Latency of POST protocol and WebSocket protocol at 1 m. (**b**) Latency of POST protocol and WebSocket protocol at 5 m. (**c**) Transmission performance test, including image format and text format. (**d**) Comparison between using CPU performance for AI recognition directly on the agricultural machinery and using GPU performance for AI recognition on the cloud server

The advantage of the cloud system is that it can utilize the idle resources of the cloud server with a high-performance graphics card to do AI recognition instead of agricultural machinery, reducing the cost and accelerating the speed of recognition. In this study, we used a computer with an NVIDIA GeForce RTX 3060M graphics card as a cloud server, comparing with the use of the CPU directly on the agricultural machinery, and the AI recognition with YOLOv5x, the average time was reduced from 2093 to 1298 ms (Fig. 9.12). Even though it is necessary to add the transmission time for recognition on the cloud server, it is still much faster than the offline recognition on the agricultural machinery because the average transmission time does not exceed 100 ms.

9.3.3 Application in Orchard

In this study, after applying the trained model and building the system, it can be connected to the orchard's camera system and the vehicle used for agricultural machinery. The latter can be automated to operate and spray, and can be controlled manually while monitoring the operation of the farm machinery. The test flow and the pseudocode for the server and client sides are shown in the appendices.

```
{'class': 'tree', 'conf': 0.8187517523765564, 'position': [732, 131, 461, 988]}
AI result:
name: tree
Confidence: 0.8187517523765564
Mid line: 962.5
Angle: 19.23334938241924_
```

Fig. 9.13 Logs from the operation of the agricultural machinery. The first line was the original JSON text received, and the following line parsed and performed arithmetic to conclude whether it should be sprayed or not, and how much it should be sprayed

In a real situation test, the returned result of the AI from the server after recognition was shown in Fig. 9.13. The server returned the object's category, confidence, and location, and then the agricultural machinery could do simple arithmetic to know whether it should be sprayed.

At the same time, all the camera's visions were recognized by the AI and transmitted to the user's monitoring interface. An unlimited number of connections can be supported as server resources allow. In the test, one camera was placed in the orchard and one was placed indoors in the T-PIRC research laboratory. Both images were correctly displayed on the monitoring interface, and the relevant information was also updated in the information display bar, as shown in Fig. 9.14. It can also be seen that we added the support of being controlled to one of the cameras, which can be controlled by clicking a button to maintain its operation.

After confirming that the cloud server and embedded systems were working correctly and that the AI, monitoring, and control functions were practical, a simulated automated spraying test was conducted in T-PIRC with a golf cart using water but not pesticide, as shown in Fig. 9.15.

The calculated spray angle, that is, the size of the trunk, was not used to control the rotation of the nozzle directly, but rather the control of the pump was conducted to control the intensity of the spray. The camera and the nozzle were in one position, so it could be seen as shown in Fig. 9.16. When the nozzle passed the fake tree, the spraying was activated, and when there was no tree, the spraying stopped automatically, which realized a more accurate spraying and reduced the waste of pesticides.

We also found a problem in that the image frame refresh rate from the camera was fixed at a 3-s refresh, a low value, to save traffic and unnecessary performance consumption. This resulted in the vehicle not being able to run too fast, or there would be a delay in spraying, or even missed spraying. However, the overall objective was achieved, which included automatic running, remote management, and automatic spraying, which improved operational efficiency.

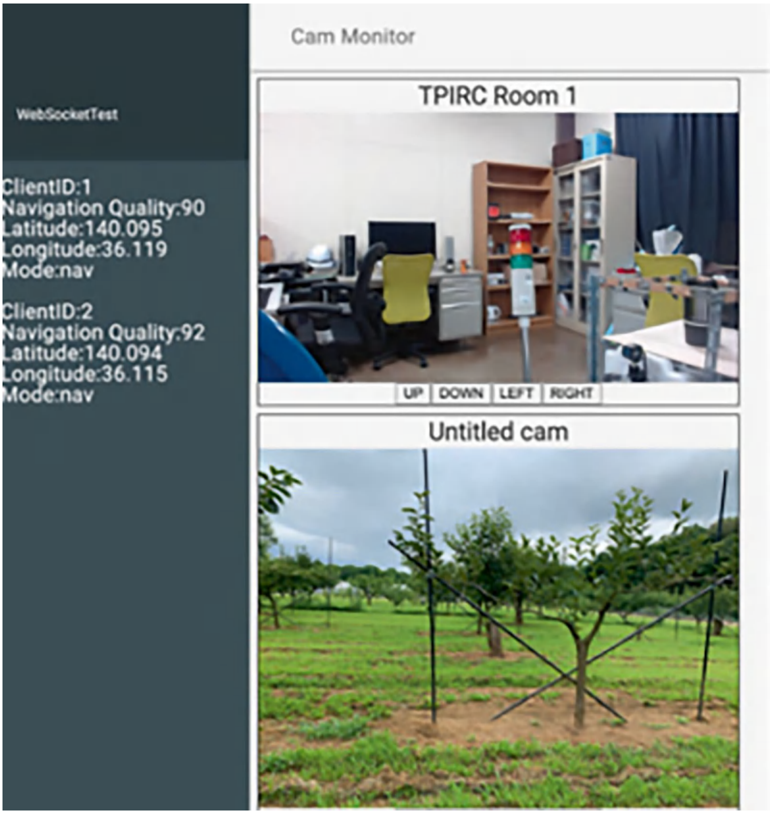

Fig. 9.14 The user interface has two cameras attached. The image frames and control buttons (if controllable) are displayed on the right side, and relevant information is displayed on the left

Fig. 9.15 Simulated environment for automated spraying testing using fake trees and a golf cart. The spray nozzles have been fixed to the rear of the cart

Fig. 9.16 Comparison of spraying or not when the golf cart passes by the fake tree

9.4 Conclusions

This chapter introduced a study that utilized the WebSocket protocol to create a real-time system for managing agricultural machinery. The system allows real-time monitoring of multiple device clusters' status, image frames, and real-time control of these devices. It takes advantage of the stability and efficiency of the WebSocket protocol for transferring large packets and moves the offline AI processing to the cloud. This allows for the utilization of unused server resources and optimizes the cost of AI hardware. This research also offers a framework to facilitate future access to further information on agricultural machinery. As proposed by this study, the resolutions to the issues outlined in this chapter are as follows.

I. Created a real-time communication system using the WebSocket module in Python and an SQLite database to facilitate role assignment and the transmission, reception, and forwarding of data.

II. Enhanced the source code of YOLOv5 to include server-side system calls and provide pertinent data. Furthermore, gathered data and trained a model specifically designed for identifying plants in the fruit tree orchard, raising the mean average precision (mAP) to 99.36%.
III. By using the serial communication protocol and CAN protocol, hardware information collection and hardware control were achieved. This was then done via a standardized communication specification for data transfer, thereby resolving the issue of varying monitoring and control standards across various devices.
IV. By using the computational capabilities of cloud servers instead of relying on AI identification in agricultural machinery, autonomous operation and spraying may be achieved at a cheaper hardware cost. This approach enhanced efficiency and minimized waste during the spraying process.

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Chapter 10
Development of Navigation System in Rural Roads Using Deep Learning Algorithm for Autonomous Crawler Tractor

Liu Yuxin, Chen Lang, and Tofael Ahamed

Abstract Labor shortages in the agricultural sector have become a global concern, especially in countries with aging population. The use of AI technology in agriculture not only addresses the lack of workforce but also increases efficiency by monitoring plant growth and diseases and enabling autonomous transportation. In agriculture, autonomous tractors have been increasingly used, requiring advanced navigation systems to support various agricultural operations. This research focused on designing an autonomous navigation system based on a camera and deep learning for a crawler tractor, allowing it to operate on farm roads without human intervention. The developed system integrated three main components: a vision system, a controlling system, and a Robot Operating System (ROS). The vision system utilized dual cameras, OpenCV, and the YOLOPV algorithm with 3500 trained images to detect drivable areas and traffic lines. The hardware includes a Raspberry Pi, PLC, and a computer dedicated to control tractor actuators. Then ROS facilitates communication between the vision system and control systems, enabling autonomous navigation for tractor. The system demonstrated effective performance with safe and accurate driving after being tested on various road shapes.

Keywords Labor shortage · Autonomous navigation · ROS · YOLOPV · Crawler tractor

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10.1 Introduction

The 2023 World Development Report by the World Bank underscores the urgent challenge of global population aging, leading to labor shortages in various sectors, particularly agriculture. The report predicts a significant decline in the agricultural workforce in the coming decades. For instance, Spain's population is expected to decrease by over a third by 2100, with the elderly population rising from 20% to 39%. Countries like Mexico, Thailand, and Tunisia, facing restricted population growth, will soon need more foreign workers to sustain their economies (World Bank, 2023). Consequently, artificial intelligence (AI) technology becomes crucial to support the dwindling labor force, especially in precision agriculture, which enhances farming efficiency through automation (Dong Liwei, 2014).

To mitigate accidents in agricultural areas amid labor shortage, AI technology in autonomous agricultural vehicles can utilize deep learning algorithms and machine vision to detect surrounding areas and navigate rugged rural roads, helping to avoid risks associated with traffic accidents. As reported in rural areas worldwide, road traffic accidents remain high, particularly in developing countries where accident rates are increasing annually. In China, the Ministry of Transport reported that in the first half of 2022, rural areas accounted for 45% of general accidents and 58% of accident-related deaths. Despite significant investments in rural road safety, issues persist due to limited funding, personnel, and technology (Ministry of Transport of China, 2023).

The rapid advancement of AI has revolutionized various sectors, from voice assistants to autonomous vehicles, making daily life more convenient and efficient (Meacham, 2020). Although AI's development dates to the 1950s, recent breakthroughs in neural networks and deep learning have driven its widespread application. AI now plays a pivotal role in agriculture, finance, healthcare, education, transportation, and entertainment (Nagarajan et al., 2022). In agriculture, AI supports farm work scheduling, in-field operations, and road transportation.

Various modern autonomous vehicle systems such as machine vision, navigation, HD mapping, and control systems have been commonly utilized (Sjafrie, 2019). Machine vision systems, employing LiDAR, radar, cameras, and AI algorithms, detect surroundings, while GPS or RTK-GNSS aids large-scale route planning. Control systems leveraging CAN, relay, and PID algorithms are often applied in automation, robotic applications, and vehicle systems. Then, AI-based autonomous technology in agricultural vehicles, such as deep learning algorithms like YOLOPV, can prioritize learning about risky rural roads, enhancing safety for agricultural drivers on rugged terrain.

The adoption of autonomous or unmanned driving technologies in agriculture depends on advanced navigation systems that can operate independently. Traditional GPS and LiDAR-based systems often struggle in rural settings due to unstable satellite signals (Muganda & Standley, 2009). Car-mounted cameras, serving as the "eyes" of autonomous vehicles, offer 360° visual perceptions, compensating for LiDAR's recognition limitations. In agricultural environments, as GPS signals frequently interrupt, intelligent models that can navigate varied rural road patterns and assist farmers in transporting products efficiently are required. Therefore, many researchers around the world have focused on camera vision and deep learning algorithms to address these challenges (Huval et al., 2013).

This chapter aims to introduce an autonomous vision navigation system for crawler tractors to facilitate the transportation of goods on diverse rural roads with minimal human intervention. The system is proposed to address the need for human labor and to enhance agricultural efficiency. The proposed system utilizes machine vision and deep learning algorithms like YOLOPV to detect drivable areas and road lanes as inputs to the tractor's control system. This system, powered by a microcontroller (Raspberry Pi 4B+), PLC, and relay, will enable autonomous operation using deep learning detection and PID algorithm results (Wang, 2020).

10.2 Objectives

This study aims to develop an autonomous navigation system for a crawler tractor using a camera and deep learning algorithms, enabling the vehicle to operate independently on farm roads and assist in goods transportation with minimal human intervention. The system integrates machine vision for detecting drivable areas and road lines (via YOLOPV), a Robot Operating System (ROS) for communication between components, and a lower control system using a PID algorithm to guide tractor movement. In addition to achieving accurate and safe navigation performance across different road types, the research also evaluates the economic feasibility of large-scale adoption in agriculture by analyzing labor savings, cost-effectiveness, and return on investment. Ultimately, this study seeks to provide a practical and scalable solution to improve farming efficiency and address labor shortages through autonomous vehicle technology.

10.3 Materials and Methods

The navigation system developed in this study comprises three main components: the upper controlling system (machine vision), the Robot Operating System (ROS), and the lower control system (LCS). The machine vision system detects the surrounding environment, including drivable areas and traffic lines, using the YOLOPV deep learning algorithm. The lower controlling system utilizes the PID algorithm to control the tractor's movement direction based on the outputs from the machine vision system. ROS acts as the middleware, enabling communication between the machine vision and control systems.

For the machine vision system, two cameras were used, one for detecting drivable areas and the other for traffic lines. The images captured by these cameras were processed using OpenCV and Bird's Eye View (BEV) transformation. A total of 3500 images from rural roads were used to train the YOLOPV deep learning model based on the PyTorch framework. The images were annotated using the EISeg

(Efficient Interactive SEGmentation) annotation tool, and segmentation masks were generated for drivable areas and traffic lines.

The YOLOPV model was structured with a shared encoder and three decoders, handling drivable area segmentation, traffic line segmentation, and their combination. The model's performance was evaluated using confusion matrices and metrics such as Accuracy, Precision, Recall, and Specificity.

10.3.1 Navigation System Structure

The navigation system designed comprises two main components: the upper controlling system (machine vision system) and the lower controlling system. The upper controlling system includes cameras, and a PC equipped with AI algorithms, while the lower controlling system utilizes a Raspberry Pi, remote control, and a Programmable Logic Controller (PLC) unit. The computer utilized in this research is DELL G16 7620 that has RTX3060 GPU, intel CORE i7 CPU, and 16G volume of memory. Figure 10.1 shows the autonomous driving system flow chart of a crawler tractor. The Robot Operating System (ROS) platform serves as the foundational software to connect the machine vision system, and the lower controlling system then controls the tractor to move autonomously.

10.3.2 Upper Controlling System

The machine vision system is essential for detecting the surrounding driving environments. This system consists of two cameras integrated with image processing algorithms and a deep learning algorithm. One camera detects the drivable area of

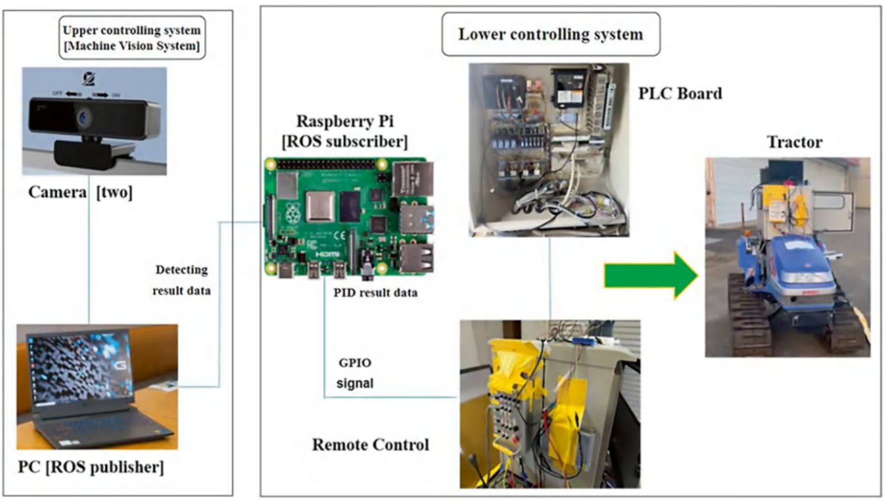

Fig. 10.1 Autonomous driving system flow chart of a crawler tractor

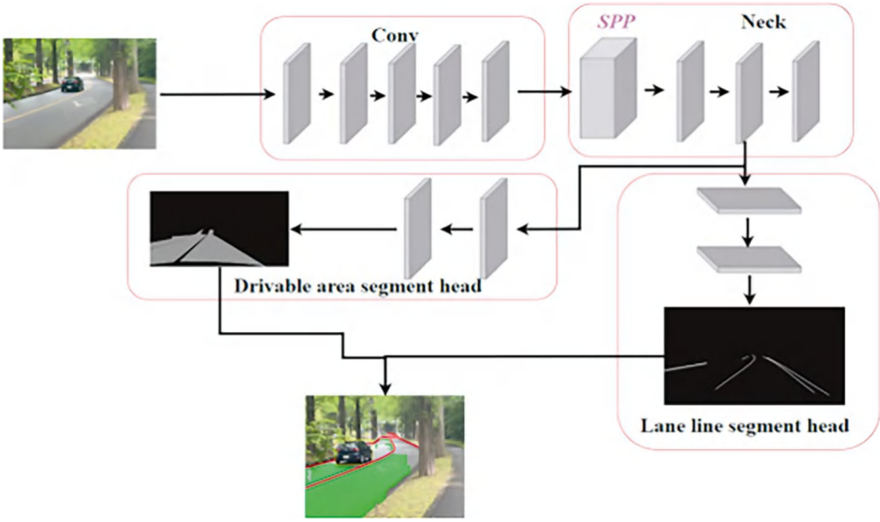

Fig. 10.2 YOLOPV network structure

roads, while the other focuses on traffic lines. The image process utilizes OpenCV and Bird Eye's Vision (BEV) algorithms, while the deep learning algorithm employed was YOLOPV (Fig. 10.2). Identifying traffic lines on the road using normal camera vision proved challenging due to their small representation in the deep learning model. Consequently, implementing BEV vision to create overlooking vision becomes necessary for OpenCV and YOLOPV to achieve convenient and accurate identification. Figure 10.3 shows the OpenCV detection result based on YOLOPV for drivable area and traffic lines.

In the upper controlling system, one camera used the laptop built-in camera, and another camera utilized a Nuroum web camera that had autofocused function, 75° viewing angle, mute function, 3-Level dimming, and auto dimming compensation. These two cameras were used for detecting forward operating directions for the tractor.

10.3.3 Micro-Controlling Unit: Lower Controlling System

The lower controlling system directly interacts with the tractor's control system. The system comprises a processing unit, remote control, and a PLC. The Raspberry Pi 4B+ as processing unit executes PID controlling codes based on instructions from the machine vision system. These instructions are then transmitted via the remote control to the PLC, which directly controls the tractor's movement.

Fig. 10.3 OpenCV detection result based on YOLOPV for drivable area and traffic lines

10.3.4 Robot Operating System

In this research, the Robot Operating System (ROS) was utilized as the central processing unit, facilitating communication between the upper controlling system and the lower controlling system. ROS nodes and topics are employed to manage the data flow and control signals within the system. ROS node and topic are basic concepts that are used for communication between components in robotic systems.

The fundamental architecture of ROS is based on the publisher-subscriber communication model. As shown in Fig. 10.4, ROS Core (Master) coordinates the interactions between functional nodes, such as camera, vision processing, and control logic. Each node can publish information (e.g., detection results) to a topic, and other nodes can subscribe to that topic to receive data. This design enables modular, scalable, and real-time communication within the autonomous tractor system.

10.3.5 Combination of Upper and Lower Controlling Systems Using ROS

The integration of the machine vision system and the lower controlling system was achieved through ROS. The machine vision system acts as a publisher, sending detection results to the lower controlling system, which acts as a subscriber. This ensures seamless communication and control of the autonomous tractor.

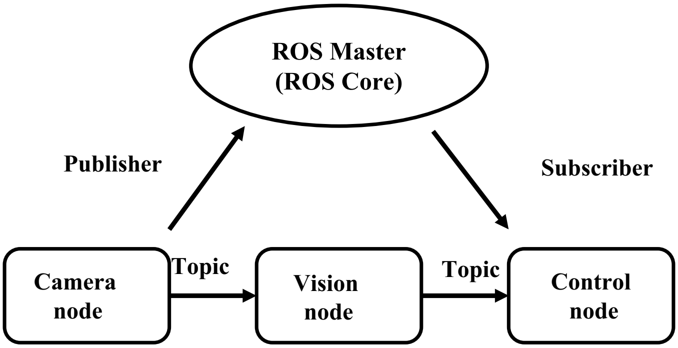

Fig. 10.4 Basic working architecture of Robot Operating System (ROS)

10.3.6 Coordinate Calculation

The coordinate calculation in this study was entirely based on a machine vision system without relying on RTK GNSS technology. Using dual cameras and the YOLOPV deep learning model, the system detects drivable areas and traffic lines in real time and extracts their positions as pixel coordinates on the image plane.

To estimate the tractor's driving trajectory, a BEV perspective transformation was applied, converting pixel coordinates into a top-down view. This transformation enables the system to infer spatial relationships between features and determine the direction and shape of the path.

The resulting trajectory, initially represented in image-space coordinates, was then converted into control signals such as steering direction and angle. These signals are processed by the lower control system, where a Raspberry Pi and a PLC execute movement commands via a PID controller. This vision-based coordinate calculation method ensures stable and accurate navigation, especially in environments where GNSS signals are weak or unavailable.

10.3.7 Trajectory Error Analysis

The accuracy of the tractor's trajectory evaluated using the Root Mean Square Percentage (RMSP), which measures the deviation between the observed and true values. This metric is crucial for assessing the performance of the navigation system under different road conditions.

10.3.8 Experimental Setting

The objective of the experimental setup was to evaluate the performance and accuracy of the proposed autonomous navigation system under various road conditions. To achieve this, the research includes experiments on five types of road tasks:

I-shaped, L-shaped, large-angle curve, S-shaped, and O-shaped roads. Each road condition was tested multiple times to collect reliable data for trajectory error analysis and to assess the system's ability to handle different path geometries.

These research methods provide a comprehensive framework for developing and evaluating the navigation system for autonomous crawler tractors, ensuring accurate and reliable operation in various rural road conditions.

Additionally, the experimental plan considers various environmental conditions such as weather, lighting, and road surface quality to ensure the robustness of the navigation system. Each experiment was designed to simulate real-world conditions as closely as possible to validate the system's performance in practical scenarios.

10.4 Results and Discussion

10.4.1 Model Training and Performance

In this research, the YOLOPV deep learning model was trained using 3500 images annotated with the EISeg tool for semantic segmentation. The training aimed to accurately detect drivable areas and traffic lines on rural roads. The evaluation metrics for the training included segmentation accuracy, with the model demonstrating high precision and recall rates for both the drivable areas and traffic lines. Tables 10.1 and 10.2 show the average accuracy of the model on the segmentation tasks of "drivable area" and "traffic line." IoU (Intersection over Union) and mIoU (mean Intersection over Union) are metrics used to measure the accuracy of drivable area segmentation by comparing the intersection and union ratios between the ground truth and prediction. The higher the intersection ratio, the higher the overlap between the predicted and actual areas of the model, reflecting the overall segmentation accuracy of the model.

Confusion matrix (error matrix) is a standard format for representing accuracy evaluation, expressed in the form of a matrix with n rows and n columns. Accuracy refers to the number of correctly recognized samples (correct pixel of drivable area and traffic line) in total number of samples (whole pixel data). Precision refers the proportion of samples (identified drivable area and traffic line) recognized as positive by the model that are truly positive. Recall refers to how many positive samples (identified drivable area and traffic line) have been found (how many have been recalled). Specificity refers samples (non-drivable area and non-traffic line) recognized as negative by the model to the total number of negative samples.

Table 10.1 Drivable area average accuracy

Average segmentation accuracy	IoU	mIoU
0.971	0.897	0.936

Table 10.2 Traffic line average accuracy

Average segmentation accuracy	IoU	mIoU
0.873	0.571	0.624

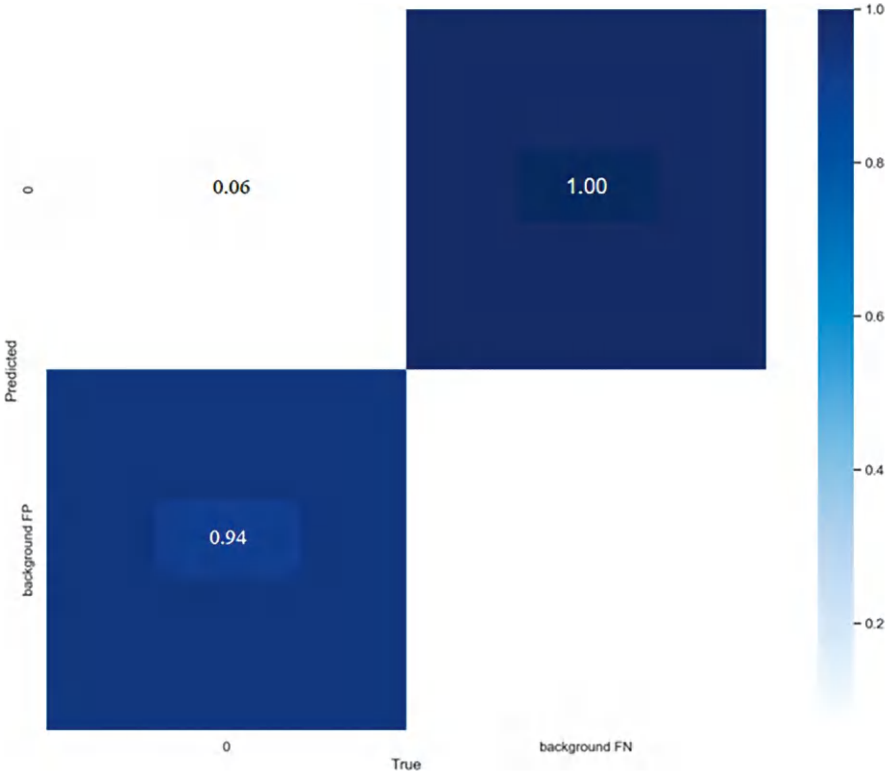

Fig. 10.5 Confusion matrix of trained YOLOPV model

Figure 10.5 shows the confusion matrix of the YOLOPV model for this research. It reflects the performance of the model in classifying different pixels as "drivable area," "traffic line," and "non-drivable area," including the number of correctly and incorrectly classified pixels. The model's classification effectiveness on different categories was demonstrated through metrics such as Accuracy, Precision, Recall, and Specificity.

The training process involved several iterations, with adjustments made to the model parameters to optimize performance. This iterative approach helped in fine-tuning the algorithm to better handle the diverse conditions encountered in rural road environments. The use of data augmentation techniques such as rotation, scaling, and translation further enhanced the model's robustness.

10.4.2 Experimental Results for Road Tasks

Experiments were conducted on five types of road tasks: I-shaped, L-shaped, large-angle curve, S-shaped, and O-shaped roads. Each road shape was tested three times to ensure reliability and accuracy of the results (Fig. 10.6).

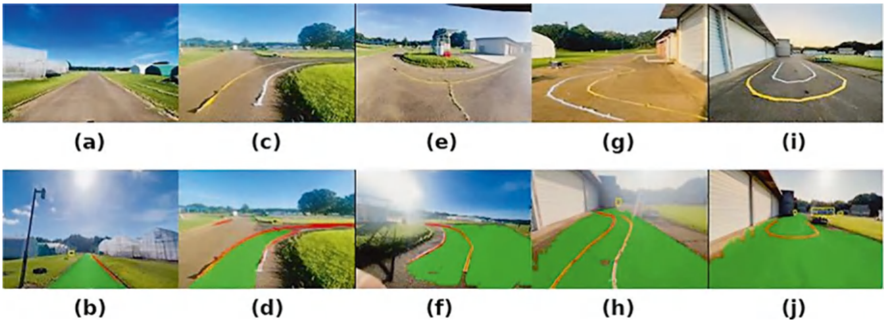

Fig. 10.6 Prediction result of YOLOPV on five types of roads: (**a**) I-shaped road, (**b**) L-shaped road, (**c**) large-angle curved road, (**d**) S-shaped road, (**e**) O-shaped road, and (**f–j**) their respective prediction results

Table 10.3 RMSP result of I-shaped road task's trajectory

First experiment	Second experiment	Third experiment	Average
1.151%	1.142%	1.233%	1.269%

I-Shaped Road Task The system performed optimally with an average Root Mean Square Percentage (RMSP) of 1.269%, indicating high accuracy in straight-line navigation. The model successfully identified drivable areas, allowing the tractor to maintain a straight trajectory. Table 10.3 shows the RMSP result of I-shaped road task's trajectory, and Fig. 10.7 shows the actual trajectory of the autopilot on a Type I roadway compared to the predetermined trajectory.

To enhance clarity regarding the coordinate axes in Figs. 10.7, 10.8, 10.9, 10.10, and 10.11, it is important to note that each figure contains two *Y*-axes. The left *Y*-axis corresponds to the real operation trajectory coordinate of the autonomous tractor during the experiment, while the right *Y*-axis corresponds to the ground truth coordinate defined for evaluation.

This dual-axis setup allows for direct visual comparison of the real and expected trajectories under each road condition.

L-Shaped Road Task The average RMSP was 2.844%, demonstrating good performance in handling right-angle turns. The YOLOPV model effectively detected traffic lines, guiding the tractor through the turns accurately. Table 10.4 shows the RMSP result of L-shaped road task's trajectory, and Fig. 10.8 shows how the actual trajectory of the model in a 90-degree turn compares to the ideal trajectory.

Large-Angle Curved Road Task For this task, the RMSP was 4.045%, showing the system's capability in navigating large-angle curves. The model's detection of traffic lines ensured smooth and precise turning. Table 10.5 shows the RMSP result of large angle turning shape road task's trajectory, and Fig. 10.9 provides the control effect of the model in complex large-angle turns, which was convenient to show the accuracy performance under large-angle turns.

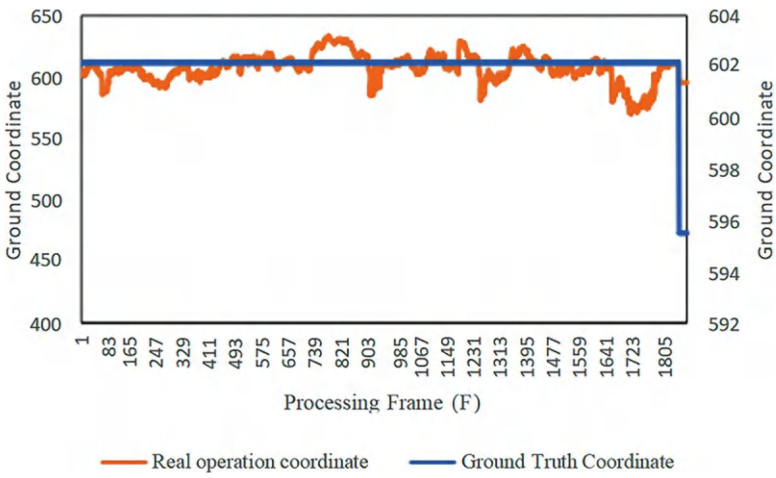

Fig. 10.7 I-shaped experimental road's trajectory coordinate and ground truth coordinate

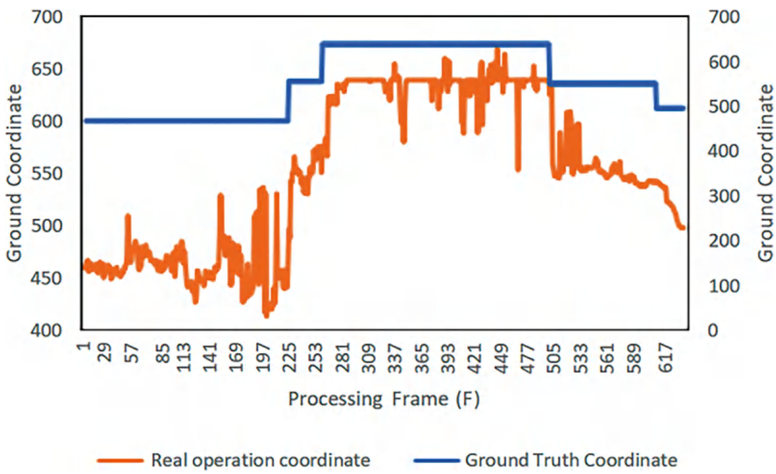

Fig. 10.8 L-shaped experimental road's tractor trajectory coordinate and ground truth coordinate

S-Shaped Road Task The system achieved an RMSP of 4.4618%, indicating reliable performance in navigating S-shaped paths. The detection accuracy of the YOLOPV model allowed the tractor to follow the complex curves effectively. Table 10.6 shows the RMSP result of S-shaped road task's trajectory, and Fig. 10.10 shows the actual trajectory compared with the expected trajectory in multiple turning situations, which can visualize the performance of the model in continuous turning.

O-Shaped Road Task The average RMSP was 5.312%, which, although slightly higher than other tasks, still reflects acceptable performance within the safety

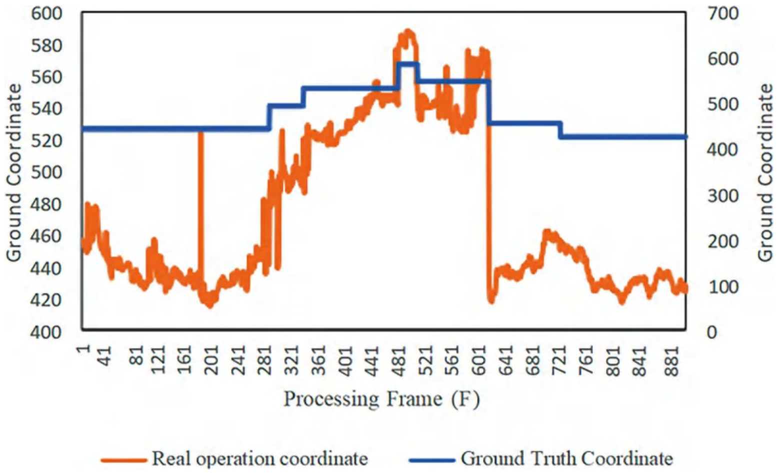

Fig. 10.9 Large angle shape experimental road's tractor trajectory coordinate and ground truth coordinate

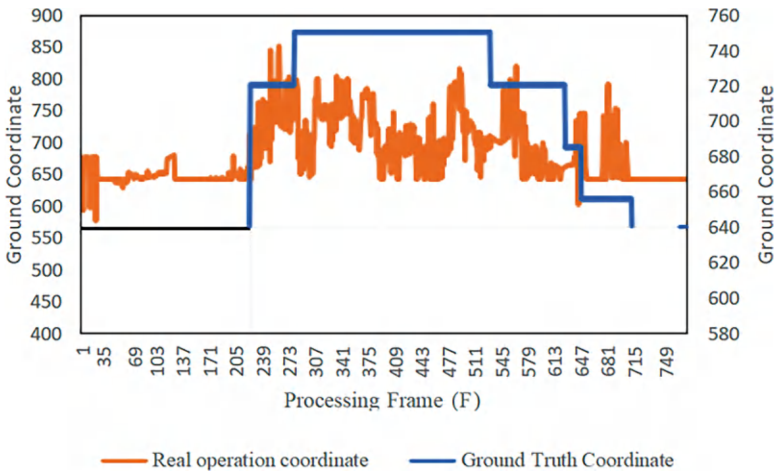

Fig. 10.10 S-shaped experimental road's tractor trajectory coordinate and ground truth coordinate

threshold. The circular path presented more challenges, but the model's detection capabilities ensured overall safe navigation. Table 10.7 shows the RMSP result of O-shaped road task's trajectory, and Fig. 10.11 shows how well the model travels on a circular path and demonstrates the accuracy of continuous curve control.

These results highlight the system's robustness and versatility in handling various road shapes and conditions. Further analysis of the error metrics revealed that most deviations were within acceptable limits, and adjustments to the model and control algorithms could potentially reduce these errors even further.

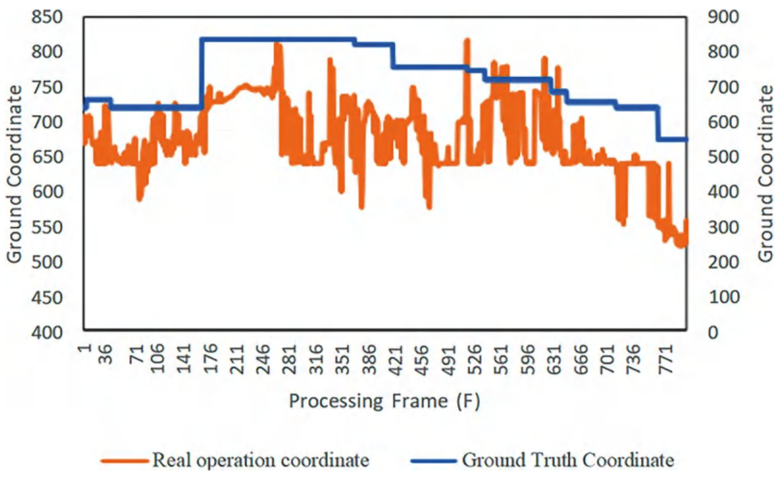

Fig. 10.11 O-shaped experimental road's tractor trajectory coordinate and ground truth coordinate

Table 10.4 RMSP result of L-shaped road task's trajectory

First experiment	Second experiment	Third experiment	Average
2.948%	2.918%	2.667%	2.844%

Table 10.5 RMSP result of large angle turning shape road task's trajectory

First experiment	Second experiment	Third experiment	Average
3.600%	4.670%	3.865%	4.045%

Table 10.6 RMSP result of S-shaped road task's trajectory

First experiment	Second experiment	Third experiment	Average
4.061%	4.872%	4.453%	4.462%

Table 10.7 RMSP result of O-shaped road task's trajectory

First experiment	Second experiment	Third experiment	Average
4.079%	8.464%	3.410%	5.318%

In addition to the road tasks, the system was tested under different weather conditions, including sunny, rainy, and foggy days, to evaluate its performance in diverse environments. The results showed that while performance slightly decreased under adverse weather conditions, the system still maintained a high level of accuracy and reliability.

10.5 Conclusion

This navigation system based on a camera and a deep learning algorithm for an autonomous crawler tractor has been developed. This system comprises three main components: the upper controlling system (machine vision), the Robot Operating System (ROS), and the lower control system (LCS). The machine vision system detected the surrounding environment, including drivable areas and traffic lines on roads, using the YOLOPV deep learning algorithm. The lower controlling system utilized the PID algorithm to control the tractor's movement direction according to the results from the machine vision system, while ROS provided a corresponding platform for the machine vision and lower controlling systems.

This research successfully enabled the tractor to operate autonomously within the drivable areas and traffic lanes of agricultural roads. The evaluation of the YOLOPV training model for drivable areas and traffic lines demonstrated that the system could operate accurately and safely on various road shapes, with an average RMSP of 1.233% on I-shaped roads. The result was considered accurate and safe because the RMSP was below 5.0%.

Overall, the proposed autonomous vision navigation system for the crawler tractor showed promise in improving the working efficiency of the agricultural industry and addressing the issue of labor shortages. The combination of machine vision, deep learning algorithms, and control systems created a robust platform for autonomous agricultural vehicles, paving the way for future advancements and applications in smart farming.

Future research could focus on further enhancing the system's capabilities by integrating additional sensors and improving the deep learning algorithms. For example, combining data from LiDAR and radar with the existing camera inputs could provide more comprehensive environmental awareness. Additionally, exploring the use of advanced AI techniques such as reinforcement learning could further optimize the tractor's navigation and control strategies.

Furthermore, the economic and social impacts of deploying such systems on a large scale should be studied. This includes understanding the potential job displacement effects and identifying strategies to mitigate any negative consequences. Policymakers and stakeholders should consider these factors to ensure that the transition to autonomous agricultural systems benefits the entire agricultural community.

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Chapter 11
Development of Orchard Autonomous System Using Zigbee Communication and Visual SLAM Technology

Sun Jiawei, Arkar Minn, and Tofael Ahamed

Abstract The orchard management system encounters skilled labor shortages globally. Additional care, such as spraying at the tree location and continuous monitoring, is also required for the site-specific plantation in the orchard. Automation systems could be used in the agriculture sector to address labor shortages. Object detection is a significant task in autonomous operation to avoid collisions and ensure safety in orchards. Moreover, data sharing is one of the key points in innovative agricultural practices. A Zigbee sensor network is one of the potential ways for data sharing and being used because of its low power consumption, independent networking, and scalable capabilities, which provide accurate monitoring at the individual orchard tree management level. In visual SLAM navigation, a customized iteration of VINS Fusion was chosen primarily because of its remarkable real-time operational efficiency and precision, attributed to its IMU and GPS data incorporation. In brief, this study presents the Simultaneous Localization and Mapping (SLAM) and YOLOV5, which is referred to in the survey as a Visual Simultaneous Localization and Mapping (VSLAM) system. It can be used for autonomous navigation on orchard vehicles. Furthermore, the performance of the orchard autonomous system using Zigbee communication and visual SLAM technology can also improve the efficiency of agricultural works for site-specific management in the orchard.

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Keywords SLAM · VINS Fusion · Zigbee network · Autonomous navigation

11.1 Introduction

Orchard farming is prominent in agriculture since it encompasses cultivating and planting fruit trees in designated orchard areas. Recent research has demonstrated that the development of fruit trees, both in Japan and China, plays a significant role in the broader context of agricultural activities (Klerkx et al., 2019). However, considering social advancements and the increasing elderly population, the agriculture industry faces many concerning issues. For instance, the decline in the agricultural labor force has challenges and impacts for food production (Minn et al., 2023). In orchard management, the precision application of fertilizers, herbicides, and pesticides is essential. In recent trends, precision agriculture has become adapted to the farming community with the technologies and data analytics supports based on Geographic Positioning System (GPS), Internet of Things (IoT) management, and Simultaneous Localization and Mapping (SLAM) technology (Radočaj et al., 2023). The IoT management system is an innovative system that detects the condition of plants or crops in a greenhouse or orchard based on multiple sensors (Ahamed et al., 2016).

Furthermore, SLAM enables agricultural robots to effectively determine their positions while concurrently creating maps of their immediate surroundings within a dynamic context (Fujinaga, 2025). Based on SLAM technology, agricultural robots could respond to dynamic environmental conditions in fields, facilitating accurate execution of activities such as monitoring and planting. SLAM is one of the advanced outcomes of researchers. This capability enhances operational efficiency and minimizes the unnecessary utilization of resources (Singandhupe & La, 2019). In the SLAM application, laser range finder and stereo vision have advanced compared to the other sensors.

Automation in fruit tree orchards still poses complex problems that plague those working in them (Fig. 11.1).

In brief, all challenges faced in orchard autonomous management include the following:

- The current generation of robots frequently fails to adequately account for the real-time nature of operations and the associated cost concerns.
- The present system cannot accurately detect each tree and lacks good compatibility with orchards of different specifications.
- The exploration of sensor integration with SLAM to enhance the efficiency of agricultural systems has not been significantly undertaken. Subsequent operations still require manual labor.

With the development of technology, advanced technologies are required to solve the challenges and problems presented in orchard autonomous management. Sensor networking is required to establish a communication protocol. A Zigbee

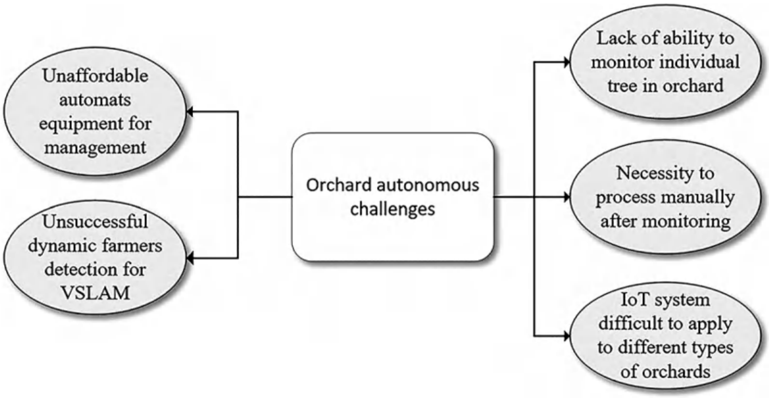

Fig. 11.1 Challenges orchard management faced

sensor network can be connected, which refers to technology using the Zigbee communication principle, multiple sensors, and affordable microcomputers to detect individual trees in an orchard. Integrating several sensors and Visual SLAM (VSLAM) can be proposed as a new system to address the abovementioned problems for orchard management.

11.2 Principle of Zigbee

Zigbee was a communication protocol (Fig. 11.2) that operated at a high level and was founded upon the IEEE 802.15.4 standard (Farahani, 2007). Its primary use was facilitating wireless communication with minimal power consumption across short distances. Several essential characteristics could be identified. One notable advantage of Zigbee was its low power consumption, which was specifically engineered to maximize battery life. This feature rendered Zigbee particularly well suited for devices with extended operation durations and infrequent communication requirements.

The concept of self-organizing and self-healing refers to the ability of a system to organize and repair itself autonomously without external intervention. Zigbee networks could autonomously organize themselves and establish and sustain network connections. Moreover, it supported mesh network design, thus enhancing the network's stability and range. Due to the four benefits, the ZigBee network was appropriate for IoT nodes situated at moderate distances. Additionally, owing to its inherent self-organizing network properties, the network exhibited robust scalability, enabling seamless connectivity with various sensors for efficient node-to-node information transmission.

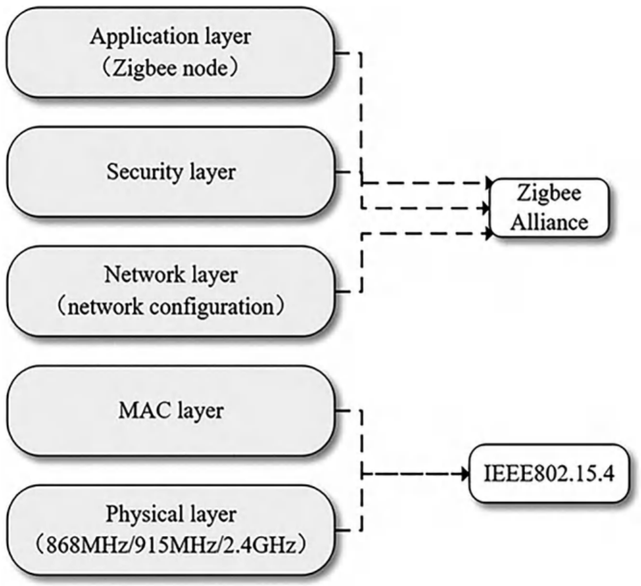

Fig. 11.2 Underlying architecture of Zigbee

11.3 Zigbee Sensor Network System

Zigbee sensor network systems have gained significant popularity and applications in contemporary life and research (Farahani, 2007). They are primarily used in IoT networks and large-scale monitoring systems. Typically, a Zigbee system comprises three main components: nodes, routers, and coordinators. The DL-LN33 module was chosen as the Zigbee module due to its integrated and efficient characteristics.

11.3.1 Hardware System

The hardware system consisted of various components, namely, a golf cart, an STM32 microcontroller, a DL-LN33 module, an Intel® RealSense™ D435i camera, a Controller Area Network (CANbus) communication protocol, a GPS module, and multiple sensors (as depicted in Fig. 11.3). To enhance clarity, the structural arrangement was partitioned into two distinct components. The Zigbee network system, sensors, GPS module, and DL-LN33 were all interconnected with the STM32 microcontroller through a socket connection. This approach facilitated smooth communication among these components. As previously stated, the STM32 microcontroller served as a central repository for data, containing information regarding the spatial configuration of each tree in the orchard and gathering data from sensors to oversee tree conditions. Afterward, the data was sent to a laptop linked to the golf

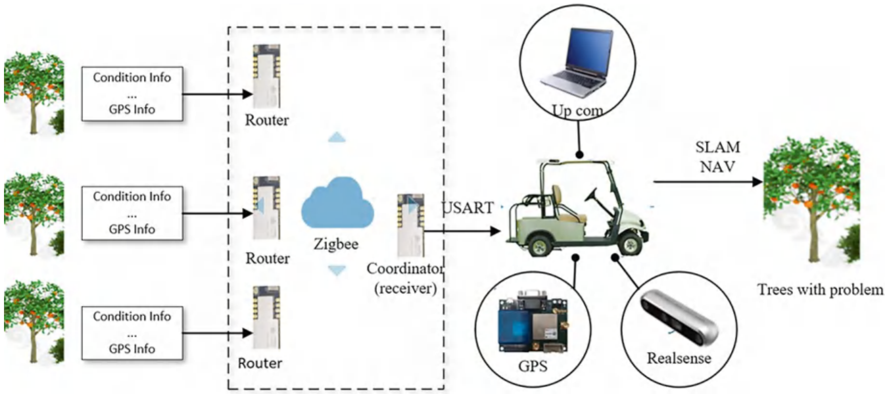

Fig. 11.3 The schematic diagram of the smart system

cart through a Universal Asynchronous Receiver-Transmitter (UART) interface. This data was pivotal in determining the golf cart's assigned tasks and corresponding behaviors.

The VSLAM feature was another crucial hardware component pivotal to the system's functionality. By positioning the RealSense™ 435i camera at the front of the vehicle, it was possible to create a three-dimensional representation of the surroundings, known as a point cloud map, which could then be analyzed. The camera and the STM32 microcontroller could transfer data through a Universal Serial Bus (USB) connection. The golf cart was equipped with a GPS module that utilizes GEO-M8 technology and was connected to the system through a USB port. The CAN bus protocol established communication between the golf cart and the SLAM model. The synergy of these hardware components facilitated seamless data acquisition, analysis, and cartography within the system.

11.3.2 Software System

11.3.2.1 Zigbee Network System

The STM32 was the most important component of our intelligent Zigbee system (Fig. 11.4) and acted as the central hub that coordinated the actions of the entire network. To ensure that a wide variety of sensors, such as those that assessed soil humidity, light intensity, and temperature, could communicate with the Zigbee nodes continuously, the STM32 microcontroller was an essential component. Utilizing the GPS module ATGM332D, the detailed integration made it possible to effectively transfer critical data gathered from individual trees. This data included important information on the levels of soil moisture as well as the correct geographical coordinates.

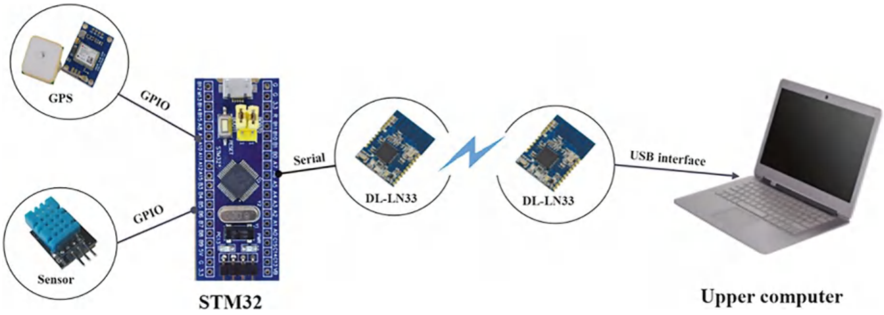

Fig. 11.4 Flowchart for sensor network

Assuming the function of the principal data processing unit, the laptop was tasked with the responsibility of precisely documenting and interpreting the data streams that were coming in. Additionally, the system was able to successfully interface with a VSLAM navigation system, making use of the information that was gathered from the field. Both real-time environmental monitoring and increased decision-making capabilities for efficient orchard management were made possible by combining technology and software. By effectively integrating data from various sources and facilitating immediate communication, the technology made it possible to practice precision agriculture. It offered a comprehensive strategy to satisfy the ever-evolving requirements of orchard management.

11.3.2.2 Visual SLAM Navigation System

The VSLAM navigation system's main goal was to enhance vehicles' capabilities by enabling them to perceive and accurately determine their precise location within their immediate surroundings. This device could independently drive to designated regions near certain trees using GPS signals supplied by the Zigbee system. Once in the vicinity, it effectively carried out a series of predetermined duties, such as automatic watering or pesticide spraying, without interruption. The specifications of each component inside this system were presented in the subsequent section.

11.3.2.3 VINS Fusion Algorithm

VINS Fusion (Visual-Inertial Navigation System Fusion) used state estimation methods like Kalman filters to determine the device's location, direction, and speed. It also generated three-dimensional maps of the area (Chen et al., 2018), which helped autonomous cars and augmented reality apps work. Loop closure and optimization were used to correct positioning errors over time, maintaining system accuracy. VINS Fusion performed well in dynamic, indoor environments with low GPS signal strength, making it a widespread automation and robotics option (Wang

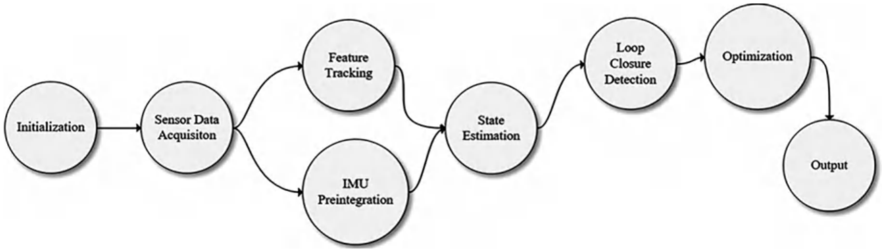

Fig. 11.5 Work process of VINS Fusion

& Ahmad, 2024). The system used camera and IMU (Inertial Measurement Unit) data to provide real-time location and mapping, especially when GPS signals were inaccurate or unavailable (Al-Tawil et al., 2024). Therefore, the advanced navigation system used VINS Fusion as its SLAM model.

The advanced computational method VINS Fusion was used in robotics and autonomous systems for SLAM. This model had many advantages over ORBSLAM2 (Oriented FAST and Rotated BRIEF SLAM Version-2). It used a camera and IMU data to provide real-time location and mapping. This was especially useful when GPS signals were inaccurate or unavailable. This significantly improved accuracy. Visual processing extracted spatial and geometric information, IMU data processing estimated motion and orientation, and data fusion integrated visual and IMU data (Xiao et al., 2024). Fusion solved sensor limitations. Integrating optical and inertial data reduced sensor limits, improving precision and resilience (Sun et al., 2023).

VINS Fusion excelled in interior and complex exterior settings. Due to its versatility and efficacy, this technology was popular for autonomous cars, drones, robotic systems, and augmented reality (Rodríguez-Martínez et al., 2025). The algorithm performed well in low-light and high-dynamic scenarios, demonstrating its improved ability to navigate and understand complex environments. The process is displayed in Fig. 11.5.

11.4 Zigbee Network Implementation

11.4.1 Connection Method

The STM32 microcontroller was utilized as the central control unit in this project. It was tasked with acquiring and analyzing data obtained from temperature and humidity sensors. The purpose of this section was to inform the reader about the process of establishing a connection between the entities. One of the first topics discussed was utilizing humidity and temperature sensors, specifically the DHT11 model. Dedicated pins were used to connect these sensors and the STM32 microcontroller. Serial data lines were also employed. The DL-LN33 was a self-contained

Table 11.1 Connection method and interface of STM32

Device	Model	Connection type	Purpose
Humidity sensor	DHT11	Serial data	Humidity data
Temperature sensor	DHT11	Serial data	Temperature data
Light intensity sensor	ADC	Serial data	Light intensity
Networking module	DL-LN33	Serial port	Transmit sensor data
GPS module	ATGM332D	Serial port	GPS signal reception

module that was designed to enable the transmission and reception of messages, as well as to facilitate seamless networking. STM32 was intended to ease the transmission of sensor data to the DL-LN33. The DL-LN33 module was connected to the STM32 microcontroller to enable communication through the serial port. To be more specific, it was utilized to receive data from the STM32 and to transmit data to the coordinator, which was connected to an upper computer (laptop) through a USB serial connection. The connection method and interface of the STM32 were expressed in Table 11.1.

The STM32 microcontroller could process the data from the humidity and temperature sensors. This was accomplished using a meticulously crafted circuit arrangement and sophisticated software programming techniques. The DL-LN33 module made it possible to wirelessly transmit data to a monitoring system or mobile device, which made it possible to conduct environmental monitoring that was both effective and intelligent. The configuration provided made it possible to collect data with high accuracy and enhanced the monitoring system's overall usability and effectiveness. As a result, it was ideally suited for applications that required real-time analysis and reporting of environmental data.

11.4.2 Method for Operating Data

This discourse was expounded upon carefully choosing and executing a data storage solution. Initially, WebSocket technology was utilized to facilitate real-time data transfer and storage on a cloud server. One notable benefit of employing this approach was its capacity to get data from many locations and its potential for theoretical scalability. Nevertheless, during practical implementation, it was observed that this technique harmed the system's efficiency. The necessity for instantaneous transmission increased time consumption, which was a disadvantage in situations that demanded prompt reactions.

Given the constraints, a transition was made toward implementing a data-capturing method characterized by enhanced efficiency. The decision was made to save the data immediately on the supervisory computer in Excel format. This approach optimized the workflow for data processing and resulted in a notable reduction in latency by eliminating possible delays associated with network transmission. Additionally, using Excel files for data storage allows convenient data analysis and processing. Excel is well recognized and often employed by academics and engineers as a data analysis tool. Implementing this enhancement improved the overall system reaction time and data processing efficiency, effectively satisfying the requirements for real-time data handling.

11.5 Design for the Visual SLAM System

This research focused on refining the YOLO (You Only Look Once) algorithm, particularly emphasizing its backbone structure. Motivation for this improvement stemmed from a critical observation: Visual SLAM inherently placed a significant computational burden on systems. Operating standard YOLO in conjunction with Visual SLAM exacerbated this load, potentially compromising the robustness of the entire system. Thus, an urgent need was identified for further lightweight processing of the YOLO architecture.

11.6 Result and Discussion

11.6.1 Zigbee Monitoring System in the Orchard

The STM32 microcontroller was used as a central data hub analogous to a centralized data center. This microcontroller was an essential component in compiling data on each tree's state and positional information obtained from sensors positioned underneath each tree. This data was sent to the microcontroller via a specific port, and the Zigbee module DL-LN33 was used to transport this data to the upper-level computer of the DL-LN33, which was linked to the microcontroller through a serial port connection. An exhaustive experiment was carried out at the Tsukuba Plant Innovation and Research Center (T-PIRC), Ibaraki, Japan, under the canopy of five different trees to demonstrate that this highly developed detection technology was applicable in real-world situations. Each node in the experimental setup was methodically placed to coincide with the placement of a white ball, as shown in Fig. 11.6. This was done to ensure that the experiment was carried out accurately. Furthermore, Fig. 11.7 illustrates the comprehensive data acquired for each node. This demonstrates that the system can systematically monitor and store important environmental and positional data for each tree that has been described.

Fig. 11.6 Node placement in orchard

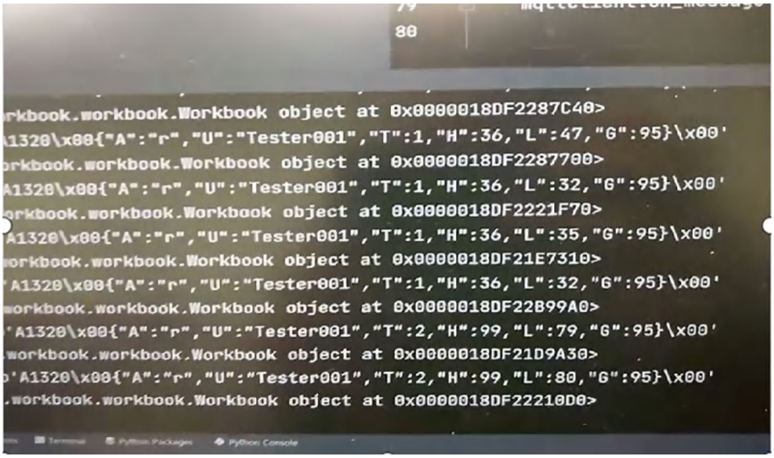

Fig. 11.7 Real-time sensor data flow at runtime

11.6.2 Dynamic Detection of Obstacles

As stated in the previous section on methods, this research replaced the backbone in YOLOv5 with a lightweight target classification model, thus making the detection model lighter. The Robot Operating System (ROS) topic subscription and publication were utilized to facilitate the integration of the VINS Fusion model. This model lacks a dynamic detection function; however, subscribing to the target coordinates in the current frame minimizes the interference caused by the related objects in the SLAM construction. Subsequently, we performed multiple experiments on this novel functionality, encompassing real-world trials and studies on the TUM dataset, provided by the Technical University of Munich, specifically designed to study SLAM and visual odometry. It encompassed various scenarios and motions and included data from multiple sensors. Based on numerous studies, it can be inferred that the inclusion of dynamic object removal in the VINS Fusion model yields highly favorable results.

11.6.3 Path Planning

Performance tests on route planning were carried out in the T-PIRC orchard using a golf cart equipped with a RealSense™ 435i depth camera and a U-blox® NEO-M8 GPS module. In addition, the vehicle was equipped with a water spraying system that sprayed when the golf cart arrived near a particular tree. When the predetermined condition of the tree exceeded a certain threshold, the vehicle would automatically proceed to the area of the tree's GPS position and carry out the spraying operation.

11.7 Conclusion

An advanced smart orchard management system was devised by ingeniously combining Zigbee sensor networks with state-of-the-art SLAM algorithms and deploying them within autonomous ground vehicles. The integration heralds a new era in precision agriculture, demonstrating the vast capabilities of the IoT to revolutionize traditional farming practices. At the heart of this system, the STM32 microcontroller functioned as an efficient data nexus. At the same time, the DL-LN33 Zigbee module facilitated seamless data transmission, ensuring the system's robust performance even under the diverse and unpredictable conditions of orchard environments.

Furthermore, the strategic incorporation of GPS data into the visual SLAM system marked a substantial leap forward, granting the autonomous vehicles the sophistication needed for precise navigation within the intricate settings of modern agriculture. The research yielded several significant insights and outlined promising future directions:

- ZigBee Network Formation: The integration of IoT with agricultural practices proved transformative, significantly elevating the efficiency of orchard management. This underscores the crucial role that precision agriculture can play in the modernization of farming techniques.
- VSLAM Development: The field experiments were conducted to validate the system's operational reliability and illuminate its potential scalability.
- Path Planning in Orchard: The A* path planning algorithm and the improved VINS Fusion algorithm autonomously navigated and sprayed a single tree in an orchard, eliminating manual labor after detecting ordinary Internet of Things, and creating intelligent orchards.

The findings suggest that such a system could be effectively adapted to various agricultural contexts, thus broadening its applicability. Looking to the future, infusing the smart orchard management system with AI and machine learning promises to refine predictive models and optimize data analysis. Technological advancements are poised to revolutionize agricultural efficiency, disease management, and yield production. Continued research aims to perfect these systems, paving the way for a sustainable, automated, and data-centric agriculture industry.

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Chapter 12
Deep Learning-Based Instance Segmentation for Autonomous Navigation in Orchards

Rizky Mulya Sampurno and Tofael Ahamed

Abstract Autonomous navigation in orchards presents unique challenges due to dynamic environmental conditions and farming tasks such as monitoring, weeding, spraying, harvesting, and transporting goods. In field operations, GNSS-based navigation systems often experience signal interference caused by dense tree canopies, making them unreliable for precise local environmental perception. As an alternative, using cameras supported by computer vision techniques has emerged as a promising solution for local navigation in orchards. Compared to traditional computer vision techniques, the deep learning approach offers greater performance, better adaptability to complex environments, and efficient integration into field robots that require real-time processing. This chapter explores deep learning-based instance segmentation to support autonomous navigation in orchards by taking advantage of objects and their shape information. Some recent instance segmentation models are highlighted as fundamental components for navigation paths estimated from the tree trunk's location. This chapter also describes the vision-based navigation system development pipeline: data acquisition, annotation, model training and validation, prediction, and model deployment on edge devices. Moreover, the extraction of the navigation path for robot guidance to track the tree row is explained. This chapter provides a comprehensive overview and practical insights into deep learning-based instance segmentation for autonomous navigation robots in orchards.

Keywords Deep learning · Instance segmentation · Navigation · Tree row · Orchard

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12.1 Introduction

The advancement of computers and electronics has driven robotics applications in orchards, promoting agricultural sustainability and addressing labor shortages. Robotics can support precision agriculture by optimizing production input while reducing chemical use and other negative environmental impacts (Lee et al., 2010; Liu et al., 2023). Autonomous robots can be operated in various tasks like planting, weeding, pruning, spraying, and harvesting, allowing farmers to focus on more complex work. They also enhance the farmer's safety by reducing exposure to heavy equipment vibration associated with musculoskeletal issues (Aiello et al., 2022; Fethke et al., 2018). Moreover, robots can operate for longer durations and have higher durability than human laborers, improving the quality and quantity of agricultural products.

Developing effective farming robots must address the challenges related to autonomous navigation (Wang et al., 2022). The robotics system is essential for defining position, avoiding obstacles, planning routes, and controlling movements. Orchard robots rely on sensors, decision-making systems, and controllers for navigation. Standard sensors, such as the Global Navigation Satellite System (GNSS), light detection and ranging (LiDAR), and cameras, are used individually or in fusion. GNSS provides location data within an orchard or globally, while LiDAR creates 3D point cloud maps and detects obstacles through light measurements. Vision-based sensors help robots recognize objects in an orchard, such as crops, poles, and support structures, based on color and depth sensors that measure object distances. The sensor data is processed to generate movement decisions with controllers like Proportional-Integrated-Derivative (PID) and machine learning algorithms, enabling autonomous and efficient navigation (Jiang & Ahamed, 2023).

While various sensors contribute to autonomous navigation, this chapter focused on vision-based systems, as cameras offer rich visual information that can be leveraged for object recognition, obstacle avoidance, and path planning. Recent advances in deep learning, especially in real-time object detection and segmentation models, have further enhanced the viability of vision-based approaches for precise and cost-effective navigation in orchards. The following sections present an overview of the current vision-based navigation system approaches and describe our implementation of a YOLO-based instance segmentation model for real-time perception and control on a custom-developed orchard robot.

12.2 Computer Vision for Navigation in Orchards

Navigation in orchards can rely on various sensors, each offering distinct advantages and limitations. The selection of sensors depends on the intended application and level of autonomy required. Dense canopies and cloud cover can interfere with GNSS signals in orchards, leading to positioning inaccuracy. LiDAR offers high-precision distance estimation and obstacle detection but struggles to distinguish between different object types on the farm (Jiang & Ahamed, 2023). Conversely, cameras provide rich visual information for object identification and classification but are highly sensitive to light conditions. While sensor fusion has been explored to compensate for individual sensor limitations (Liu et al., 2023), research on single-sensor approaches remains valuable for reducing the cost of hardware requirements. One promising strategy is to combine these sensors with artificial intelligence and intense learning to improve navigation performance.

In a vision-based navigation, cameras and image processing play a key role in robotics. Common camera types include Red, Green, Blue (RGB), depth, and infrared (IR) channels. RGB cameras help robots distinguish objects by color, while hyperspectral cameras capture a broader range of wavelengths for richer spectral data. Depth cameras, such as stereo and Time-of-Flight (ToF), determine the object distance using two lenses for 3D imaging. ToF cameras determine range by measuring light travel time. IR cameras detect heat, which helps identify hidden objects and low visibility, for example, fruits obscured by leaves and tree trunks hidden by grass. Combining these cameras with image processing enhances navigation, fruit detection, and obstacle avoidance in an orchard.

In the early stages of its development, vision-based navigation systems relied on traditional image processing techniques such as edge detection, image segmentation, filtering, and pattern recognition. However, adapting to changing physical landmarks is a key challenge in orchard navigation. Figure 12.1 illustrates an example of an orchard landmark used for robot navigation. Tree rows create structured patterns that help extract tree row lines, enabling robots to navigate autonomously between them.

For example, sky-based guidance used for robot navigation in orchards (Radcliffe et al., 2018). This approach involves cropping camera images, applying thresholding to isolate the sky, and filtering to create a path plane. The centroid of the plane is then calculated to direct the robot toward a set point (Fig. 12.2). In real-world applications, the robotic platform processes images in real time, updating every second as the camera continuously captures new frames. This rapid processing allows the system to adapt to changing environmental conditions, ensuring accurate

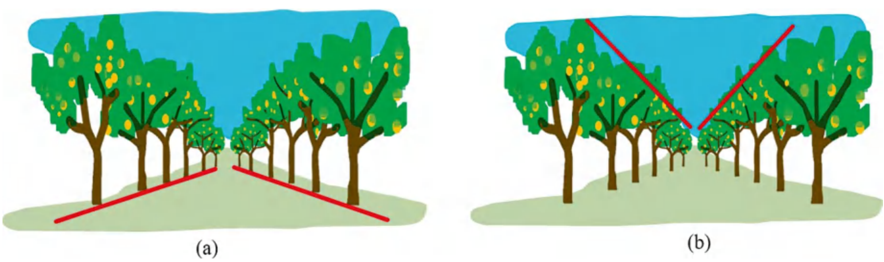

Fig. 12.1 Computer vision technique for orchard robotic navigation; (**a**) ground-based, and (**b**) sky-based guidance

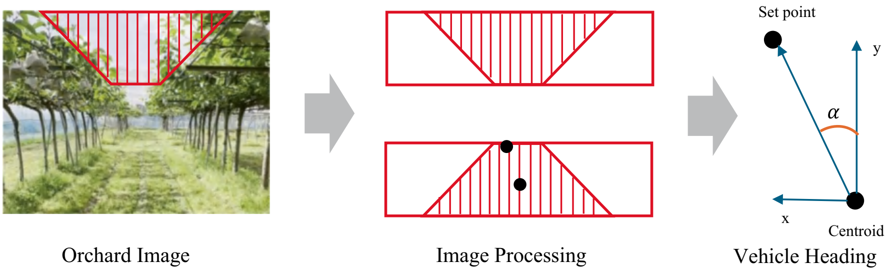

Fig. 12.2 Real-time agricultural vehicle orientation using sky-base guidance and image processing for heading angle extraction

navigation by integrating set point, centroid, and vehicle heading to the motor controller to follow a particular path in the orchard.

The traditional computer vision methods mentioned, such as thresholding and color segmentation, have notable limitations. The vision performance is sensitive to illumination variations, shadows, and occlusion from leaves and branches (Bargoti & Underwood, 2017). Some handcrafted features, such as poles and other support structures, sometimes fail to generalize across tree variation or different orchards, which reduces robustness and scalability (Kamilaris & Prenafeta-Boldú, 2018; Sampurno & Ahamed, 2024). Those methods also struggle to accurately distinguish multiple objects in a class, which leads to erroneous perception. Therefore, a more adaptable method to complex backgrounds and environmental variability is highly required to overcome these constraints.

12.3 Deep Learning-Based Instance Segmentation for Navigation in Orchards

Accurately distinguishing and understanding individual objects in complex images remains a critical challenge for traditional computer vision. Instance segmentation addresses this issue by providing pixel-wise annotations that separate objects of the same class, even under overlap or occlusion. This capability is critical across various fields such as automated driving, surveillance, medical imaging, and agricultural robotics. The inability to accurately identify both individual and grouped objects can lead to significant errors. For example, misidentifying fruits may cause a robotic arm to harvest unripe instead of ripe fruit.

Instance segmentation detects objects in an image and masks them from the background. This feature enables a deeper understanding of complex visual scenes. There are three segmentation categories: semantic, instance, and panoptic. Semantic segmentation involves classifying each pixel in an image into a predefined category by assigning labels to regions based on the semantic meaning. Instance segmentation involves detecting individual objects and providing a detailed understanding of each instance, such as the form of the object. Panoptic segmentation is a holistic approach that combines semantic segmentation and instance segmentation. Figure 12.3 shows object detection, along with the difference between instance segmentation and panoptic segmentation.

Deep learning-based navigation is becoming popular because it offers more features and accuracy than traditional computer vision methods. Conventional approaches often struggle with limited flexibility, complex image processing, and low performance when handling frequently updated data, leading to big datasets. In deep learning, trees are detected first, and aligned trees are used to extract the navigation guidelines, representing the center lines between two tree rows (Fig. 12.4a). For instance, YOLO detects the tree trunks, which are then connected to form a line. A navigation line is generated by combining these lines, providing a clear path for

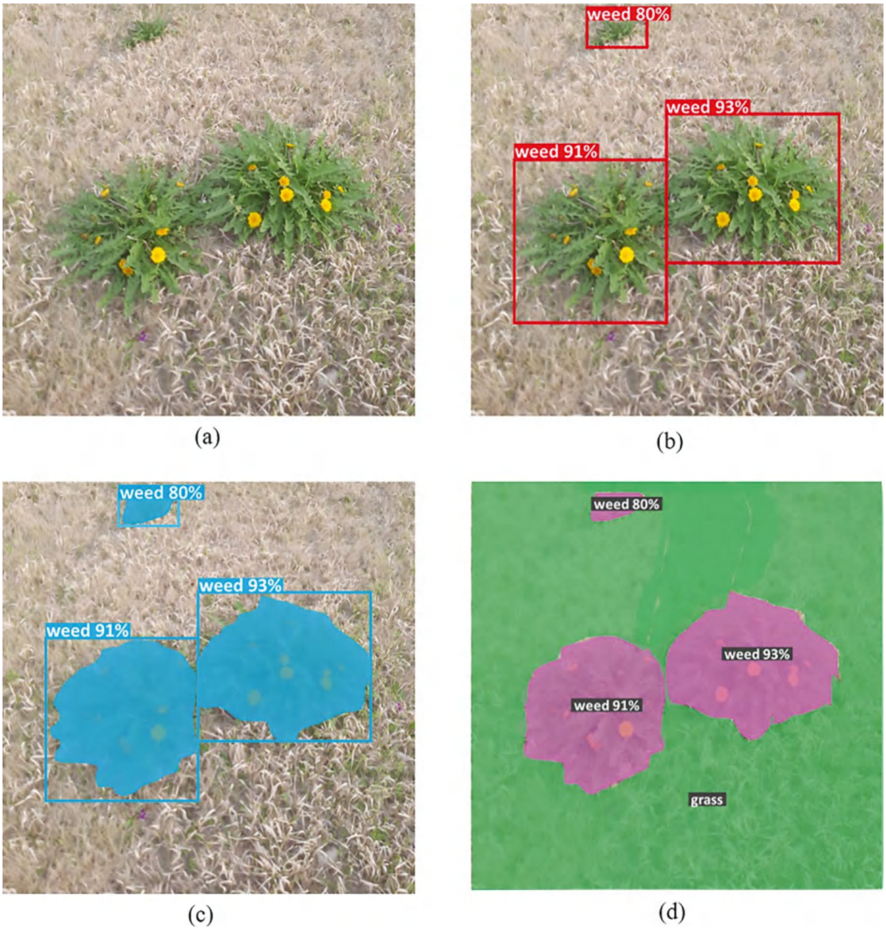

Fig. 12.3 Weed detection (**a**) original image, (**b**) object detection, (**c**) instance segmentation, and (**d**) panoptic segmentation

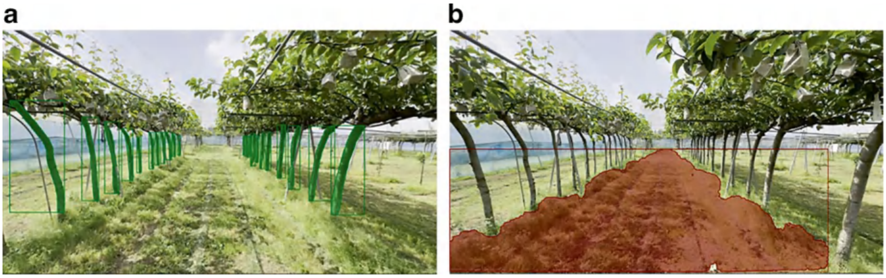

Fig. 12.4 YOLO-based segmentation results for agricultural robot navigation, (**a**) detected tree trunks for localization and row extraction, (**b**) identified drivable intra-row area for path planning

autonomous robots (Gu et al., 2023). Another approach in deep learning is extracting the driving area (Fig. 12.4b). The area between two rows of trees can be considered drivable, represented in a polygonal form. Then, the central line of this polygon can be derived as the driving path (Opasatian & Ahamed, 2024).

12.4 Instance Segmentation Models

A robust deep learning model is essential to develop a reliable autonomous navigation for field robotics. For instance, deep learning models are commonly used in segmentation, including Mask R-CNN, You Only Look At Coefficients (YOLACT), and YOLO (Table 12.1). Mask R-CNN is an improvement over Faster R-CNN, adding a mask prediction branch to its network. It is commonly used for autonomous driving and human pose estimation. The accuracy of Mask R-CNN is very high; however, it requires a high-spec computing device, which struggles and runs slowly on resource-constrained devices. This means it prioritizes accuracy over speed, making it more suitable for applications where performance is more critical than real-time processing.

However, one-stage family for object detection like YOLO and SSD surpassed others in their real-time application while developing their segmentation parts. YOLACT fills that gap as a one-stage instance segmentation that is highly accurate for real-time applications. Each deep learning model has advantages depending on the needs of the application. YOLO is the fastest among them and is suitable for robotic and autonomous vehicles requiring detection and instance segmentation. YOLACT offers a balance of speed and accuracy, making it a good choice for resource-constrained devices for real-time video processing. Meanwhile, Mask R-CNN has high segmentation accuracy but slow speed due to its two-step architecture. Therefore, Mask R-CNN suits high-precision medical and satellite image analysis tasks. The choice of the appropriate model depends on whether the main priority is speed or segmentation accuracy.

Table 12.1 Overview and comparison of instance segmentation models

Feature	Mask RCNN	YOLACT	YOLO-seg
Base architecture	Two-stage detector based on Faster R-CNN	Lightweight, single-stage detector	Single-stage detector with advanced features
Segmentation method	Uses Region Proposal Networks (RPN) to generate a mask for each object	Creates prototype masks for each instance	Uses grid-based segmentation, like the YOLO family, for instance segmentation
Multi-task architecture	Detect objects first, then apply segmentation per instance	Create masks first, then link them to detection	Combines detection and segmentation in one step
Speed	Slow	Fast	Very fast
Segmentation accuracy	High accuracy	Balance between accuracy and speed	Good, but less precise than Mask R-CNN
Model complexity	Complex due to its two-stage architecture	Lightweight and simpler than Mask R-CNN	Simpler than Mask R-CNN

Source: Bolya et al. (2019) and Sapkota et al. (2024)

12.5 Tree Trunk Detection Using Instance Segmentation

12.5.1 Data Preparation and Annotation

Deep learning models require large and diverse datasets to achieve high detection accuracy, as greater variability enables better recognition of objects in various conditions. As illustrated in Fig. 12.5, data was acquired using a camera mounted on an unmanned ground vehicle (UGV) robot operating in an orchard. The process began by recording orchard videos, from which thousands of frames were extracted at fixed intervals (e.g., every 30 ms) using a Python script and subsequently stored in image format. The extracted images were then annotated to produce image-label pairs required for supervised learning. After labeling, the dataset was divided into training, validation, and testing subsets, typically following an 80:10:10 ratio. While training and validation support proper learning and minimize overfitting, the testing subset evaluates the model's accuracy on unseen data. For example, from 2000 annotated images containing tree trunks, 1600 were allocated for training, 200 for validation, and 200 for testing to ensure reliable model development.

12.5.2 Model Training and Validation

Deep learning-based instance segmentation models, whether two-stage or one-stage, share similar principles in training and validation. Most networks consist of three main components: the backbone for feature extraction, the neck for

Fig. 12.5 The data preparation workflow for deep learning techniques

multi-scale feature fusion, and the head for task-specific output such as detection, segmentation, and classification. Training such models requires high-performance computing devices like GPUs to handle large-scale parallel computation efficiently. CUDA-enabled environments, deep learning frameworks such as PyTorch or TensorFlow, and libraries like OpenCV typically support the training process. Model configuration involves tuning hyperparameters such as input size, batch size, learning rate, momentum, and epochs. In the deployment stage, lightweight models are often preferred to balance computational efficiency and accuracy, and they are suitable for edge devices commonly used in real-time applications (Liu et al., 2024). For validation, metric parameters such as mean Average Precision (mAP), Intersection over Union (IoU), precision (P), and recall (R) provide a comprehensive assessment of model accuracy and generalization (Dumitriu et al., 2023).

As a case study, the YOLO11 instance segmentation was trained and validated using the framework mentioned above, with further optimizations to meet the requirements of real-time orchard navigation. The networks shown in Fig. 12.6 consist of three main parts: the backbone, the neck, and the head. The backbone is responsible for extracting features from the input image. A block called C3K2 is used in the backbone. The neck uses a module called SPPF (Spatial Pyramid Pooling Fast), which helps the model understand the objects at different scales by combining features from different levels. Another important part of the architecture is the C2PSA block, which adds a simple attention mechanism to focus on important areas in the image and improve detection accuracy. The head of the model is flexible and can be used for different tasks, including object detection, instance segmentation, pose estimation, and oriented object detection. YOLO11 comes in various sizes, from small models for edge devices to large models for high-performance systems (Khanam & Hussain, 2024).

Figure 12.7 illustrates the training and validation metrics for instance segmentation. Loss metrics are shown on the left, while accuracy metrics are on the right. Box loss measures bounding box accuracy, class loss evaluates object classification, and mask loss measures mask prediction accuracy. Precision and recall for bounding boxes (B) and masks (M) improve rapidly in early epochs, then plateau as the model converges. Notably, mAP 50 for bounding boxes and masks surpasses 0.8, indicating strong detection and segmentation performance suitable for real-time applications. This pattern is typical in deep learning, where early gains are significant, then taper off as the model nears convergence.

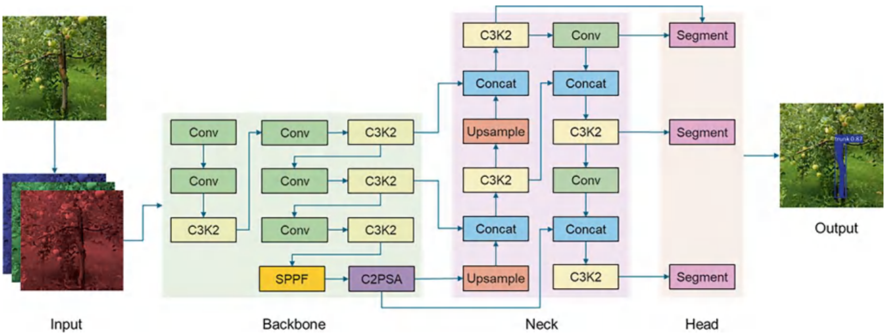

Fig. 12.6 Network structure YOLO11 used for tree trunks segmentation

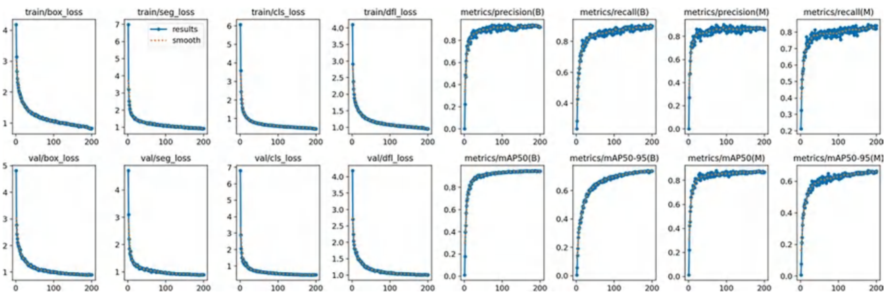

Fig. 12.7 Training result of YOLO11n for instance segmentation

12.5.3 Prediction

After training and validation, the model was applied to images with diverse orchard backgrounds. Its robustness was evaluated using a test dataset and video sequences, demonstrating efficient segmentation, accurate object detection, and fast inference. Figure 12.8 shows inference results, where bounding boxes and masks indicate detected tree trunks defined from the base near the soil up to the first branches. The text overlay displays the predicted class label along with a confidence score of 0 to 1. For example, "Trunk 0.87" indicates 87% confidence in its prediction, while "Trunk 0.27" indicates lower confidence. A confidence threshold (e.g., 0.5) filters out low-confidence detections.

Table 12.2 presents the prediction performance of the segmentation model, focusing on inference speed across different hardware platforms. In real-world agricultural robotics, inference speed is one of the key factors for successful real-time operations. While the models achieve high accuracy, their processing varies depending on the device. On high-end hardware, inference was relatively fast, but speed decreased when deployed on edge devices such as the Xavier NX or a mini-PC. It may also be real-time responsiveness. This highlights the importance of optimizing deployment by selecting appropriate hardware to ensure smooth field performance.

Fig. 12.8 Detection results of trained model

Table 12.2 Segmentation accuracy and inference speed of two YOLO models on different hardware platforms for a field robotics application

	Accuracy (%) ↑		Inference speed (FPS) ↑		
Model	mAP@.50 Box	mAP@.50 Mask	Core i7 11Gen RTX3060	Xavier NX	Core i5 12Gen
YOLOv8n-seg	94.6	87.8	32.58	17.98	16.17
YOLO11n-seg	94.9	87.4	29.87	16.57	16.46

12.6 Path Extraction for Autonomous Navigation

Before integrating with the control system, the actual position of objects such as trees in the orchard must first be identified. At this stage, using a depth camera is recommended. Figure 12.9 illustrates the pipeline, where the visual input is processed through a trained deep learning model. The camera provides image and depth data, where depth refers to the distance between the camera and the object, such as the centroid of the tree trunk that is obtained from YOLO-based segmentation. These centroids are then sorted in their position, either from left to right or by their depth (z-axis).

Trees are typically planted in rows in structured orchards, but connecting tree positions often does not yield a perfectly straight line. To address this, a machine learning algorithm like linear regression is applied to estimate the path (Fig. 12.10). This estimated line guides the robot to navigate autonomously and keep lateral distance from the tree row. If a single row of trees is detected, the robot follows a path beside the row (Fig. 12.11), while with two rows detected, it navigates along the midpoint between them (Fig. 12.12).

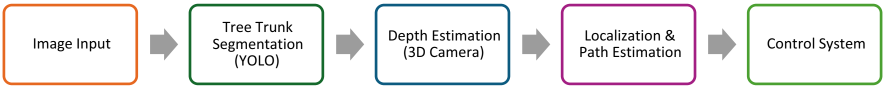

Fig. 12.9 Autonomous navigation system pipeline using deep vision system

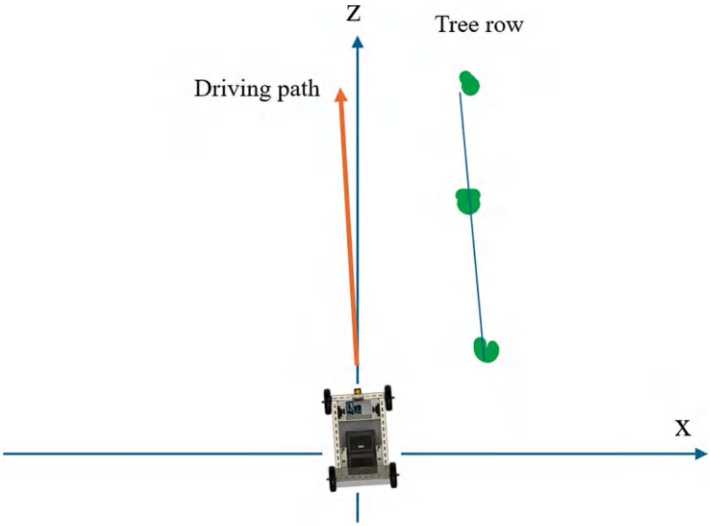

Fig. 12.10 Driving path extracted from tree row for robot's self-navigation

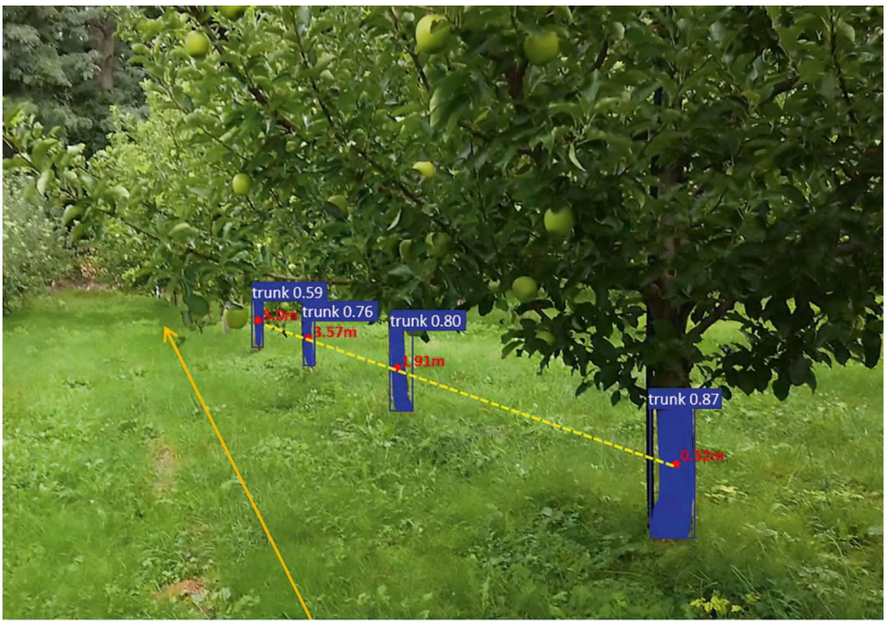

Fig. 12.11 Path extracted from a single row of trees

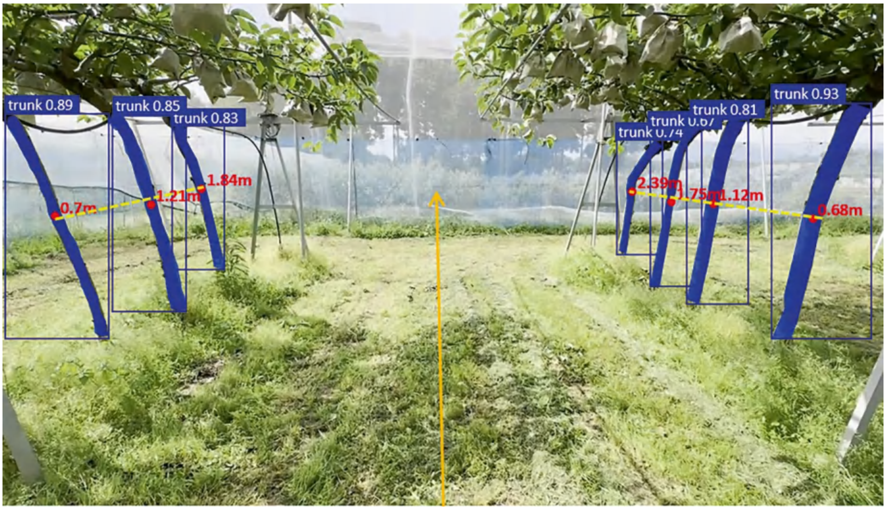

Fig. 12.12 Path extracted along the centerline between two rows of trees

12.7 Control System Integration

When the estimated path line is generated, the control system guides the robot along this path. The main objective of the control system is to adjust the robot's orientation and steering angle so that it remains aligned with the tree row. The robot's orientation is calculated based on its heading direction relative to the slope of the estimated path line. The difference between these angles determines the steering correction needed. If the robot is positioned beside a single row, the system ensures the robot maintains a fixed lateral distance from the row while moving forward. In the case of two detected rows, the robot adjusts its position to stay in the center between them. The movement is achieved by continuously updating the robot's linear and angular velocities, allowing it to follow the path smoothly and respond to changes in the environment in real time.

12.8 Challenge and Future Direction

This chapter has explored the potential of deep learning-based instance segmentation to support autonomous navigation in orchards. Compared to traditional computer vision techniques, this technique offers greater robustness and adaptability to varying environmental conditions, such as background complexity and object variability. Even when compared with deep learning-based object detection, instance segmentation provides more information about object shapes. This is especially important in orchard environments, where tree trunks appear irregular or tilted. In such cases, using the centroid of segmented regions yields more accurate positional data than bounding box centers.

Despite these advantages, several challenges remain in integrating this vision system with a field robotics system. An inappropriate hardware setup or connection may delay detection and path extraction, leading to navigation failure. Therefore, further work is required to establish an optimal hardware integration strategy for efficient autonomous control. Future work should focus on deploying a system that synchronizes detection, prediction, and path extraction with robot velocity, supported by appropriate hardware, to improve the reliability and responsiveness of autonomous navigation.

12.9 Conclusion

Overall, this chapter has demonstrated the potential of deep learning-based instance segmentation to support autonomous navigation in orchards, especially when GNSS signals are unavailable due to labor shortages. The proposed vision system offers a robust path-extraction framework by combining a trained model with additional object localization processing. These results show that the proposed vision system balances accuracy and processing speed, making it suitable for real-time deployment in orchard settings. Future development will focus on integrating the model into a complete control system and validating its performance through field trials.

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Chapter 13
Intelligent Recognition of Orchard Environment: Instance Segmentation of Trees and Roads

Ailian Jiang and Tofael Ahamed

Abstract Orchard target detection is one of the key prerequisites for realizing agricultural automation. With the continuous development of agricultural science and technology, agricultural production is gradually moving toward intelligence and automation. As an important part of the agricultural field, the management and production of orchards must also use advanced technology to improve efficiency and quality. Deep learning models utilizing instance segmentation, such as Mask R-CNN and YOLACT, can not only detect the trees in the orchard but also segment the safe range for vehicles to operate, realizing accurate identification and localization of the orchard environment, as well as guaranteeing the safety of vehicles in the process of operation. This provides an important database and technical support for agricultural automation. By automatically detecting trees and roads in the orchard, operations such as automatic inspection of the orchard, monitoring of pests and diseases, and fruit picking can be realized, thus reducing the burden of manual labor and improving production efficiency.

Keywords Agricultural automation · Orchard automation · Deep learning · Mask R-CNN · YOLACT

13.1 Introduction

As the global population grows, food and agricultural production are under unprecedented pressure. Traditional agricultural production methods have been complex in meeting the needs of modern society for efficient, precise, and sustainable agriculture (Godfray et al., 2010). In recent years, agricultural science and technology

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development have rapidly transformed agricultural production into intelligence and automation. In orchard management, an important part of agriculture, advanced technologies are also introduced to improve production efficiency and quality.

In orchard management, machine vision technology, through traditional algorithms, such as edge detection, color segmentation, and shape matching, can detect and identify key targets such as trees, fruits, or roads (Gongal et al., 2015). These methods can achieve good results for specific scenes, but have poor adaptability when dealing with complex and changing environments. The performance is usually unstable enough, and the recognition accuracy is also low. With the introduction of deep learning technology, the system performs well in dealing with complex environments and varied targets, and the recognition accuracy and efficiency have been significantly improved (Kamilaris & Prenafeta-Boldú, 2018). The deep learning model can be trained with large-scale data to optimize the detection effect and adapt to different scenarios continuously. This technological advancement not only simplifies the management process, reduces manual labor, and significantly lowers operating costs, but also dramatically improves the orchard's productivity, providing strong technical support for the automation of modern agriculture (Sa et al., 2016).

In deep learning algorithms, target detection and image segmentation are two commonly used techniques that have different applications in orchard management:

1. Target Detection: The target detection technique mainly identifies and localizes an image. It can label the bounding box of the target, but cannot distinguish the boundaries of different instances. Typical target detection algorithms include You Only Look Once (YOLO), Faster R-CNN, and Single Shot MultiBox Detector (SSD) (Liu et al., 2016; Redmon et al., 2016; Ren et al., 2015). The main advantage of these algorithms is that they are fast, accurate, and suitable for situations requiring fast target recognition.
2. Image Segmentation: Image segmentation techniques are used to divide an image into multiple meaningful regions, which are categorized into two types: semantic segmentation and instance segmentation.

Semantic Segmentation: Semantic segmentation categorizes pixels in an image into different categories but does not distinguish between the specific boundaries of different instances in the same category. Common semantic segmentation algorithms include a fully convolutional network (FCN) and a U-Net (Long et al., 2015; Ronneberger et al., 2015).

Instance Segmentation: Instance segmentation not only needs to recognize and localize the target object but also needs to segment the specific boundaries of each instance. Instance segmentation provides more detailed information about the target and can distinguish the specific shapes of different instances in the same category. Standard instance segmentation algorithms include Mask R-CNN and YOLACT (Bolya et al., 2019; He et al., 2017). The main advantage of instance segmentation is its high accuracy and fine granularity, which is suitable for scenes that require precise target boundaries and shape information.

A safe and correct navigation system is essential for autonomous agricultural machinery operating in orchards. Fruit tree trunks are usually the key reference for navigation path planning, and by recognizing the location of the trunks, the system can segment the accessible areas in the orchard, thus ensuring the safe operation of agricultural machinery in complex environments. In this study, instance segmentation methods, Mask R-CNN and YOLACT algorithms, are compared to accurately detect the location of fruit trees and distinguish between different tree instances. The result of instance segmentation can provide a reliable reference for path planning and ensure that the forward route can be planned in real time in the orchard. Meanwhile, the study also segments the roads in the orchard to identify safety ranges to prevent vehicles from crashing into objects such as trees, further enhancing the safety and efficiency of the navigation system. Through this autonomous navigation system combined with deep learning, orchard management becomes more intelligent, reducing manual intervention and significantly improving the accuracy and safety of machinery operation, providing important support for the efficient management and sustainable development of orchards.

13.2 Methodology

13.2.1 Mask R-CNN

Mask R-CNN is a two-stage instance segmentation model that extends Faster R-CNN by incorporating a segmentation branch. It consists of a backbone network for feature extraction, a region proposal network (RPN) for generating candidate object regions, and three parallel output branches for classification, bounding box regression, and pixel-wise segmentation.

The backbone network is responsible for extracting hierarchical features from the input image. Commonly used backbones include ResNet-50 and ResNet-101, often combined with a feature pyramid network (FPN) to enhance multi-scale feature representation. The feature maps generated by the backbone are then fed into the RPN, which scans the image and proposes candidate object regions. The RPN consists of a sliding window mechanism with anchor boxes of different scales and aspect ratios, predicting the likelihood of an object being present and refining the bounding box coordinates. Non-maximum suppression (NMS) is applied to eliminate redundant proposals, retaining the most relevant regions.

After the region proposals are generated, Mask R-CNN applies RoIAlign, an improved version of RoIPooling. RoIPooling, used in Faster R-CNN, introduces quantization errors when extracting fixed-size feature maps from proposed regions. RoIAlign addresses this issue using bilinear interpolation, ensuring precise spatial alignment of features, which is particularly important for accurate instance segmentation.

The extracted RoI features are then passed through three parallel branches. The classification branch assigns a class label to each detected object, distinguishing between categories. The bounding box regression branch refines the object's localization by adjusting the coordinates of the predicted bounding boxes. Unique to Mask R-CNN, the segmentation branch predicts a pixel-wise binary mask for each instance. Unlike semantic segmentation, which assigns class labels to every pixel, the segmentation branch outputs a separate mask for each detected object, improving instance-level distinction. This branch utilizes a fully convolutional network (FCN) to generate high-resolution masks, typically of size M × M per object class.

By integrating these components, Mask R-CNN effectively performs instance segmentation, allowing it to recognize individual objects and delineate their precise shapes within an image. Combining RPN for object proposal, RoIAlign for precise feature extraction, and the three-branch output structure makes Mask R-CNN highly accurate in complex environments where objects overlap or exhibit varying scales.

The model utilizes a joint loss function to improve segmentation accuracy that optimizes three tasks: category classification, bounding box regression, and mask prediction (Fig. 13.1). Mask R-CNN adopts a multi-task loss function:

$$L = L_{\text{cls}} + L_{\text{bbox}} + L_{\text{mask}}$$

L_{cls} is the softmax classification loss, L_{bbox} is the smooth L1 regression loss, and L_{mask} is the binary cross-entropy loss computed only for the actual object class.

The segmentation head is implemented as a lightweight fully convolutional network (FCN), typically composed of several convolutional layers followed by an upsampling layer. Each predicted mask has a fixed spatial resolution (e.g., 28 × 28 pixels), which is resized to fit the object's bounding box. While efficient, this structure may slightly reduce contour accuracy for small or occluded objects.

To overcome such limitations, recent advancements such as PointRend and Cascade Mask R-CNN have introduced improved techniques for high-resolution boundary prediction and multi-stage refinement (Cai & Vasconcelos, 2018; Kirillov

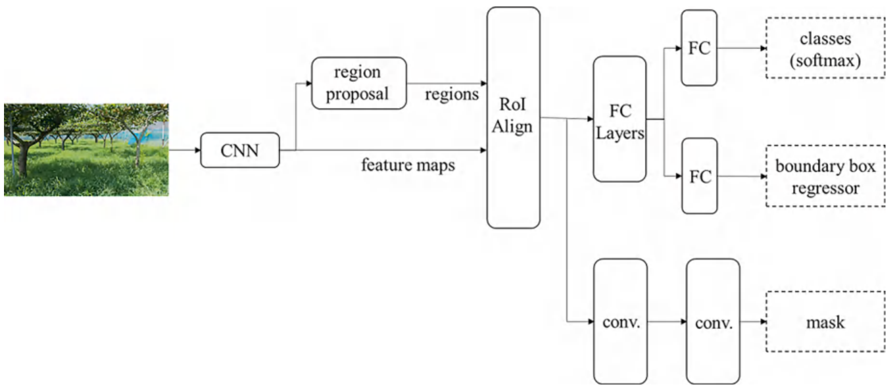

Fig. 13.1 Structure diagram of Mask R-CNN

et al., 2020). Nevertheless, standard Mask R-CNN remains a widely used baseline due to its robust trade-off between accuracy and efficiency.

13.2.2 YOLACT

YOLACT (You Only Look at Coefficients) is a fast, one-stage instance segmentation algorithm for real-time applications. Unlike two-stage models such as Mask R-CNN, which rely on region proposal and sequential refinement, YOLACT performs detection and segmentation simultaneously in a single feed-forward process, significantly improving computational efficiency.

Its architecture consists of three main components: a backbone network, a feature pyramid network (FPN), and two parallel prediction heads—one for object detection and the other for mask generation. The backbone, typically ResNet-50 or ResNet-101, extracts hierarchical features from the input image. These features are then passed through the FPN to construct multi-scale feature maps, enhancing the model's ability to detect objects of varying sizes across the image.

Instead of utilizing a region proposal network, YOLACT adopts an anchor-based detection scheme similar to SSD (Single Shot MultiBox Detector), where bounding box coordinates and classification scores are predicted directly for each anchor point on the feature map. This allows the detection head to operate quickly and without iterative refinement.

The most notable innovation in YOLACT lies in its prototype mask generation framework. Rather than generating an individual mask for each detected object (as in Mask R-CNN), YOLACT decouples the mask prediction process into two parts:

1. A prototype branch generates a fixed set of k high-level masks (e.g., 32) that serve as a shared representation of object structures.
2. A set of learned coefficients is produced for each detected instance, which is used to compute the final instance-specific mask as a linear combination of the prototype masks.

This strategy significantly reduces memory usage and computation time while achieving good segmentation quality. The predicted mask is then spatially aligned with the detected object via a mask cropping operation, which removes pixels outside the bounding box to improve boundary alignment.

Despite this efficiency, shared prototype masks can sometimes lead to coarser instance boundaries than two-stage methods. To mitigate this, follow-up works like YOLACT++ introduce additional refinement strategies such as deformable convolutions and better localization modules to boost accuracy without sacrificing speed (Bolya et al., 2022).

Overall, YOLACT strikes a practical balance between speed and segmentation precision. Its design makes it especially suitable for real-time tasks in dynamic environments, such as autonomous navigation in orchards, where rapid object detection and environmental understanding are essential (Fig. 13.2).

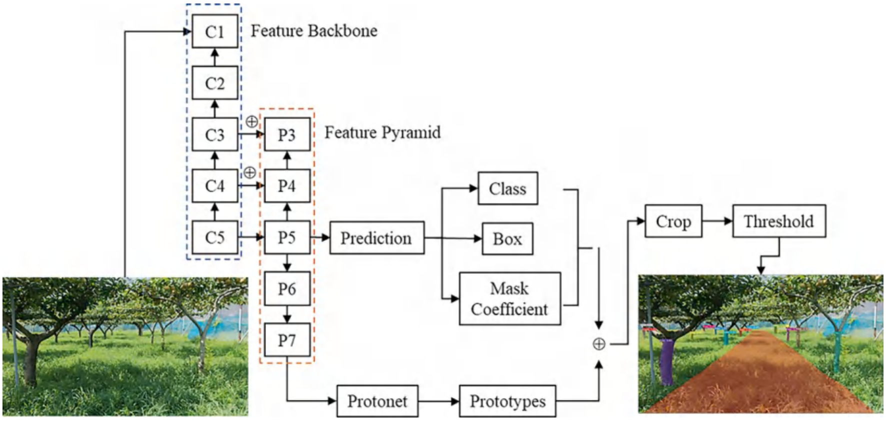

Fig. 13.2 Structure diagram of YOLACT

Table 13.1 Structural and functional comparison between Mask R-CNN and YOLACT

Attribute	Mask R-CNN	YOLACT
Architecture	Two-stage: RPN + segmentation branch	One-stage: parallel detection and mask generation
Speed	Slower (1.8–2.5 s/1080p image)	Faster (1.3–1.6 s/1080p image)
Segmentation accuracy	Higher, especially on complex or overlapping instances	Moderate, less precise at object boundaries
Mask generation strategy	Per-instance masks via FCN	Linear combination of shared prototype masks
Flexibility for small objects	Strong (due to RoIAlign + high-resolution mask)	Weaker (fixed-size prototype masks limit precision)
Suitable for	Offline high-precision tasks; detailed object understanding	Real-time applications: autonomous navigation, monitoring
Enhancements	PointRend, Cascade Mask R-CNN	YOLACT++ with deformable convolutions, better localization

13.2.3 Model Comparison

Mask R-CNN and YOLACT represent two distinct approaches to instance segmentation, with differences in architectural design, segmentation strategies, and computational performance. Table 13.1 provides a side-by-side comparison of the two models.

13.2.4 Preparation of the Dataset

The phone camera used for data acquisition had a resolution of 1920 × 1080 pixels. The dataset was collected from pear orchards at the Tsukuba-Plant Innovation Research Center (TPIRC), University of Tsukuba, Ibaraki, Japan (Fig. 13.3). Data

Fig. 13.3 Dataset collected from TPIRC

collection was carried out during the summer season under natural sunlight, and included both morning and afternoon sessions to capture different lighting angles. At the time of recording, the orchard was overgrown with dense weeds, completely obstructing the intended paths, making the environment particularly challenging for navigation.

Videos were recorded using a handheld smartphone while walking along the orchard paths to generate image data. These videos were then converted into static image frames at a rate of 1 frame/s using OpenCV, resulting in a dataset of approximately 1000 high-resolution images. This sampling strategy ensured spatial and temporal variability within the dataset, covering diverse orientations, object distances, and occlusion scenarios.

A comprehensive set of data augmentation techniques was applied to enhance the model's robustness against environmental variability. The augmentations included the following:

1. Color space transformations such as HSV adjustment, simulating variations in leaf chlorophyll content or lighting conditions.
2. Contrast enhancement using sigmoid and gamma correction to emphasize features like tree trunk texture and road boundaries.
3. Geometric transformations such as rotation (−30° to +30°), flipping (horizontal/vertical), and cropping to simulate different viewing perspectives.
4. Photometric effects include strong light simulation and blur to model overexposure, lens glare, or motion blur caused by walking.

These augmentations were implemented using the Albumentations and imgaug Python libraries, providing efficient and reproducible preprocessing pipelines. The goal was to simulate a wide range of orchard scenarios, including partial occlusions, shadowed regions, and glare from direct sunlight, thereby improving the model's ability to generalize to unseen test environments.

As a result, the final augmented dataset covered a broad visual distribution, enabling the segmentation models to learn robust feature representations and reducing the risk of overfitting to specific lighting or structural patterns in the orchard (Fig. 13.4).

Fig. 13.4 Image augmentation. (**a**) Original image. (**b**) Color enhancement (HSV adjustment). (**c**) Contrast adjustment (SigmoidContrast). (**d**) Geometric transformations (rotation). (**e**) Crop (CropAndPad). (**f**) Weather simulation (intense light)

The collected images were carefully annotated using LabelMe, a widely used image annotation tool that supports polygonal segmentation and exports annotations in .json format. Each image was manually labeled to identify the boundaries of tree trunks and road areas, with annotations performed by trained personnel following a standardized labeling protocol.

Although Mask R-CNN and YOLACT accept annotations in .json format, their labeling requirements differ significantly due to their architectural design and segmentation objectives.

For Mask R-CNN, which performs instance-level segmentation, the annotation process requires assigning a unique label to each object instance, even if they belong to the same category. For example, if an image contains multiple pear tree trunks, each must be labeled distinctly as tree_1, tree_2, tree_3 and so on (Fig. 13.5). This fine-grained labeling ensures that the model learns to distinguish between individual trees, allowing for more accurate mask prediction and spatial separation of overlapping objects.

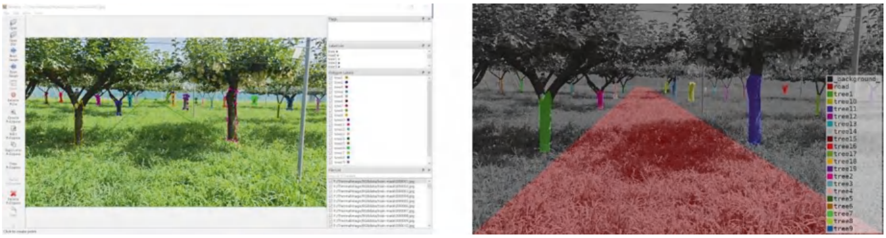

Fig. 13.5 The LabelMe-labeled dataset for Mask R-CNN

Fig. 13.6 The LabelMe-labeled dataset for YOLACT

In contrast, YOLACT adopts a simplified labeling approach suitable for class-level segmentation. All objects of the same class are grouped under a single category label (e.g., "tree"), without distinguishing between individual instances (Fig. 13.6). This reduces the annotation workload and accelerates preprocessing, but also limits the model's ability to differentiate between adjacent or overlapping objects, which may affect segmentation precision in dense orchard scenes.

The structure of the exported .json files also reflects these differences. Each polygon annotation includes a unique instance ID and corresponding class name for Mask R-CNN. At the same time, for YOLACT, only class-level information is retained, and all polygons under the same class are treated as a single group.

This rigorous annotation strategy enables both models to learn effectively from the data, with Mask R-CNN benefiting from detailed instance boundaries and YOLACT achieving speed and efficiency through class-level simplification.

13.3 Results

A total of 3000 images were selected to construct the complete dataset. These images were derived from annotated orchard scenes with varied lighting conditions, object distances, and structural complexity. The dataset was randomly split into training and validation sets to evaluate model performance effectively. Specifically, 80 images were used for training, and 20 images were reserved for validation during the experimental runs in this study.

All experiments were conducted on a standard consumer-level hardware platform consisting of Windows 10, an Intel(R) Core i5-2400 CPU @ 3.10 GHz, 8 GB RAM, and an NVIDIA GeForce GTX 1050 Ti GPU with 4 GB VRAM. The software environment included Anaconda 3, Python 3.7, and TensorFlow-GPU 1.13.1, which provided CUDA acceleration to speed up the training of deep neural networks.

The Mask R-CNN model was trained for 100 epochs, with mini-batch gradient descent using the Stochastic Gradient Descent (SGD) optimizer, a learning rate of 0.001, momentum of 0.9, and a batch size of 2 due to GPU memory constraints.

Throughout the training process, the model showed steady convergence. Mask R-CNN training involved monitoring multiple loss components to evaluate the model's learning across different tasks. The RPN classification loss, which reflects the Region Proposal Network's ability to distinguish between foreground and background, converged to 0.0634, suggesting reliable initial object detection. The RPN bounding box loss, representing the accuracy of the region proposals' spatial localization, was 0.6670, indicating some localization errors likely due to occlusions and dense vegetation in the orchard images.

The classification loss at the second stage, which measures the accuracy of assigning object categories to detected regions, achieved a low value of 0.0409, indicating that the model could classify tree trunks and roads effectively. The bounding box regression loss in this stage, used to refine object localization, was 0.0294, suggesting strong performance in coordinate adjustment. Lastly, the mask loss, responsible for pixel-level binary segmentation of each object instance, reached 0.1297, demonstrating effective mask prediction with reasonable boundary precision.

The total loss at convergence was 0.9304, indicating successful multi-task optimization of object detection and instance segmentation. The relatively low classification and mask loss values suggest that the model effectively learned object boundaries and categories. However, the relatively higher RPN bounding box loss may indicate challenges in region proposal accuracy, possibly due to visual clutter such as overlapping trunks or weed interference in the orchard dataset.

To monitor the training progress, the loss curves were plotted and analyzed per epoch (Fig. 13.7). This confirmed stable convergence behavior and the absence of overfitting on the training subset, thereby validating the effectiveness of the training strategy.

Using the same dataset and computational environment, the YOLACT model was trained for 100 epochs over approximately 7.5 h. Given its one-stage

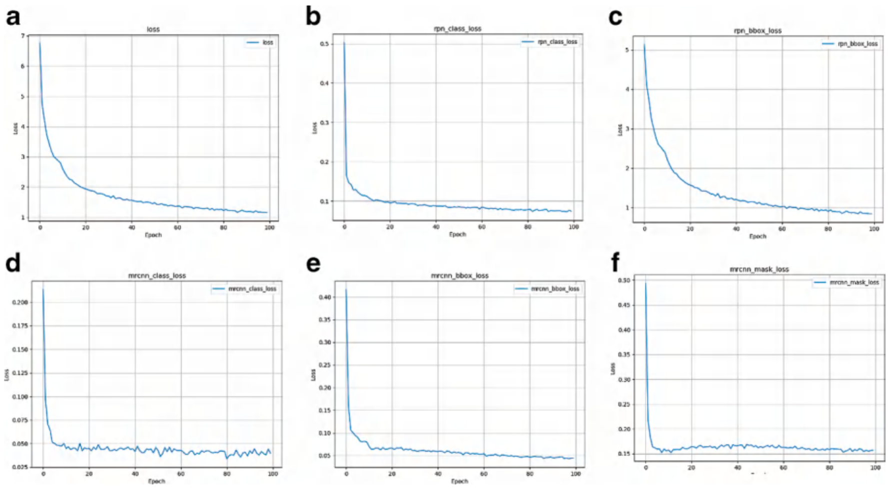

Fig. 13.7 Loss curve visualization for Mask R-CNN training. (**a**) Total loss. (**b**) RPN classification loss. (**c**) RPN bounding box regression loss. (**d**) Classification loss. (**e**) Bounding box refinement loss. (**f**) Mask segmentation loss

architecture and real-time optimization objectives, YOLACT demonstrates a considerably faster training and inference pipeline than two-stage models like Mask R-CNN.

Upon completion of training, the model was evaluated on a separate validation set. The evaluation focused on two primary performance metrics: mean Average Precision (mAP) for bounding box detection and instance mask segmentation, computed under different IoU thresholds.

At the standard COCO evaluation threshold of IoU $\geq$ 0.5, YOLACT achieved an mAP of 82.5% for bounding box detection and 69.89% for mask segmentation. These results indicate the model's capability to localize accurately and segment objects under a moderate overlap criterion. However, when evaluated using the average mAP over a range of IoU thresholds (e.g., from 0.5 to 0.95), the scores decreased to 57.04% for box detection and 47.67% for segmentation. This drop reflects the model's reduced precision in handling finer object boundaries, particularly at higher IoU requirements, a known limitation of prototype-based mask generation.

Nonetheless, YOLACT's performance remains impressive given its speed-oriented design. The relatively high mAP at 0.5 IoU confirms that the model can reliably detect and segment tree trunks and roads in orchard scenes, even under challenging conditions such as clutter, occlusion, or variable lighting.

The training progress was monitored by plotting both the loss curve and mAP values across epochs (Fig. 13.8), which showed a stable convergence pattern and no signs of overfitting. These results support YOLACT's suitability for real-time agricultural applications where quick decision-making is essential and slight trade-offs in mask precision can be tolerated.

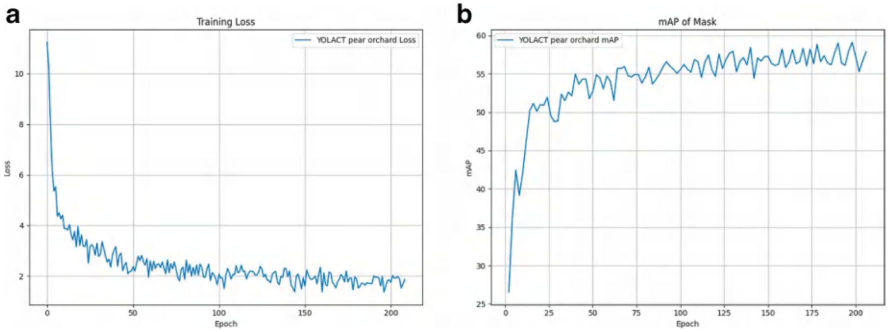

Fig. 13.8 Training progress of the YOLACT model. (**a**) Total training loss. (**b**) Mean Average Precision (mAP) for instance segmentation evaluated on the validation set

To evaluate the generalization performance of the trained models, both Mask R-CNN and YOLACT were tested on a set of previously unseen images that were excluded entirely from the training process. These test images were randomly selected from the same orchard environment but captured under different lighting and angle conditions to simulate real-world deployment scenarios better.

The evaluation was conducted under the same hardware environment used during training. All inference times were measured using input images with a 1920 × 1080 resolution on a system equipped with an Intel i5-2400 CPU and NVIDIA GeForce GTX 1050 Ti GPU.

The average detection and segmentation time per image was approximately 1.885 s for Mask R-CNN and 1.530 s for YOLACT. The noticeable difference in inference speed can be attributed to the architectural differences between the two models. Mask R-CNN, being a two-stage model, requires multiple processing steps, including region proposal generation, RoI alignment, and separate mask prediction per instance. In contrast, YOLACT's one-stage design allows faster forward pass by simultaneously predicting all components (bounding boxes, class scores, and masks).

This performance gap suggests that while Mask R-CNN provides more refined segmentation masks (Fig. 13.9), YOLACT is significantly better suited for real-time or near real-time applications, such as autonomous navigation in agricultural environments, where decisions must be made within a short time window (Fig. 13.10).

These results highlight a key trade-off between segmentation precision and inference efficiency, which should be carefully considered when selecting models for deployment in time-sensitive field operations.

13.4 Discussion

A comparative analysis of the detection and segmentation results on the same test images reveals distinct strengths and weaknesses between Mask R-CNN and YOLACT, influenced primarily by their architectural differences.

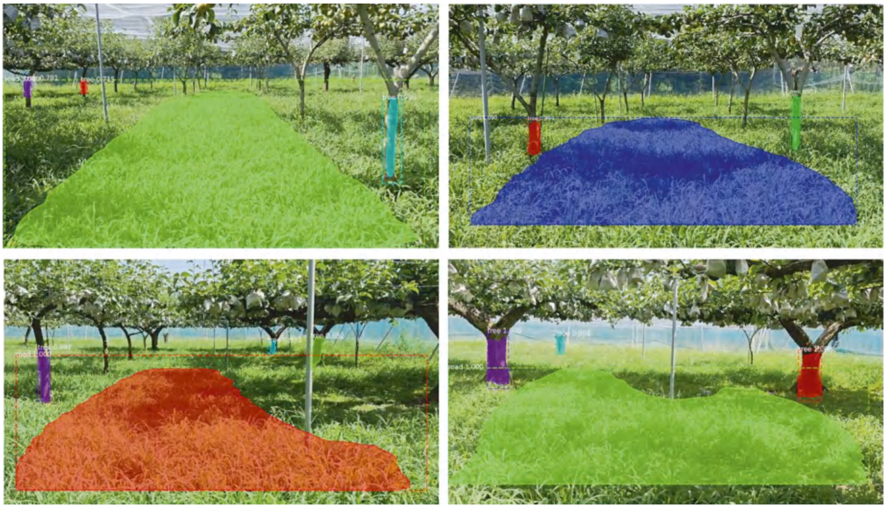

Fig. 13.9 Mask R-CNN image segmentation results

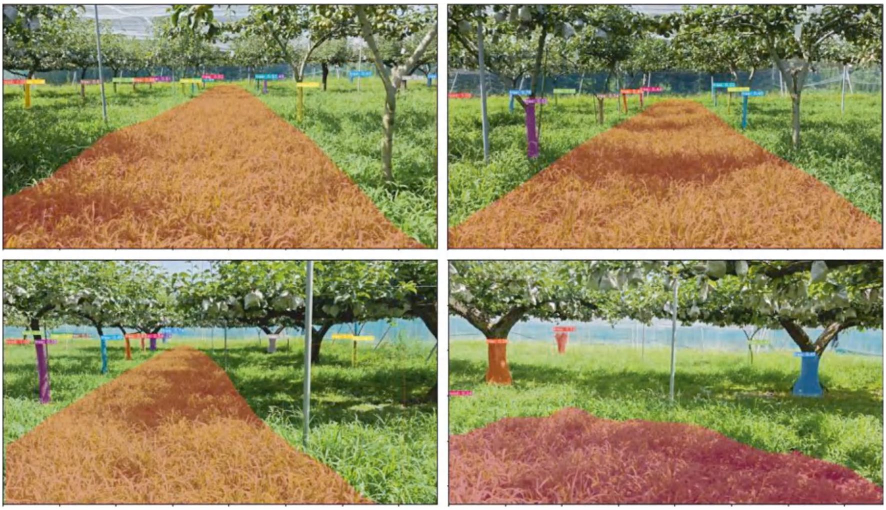

Fig. 13.10 YOLACT image segmentation results

Both models exhibited comparable performance in detection accuracy for near-range objects, particularly tree trunks close to the camera. They could localize and outline the trunks with minimal deviation, indicating that both models effectively captured essential shape and texture features in close-range scenarios.

However, regarding runnable area segmentation, which is critical for safe autonomous navigation, Mask R-CNN demonstrated superior performance. It successfully segmented nearly the entire drivable area with high precision, reflecting the advantages of its fine-grained instance segmentation mechanism. This can be attributed to its use of RoIAlign and per-instance mask prediction, which allows the network to generate more detailed masks, particularly for irregular or partially occluded regions.

Despite this strength, Mask R-CNN also showed a limitation in detecting objects near the image boundaries. In several test cases, targets located at the periphery of the image were either partially detected or missed entirely. This limitation may stem from its fixed-size feature extraction mechanism, which becomes less accurate at the edges of the feature maps.

In contrast, YOLACT showed stronger recognition capabilities at longer distances, detecting more distant tree trunks and extending the recognized drivable regions further into the scene's depth. This suggests that YOLACT's one-stage design, which processes full-resolution feature maps with shared prototype masks, is better suited for capturing global scene context, allowing it to generalize well over larger spatial extents.

From a computational efficiency perspective, YOLACT outperforms Mask R-CNN in inference speed, with a significantly lower average processing time per image. This makes it better suited for real-time applications, where timely perception and decision-making are critical, such as dynamic obstacle avoidance and adaptive path planning in orchard environments.

In summary, Mask R-CNN is advantageous for tasks requiring high segmentation precision at close range, while YOLACT provides faster inference and improved long-range detection. Each model is suitable for different operational priorities in autonomous agricultural systems. These findings emphasize the importance of balancing segmentation quality and speed based on the specific demands of the deployment environment.

13.5 Conclusion

This study compared two prominent instance segmentation models—Mask R-CNN and YOLACT—for detecting tree trunks and identifying drivable areas in orchard environments. These models were selected based on their complementary design philosophies: Mask R-CNN prioritizes segmentation accuracy through a two-stage approach. At the same time, YOLACT emphasizes inference efficiency via a streamlined one-stage architecture.

Experimental results demonstrated that Mask R-CNN excels in pixel-level segmentation quality, particularly in accurately delineating object boundaries and drivable zones at close range. Its ability to generate detailed, per-instance masks makes it a strong candidate for high-precision applications in structured and cluttered environments such as orchards. However, its relatively longer inference time and higher computational demands may pose limitations in scenarios requiring real-time decision-making.

In contrast, YOLACT achieved significantly faster inference speeds, making it well suited for real-time navigation and perception tasks in dynamic agricultural settings. Although its segmentation granularity is slightly lower, YOLACT exhibited better performance in recognizing distant objects and extending detection range, demonstrating its strength in scene-level generalization and fast object recognition.

Overall, the findings highlight a trade-off between segmentation precision and computational efficiency, with each model offering unique advantages depending on application priorities. Mask R-CNN is ideal for tasks requiring accurate object boundary detection, while YOLACT provides the speed necessary for responsive autonomous control in time-sensitive field operations.

These insights can serve as a reference for designing and deploying deep learning-based perception systems in autonomous agricultural vehicles. Future work may focus on integrating the strengths of both models, exploring hybrid architectures, or extending the evaluation to include other segmentation methods such as YOLACT++, PointRend, or real-time transformer-based models, to further improve the balance between accuracy and efficiency in precision orchard management.

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Chapter 14
Prospect of Small-Scale Agricultural Mechanization for Sustainable Agriculture in a Climate Change Context

AFM Tariqul Islam and Md. Ashraful Alam

Abstract Intensifying climate shocks, ranging from unpredictable rainfall to extreme heat, are heightening the vulnerabilities of smallholder farmers, who dominate agricultural landscapes across the globe. Relying on traditional, labor-intensive practices, they are increasingly under-equipped to adapt to evolving climate realities. Small-scale mechanization offers a promising solution, expanding beyond basic tools to include affordable, context-specific equipment integrated with digital technologies such as sensors, IoT, and solar energy systems. These innovations support climate adaptation by improving water efficiency, reducing soil degradation, and enabling timely interventions. Additionally, they contribute to climate mitigation through conservation tillage, organic farming, and carbon sequestration. The opportunities include increased productivity, socio-economic empowerment, and enhanced resilience across diverse agro-ecologies. However, high initial costs, infrastructural deficits, skills gaps, and socio-cultural resistance hinder adoption. Strategic policy support, capacity building, and locally tailored innovations are crucial to unlocking mechanization's full potential. Embedding small-scale mechanization within mixed market systems where public, private, and community actors collaborate and supporting sustainable business models such as custom hiring centers and service platforms can ensure affordability, scalability, and long-term impact. In the face of ongoing climate threats, small-scale mechanization, especially when integrated with smart farming solutions, is a vital pathway toward resilient, sustainable, and climate-smart agriculture.

Keywords Agricultural mechanization · Climate change · Small scale

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14.1 Introduction

Agriculture in low- and middle-income countries stands at a critical crossroads as climate change intensifies threats such as erratic rainfall, rising temperatures, and extreme weather events. Smallholder farmers who cultivate the majority of farmland and contribute significantly to global food security are disproportionately vulnerable due to their reliance on labor-intensive practices and fragmented landholdings (Ricciardi et al., 2021; IPCC, 2023). Addressing these challenges demands transformative, scalable solutions that improve productivity while enhancing climate resilience. Small-scale agricultural mechanization (SSAM) offers a strategic pathway to sustainable agriculture by providing affordable, context-appropriate tools and service models tailored to smallholders. Unlike large-scale mechanization, SSAM emphasizes ecological compatibility and inclusivity, facilitating timely field operations, labor savings, and climate-smart practices such as conservation tillage and precision input use (Giller et al., 2020; FAO & UNEP, 2022).

Furthermore, innovations, including solar-powered equipment and digital service platforms, have expanded the role of mechanization in climate adaptation and mitigation. Strategically embedding SSAM within national climate action plans, rural employment policies, and green growth frameworks unlocks a triple dividend of productivity, resilience, and environmental sustainability. Successful mixed market approaches in countries like Ethiopia, Nepal, and Bangladesh demonstrate how public, private, and community partnerships can scale mechanization services effectively (van Loon et al., 2020). As climate pressures mount, SSAM transcends its traditional role to become a cornerstone for achieving Sustainable Development Goals related to food security, climate action, and decent work. This short note highlights the current prospects of SSAM, its critical role in climate-smart agriculture, and the systemic enablers needed to realize its full potential in transforming vulnerable farming systems.

14.2 Scope and Prospect of SSAM in Climate Change Contexts

Small-scale agricultural mechanization (SSAM) encompasses various tools, technologies, and service models for smallholder farmers managing fragmented, resource-limited farms. Unlike conventional large-scale mechanization, SSAM prioritizes affordable, adaptable, and context-appropriate technologies that boost productivity while preserving ecological sustainability (FAO & UNIDO, 2021; Malabo Montpellier Panel, 2018). In the face of climate variability, SSAM offers practical solutions to enhance productivity and resilience. These include manual and motorized implements, solar-powered pumps, precision seeders, conservation tillage devices, and low-cost sensors (Sims and Kienzle, 2017; Giller et al., 2020). Digital tools such as mobile applications and weather-linked advisories further empower farmers with timely, data-driven decisions (Tschirley et al., 2020). SSAM facilitates climate adaptation through timely operations and precision interventions such as moisture sensor–guided irrigation in drought-prone areas and conservation tillage that minimizes erosion during floods and dry spells (Kassie et al., 2020; Diao & He, 2019). It supports diversified cropping systems that reduce vulnerability to pests and climate shocks. Integrating digital advisories enhances proactive farm management based on real-time forecasts and agroclimatic data (Tschirley et al., 2020). On mitigation, SSAM enables reduced tillage, optimized nutrient management, and organic inputs that improve soil carbon sequestration and reduce chemical runoff (Giller et al., 2020; Paustian et al., 2018). Renewable energy–powered equipment, such as solar pumps and electric tillers, cuts fossil fuel dependency (Babagana et al., 2020). Mechanization also facilitates ecosystem-based practices such as agroforestry, cover cropping, and erosion control, contributing to biodiversity conservation and long-term carbon storage (Paustian et al., 2018).

14.3 Challenges and Strategic Roadmap for Adoption

Adopting small-scale agricultural mechanization (SSAM) in climate-vulnerable regions faces persistent barriers, including high costs, inadequate infrastructure, limited technical capacity, and socio-cultural resistance (Sheahan & Barrett, 2023). Smallholders often lack access to credit, spare parts, and repair services, while poor roads, unreliable electricity, and weak digital connectivity further constrain uptake, particularly in remote areas (FAO, 2016). Gender norms and skepticism toward new technologies also inhibit adoption, and fast-paced innovation risks obsolescence without strong local adaptation capacity. To address these challenges, SSAM and smart automated farming solutions must be embedded within broader innovation ecosystems that prioritize local design, skills development, and domestic manufacturing. Establishing machine standardization protocols, regional testing facilities, and accredited service providers is equally critical to ensure safety, performance, and long-term usability. Without structured after-sales ecosystems, even the best technologies risk abandonment. A strategic roadmap requires enabling policies combining smart subsidies, inclusive financing, and targeted R&D with expanded repair and maintenance networks and investment in rural infrastructure. Critically, scaling SSAM depends on mixed market models, where public, private, and community actors collaborate. When aligned with viable business models such as custom hiring centers and digital platforms, these approaches ensure accessibility, operational sustainability, and climate resilience.

14.4 Conclusion

Small-scale mechanization is critical for transitioning agriculture toward sustainability and climate resilience. It enhances productivity, reduces environmental impacts, and enables timely, adaptive responses to climate shocks. When integrated with smart technologies and inclusive policy frameworks, its adoption accelerates and benefits scale across regions. Realizing this potential requires targeted investment in rural infrastructure, local innovation, service ecosystems, and skills development. Ultimately, coordinated action among governments, private actors, and farming communities is essential to build resilient food systems that not only withstand climate challenges but also advance food security, livelihoods, and ecological stewardship for future generations.

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Chapter 15
Robotic Orchard and Greenhouse Fruit Harvesting Challenges and Future Trends

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Abstract Greenhouse and orchard fruit harvesting has posed a challenge due to being time-consuming and labor-intensive, the seasonal shortage of skilled laborers, and the aging workforce. The high demand for fresh market produce increases the demand for mechanized and robotic harvesting systems in greenhouses and orchards. Greenhouse automation applications have high demand due to their application success and the efficiency of fruit production. Despite significant development in greenhouse robotic applications, widespread use of state-of-the-art intelligent deep learning-based visual perception applications has yet to be applied at the field level. The trend of orchard architecture, changing and training fruit tree structure, resulted in high yield and easy management practices. Novel orchard architecture helps to replace conventional multi-degree robotic arms with smaller-degree canopy-specific multi-arm robotic systems. This chapter analyzes the existing greenhouse and orchard fruit harvesting systems by examining the appropriateness of novel, smaller-degree multi-arm systems linking with emerging concepts of digital twin and virtual reality application.

Keywords Harvesting robotic systems · Smaller-degree multi-arm systems · Digital twin · Virtual reality

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15.1 Introduction

Robotic applications in the agricultural sector are challenging (Wang et al., 2022) due to the uneven nature of plants and changes in environmental conditions. The ever-growing human population created a massive demand for global food production while creating challenges to increase productivity by 50% in the next 30 years (Peters et al., 2008; Davis et al., 2016). Agriculture requires skilled labor, which is currently in short supply (Luo & Escalante, 2017), and there is high demand during the harvesting season. Seasonal overseas labor force shortage is also a considerable factor in un-harvestable fruits, which is a waste in every harvesting season, especially in developed countries (Chandler, 2020). Moreover, manual harvesting operations create health problems for the workers due to the repetitive tasks (Jain et al., 2018). As a solution, introducing mechanical and robotic harvesting approaches can overcome these problems while increasing productivity.

Harvesting is significant in precision agriculture, followed by other management practices. The application of artificial intelligence in agricultural management practices paves the way for increased production and quality of orchard fruits (Zhang et al., 2019). Management practices that incorporate artificial intelligence and machine learning are being applied in various areas, including thinning pollination (Yağ & Altan, 2022), sorting (Zhang & Lu, 2021), and bagging (Wang et al., 2018).

Over the past few decades, significant research and development have been made for developing robotic applications (Bac et al., 2014) for harvesting fruits and trying to reach the commercial level by overcoming mechanical harvesting systems. Mechanical systems with electrohydraulic control systems developed at the beginning helped to harvest fruits in bulk by shaking the trees. Thus, recently it has been replaced by semi-automated and fully automated systems, which are more customizable, controllable, and traceable. Moreover, these robotic systems can be used to gather data and analyze it for future work. Collecting information like fruit ripeness, pose, position, and ripening time can be used for decision-making at the harvesting stage.

Developing electronic and sensing technologies to facilitate state-of-the-art detection networks, establishing methods for detecting individual fruits, and refining localization to improve robotic applications. Different detection algorithms have been developed for fruit detection based on image training, followed by robotic applications. Robotic harvesting systems are composed of sub-systems, the gripping mechanism (Zhang et al., 2020), a manipulator, controllers (Zhao et al., 2016a, b), a robotic transport unit (RTU), and a vision system (Tang et al., 2020). Thus, most of the robotic systems are site-specific, which is one barrier that hinders the widespread use of orchard harvesting robots.

Moreover, with the development of robotic systems, fruit tree structures are genetically modified and trained to have a uniform tree architecture. Additionally, this helped develop robotic systems based on fruit tree architectures, which are less complex than traditional robotic systems. Meanwhile, tree management is easy and leads to high yield. However, the occlusion from fruits, leaves, and branches causes limitations for robotic applications; thus, fruit orientation, overlapping of fruits due to fruit clusters, illumination variations, and dark spots in the canopy also affect (Abeyrathna & Ahamed, 2024). Consequently, some of the robotic harvesting research has been used on industrial manipulators equipped with custom-made grippers. Thus, some of the studies have used custom-made manipulators and grippers to optimize the applicability based on plant architecture and fruit orientation.

This chapter will provide an overview of current trends in fruit harvesting robotic systems, especially novel applications of lower-degree multi-arm robotic systems, and insights on improving efficiency while avoiding damage to greenhouse and orchard fruits.

15.2 Greenhouse Fruit Harvesting Robotic Applications

Greenhouse plant management (protected cultivated systems) requires skilled laborers; recent research has been conducted on robotic crop harvesting in greenhouses as an alternative to human labor (Arad et al., 2020). Usually, greenhouse fruit production focuses on high-value crops such as sweet peppers, strawberries, and tomatoes, to optimize production systems with limited resources. Compared with field conditions, greenhouse crop cultivation is less affected by environmental condition variations by providing favorable conditions for optimum plant growth (Shamshiri et al., 2018; Benavides et al., 2020). Greenhouse fruit harvesting requires a large amount of labor cost, compared to the total labor cost, around 30% of the total production cost (van Henten et al., 2002).

Fruit production in greenhouses follows a unique plant arrangement style, which helps develop robotic applications for repetitive tasks (Zhao et al., 2019). Also, greenhouse robotic applications protect human workers from hazardous environments like chemicals, dust, and humidity. Some robotic systems developed and tested in greenhouse conditions for fruit harvesting are listed in Table 15.1.

The abovementioned robotic systems showed the potential of robotic applications for greenhouse operations. Some robotic systems were mounted on a rail system, and some have independent navigation systems. The rail-mounted robotic platforms were easy to guide and move through the entire greenhouse area; most guided rails are based on either heat or nutrient-flowing tubes. Moreover, in some cases, the navigation trajectories are predefined inside the greenhouse (Tangarife & Diaz, 2017). Robotic systems with independent navigation systems have a navigation system based on a vision camera or LiDAR sensors.

The greenhouse plants are arranged in a row and have unique plant structures where researchers can apply multi-arm lower degrees of robotic manipulation options (Fig. 15.1) instead of complex robotic applications. The proposed wheel-mounted platform consists of two manipulators with 3-DoF and a gripper. Most of the developed greenhouse fruit harvesting robotic systems were based on already developed industrial manipulators; thus, these can be replaced with custom-made manipulators to reduce the overcomplicacy of the system.

Table 15.1 Summary of some of the greenhouse fruit harvesting robots

Fruit	Mechanisms	Reference
Sweet pepper	(Fanuc LR Mate 200iD) It is a 6-DoF industrial robotic manipulator with a custom-designed gripper and a cutting mechanism. It has a success rate of up to 61%.	Arad et al. (2020)
Sweet pepper	Compare two different types of end effectors—29% success rate. 1. Four-finger end effector with Fin Ray effect for gripping fruits, including a scissor-like cutting mechanism. 2. Lip-type end-effector, suction cup to hold the fruit, and circular blade to cut the peduncle. The vision system has one ToF camera and a color camera custom manipulator design.	Bac et al. (2017)
Sweet pepper	The suction cup-based end-effector and oscillating blade design failed to attach to the suction cup due to leaf obstructions and irregular shape. The UR10 manipulator had a 92% success rate.	Lehnert et al. (2017)
Sweet pepper	An image-based closed-loop control system, three cameras were used for the vision system (BFLY-U3-13S2C-CS model-FLIR), and laser light was used to identify the characteristics of red pepper. Pose-control end effector with a custom cutting mechanism. Custom manipulator.	Lee et al. (2019)
Sweet pepper	A new robotic harvester (Harvey) with a novel end-effector design with suction and cutting mechanisms. 76.5% success rate based on 68 fruits. UR10 manipulator.	Lehnert et al. (2020)
Sweet pepper	Harvey—The improved version introduces a novel peduncle segmentation system with an efficient CNN. Cutting location detection is based on three-dimensional post-filtering.	Sa et al. (2017)
Tomato	6-DoF (UR3) manipulator arm, custom-designed gripping/ scissor-shaped cutting end-effector, DL to detect peduncles in ripened tomatoes. A suction pad featuring the kirigami pattern (Jetson TX2 controller)	Jun et al. (2021)
Tomato	Four-wheel independent steering system, Ackerman steering, laser navigation control base system, 5-DoF robotic system, binocular stereo vision, Otsu algorithm, and the elliptic template method for ripe tomato recognition.	Lili et al. (2017)
Tomato	3-DoF has two manipulators, two different types of end effectors, and an Ether-CAT bus-based control and communication system.	Zhao et al. (2016a, b)
Tomato	Dual-arm cooperative approach, binocular vision, tomato detection algorithm with AdaBoost classifier, vacuum cup grasping.	Ling et al. (2019)
Tomato	Four-finger mechanical vacuum gripping.	Vu and Ronzhin (2019)
Tomato	Stereo camera-based, 60% success rate, evaluated in a semi-outdoor environment, 6-DoF UR5, three-finger gripping mechanism.	Yaguchi et al. (2016)
Strawberry	Cable-driven 6-finger gripper, RV-2AJ manipulator, 96.8% success rate for isolated single strawberries.	Xiong et al. (2019a)

(continued)

Table 15.1 (continued)

Fruit	Mechanisms	Reference
Strawberry	A single-rail multiple Cartesian arms, two end effectors, a vision system RGB-D camera, a 3-clamp gripper, and up to 97.1% success rate of isolated strawberries.	Xiong et al. (2019b)
Strawberry	Custom manipulator with 3-DoF, soft finger gripping mechanism, mounted on a mobile platform for autonomous navigation.	De Preter et al. (2018)
Cherry tomato	Additional features include a 3-DoF manipulator and a custom-made two-finger gripping mechanism.	Taqi et al. (2017)
Cherry tomato	Mounted on a railed vehicle, an 83% success harvesting rate, a 6-DoF manipulator (Denso VS-6556G), and an end effector with two fingers attached with a cutting mechanism.	Feng et al. (2018)
Cherry tomato	The continuum robot structure (TakoBot) has a recognition accuracy of 96%. The end effector consists of two semi-spherical shapes attached to cutting blades.	Yeshmukhametov et al. (2022)

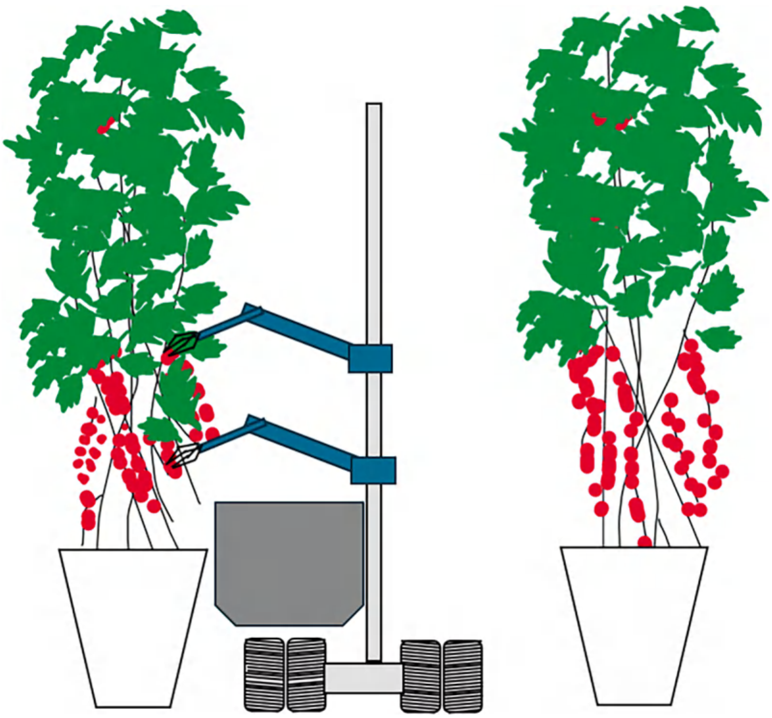

Fig. 15.1 Cherry tomato harvesting robotic system for greenhouse operations

Moreover, guiding or navigation robotic systems inside greenhouses are easier than outside orchard conditions, due to fewer disturbances. The greenhouse robotic systems can be mounted on the greenhouse roof or rail-guided support from the roof (Fig. 15.2). This kind of system can be used to perform different management practices in the greenhouse. Since the moving path is fixed, robotic manipulation can be simplified. The roof-mounted system with bottom guidance wheels will not disturb the moving area between plants, which is another advantage over the floor rail guidance robotic systems.

However, overcoming leaves, branch occlusions, diverse postures of the plants, and different sizes of the fruits are still challenging even in greenhouse conditions. One of the challenges was overcoming the leaf occlusions. There were several studies conducted to overcome this occlusion problem with multi-arm robotic applications by allocating another robotic arm to remove leaf occlusions, small branches, and fruit clusters. In contrast, another robotic arm approached the isolated fruits. In addition, another remediation management practice is fruit, flowers, and leaves thinning, which helps to overcome the fruit clusters and occlusion problems.

Most robotic harvesting gripping mechanisms were developed to harvest single fruits, and fruit clusters hinder grasping operations. Also, in terms of fruit quality and size, thinning fruits, flowers, and leaves can improve the quality of the harvestable fruits. Developing fruit, flower, and leaf-thinning robotic platforms can enhance the applicability of harvesting robotic systems, especially in greenhouse environmental conditions. As we presented in our previous chapter, vision system detection and localization angle of fruit can avoid some of the occlusion by approaching

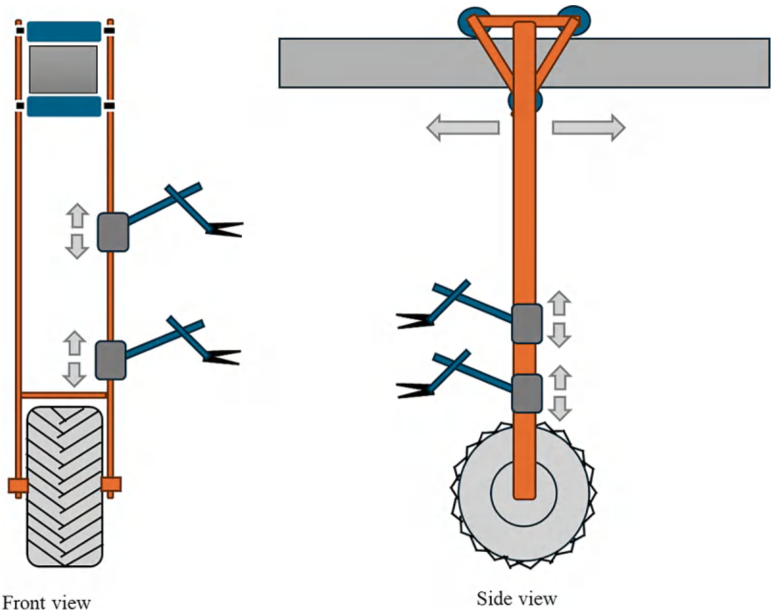

Fig. 15.2 Wheel-mounted top rail guided robotic system

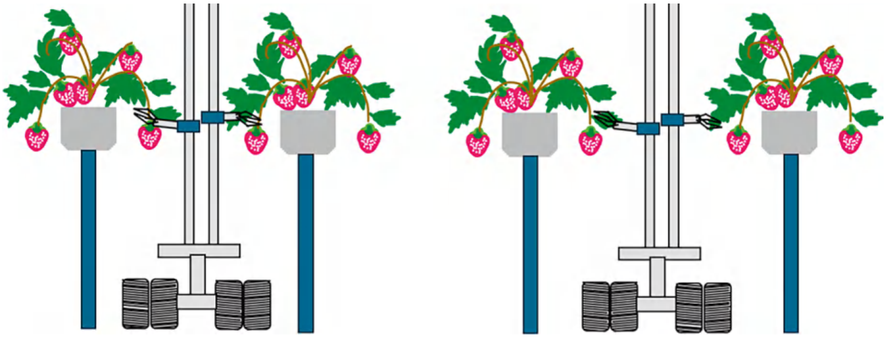

Fig. 15.3 Greenhouse strawberry harvesting robotic system with lifted plant system

different direction (Abeyrathna & Ahamed, 2024). Consequently, another study has been conducted to harvest apples with a horizontal picking attitude of the three-claw end-effector. And the apple picking test demonstrated an 82.21% success rate for an obstacle avoidance posture angle of 43°, downward picking with an obstacle-avoidance posture angle of 49°, 57.9% success rate (Zhao et al., 2025). This concept can be applied for greenhouse and orchard harvesting systems.

Another way forward for robotic applications in greenhouse systems is changing the plant arrangement. Figure 15.3 shows the strawberry harvesting robotic application. Arranging strawberry plants over the ground at a certain height creates space for multi-armed robotic systems to reach the harvestable strawberries easily.

15.3 Orchard Harvesting Robotic Applications

Applying multi-arm lower-degree robotic systems for orchard fruit harvesting is a challenging task, thus making it more critical and necessary than conventional robotic applications. Over the past few years, different robotic harvesting systems have been introduced, and multi-arm systems have become more popular, showing that the harvesting efficiency can be improved. In this section, we are more focused on the insights into possibilities for applying lower-degree multi-arm robotic systems for orchard fruit harvesting.

Kiwi fruit, apple, grape, orange, and citrus are the most famous orchard fruit crops that require a vast labor force during harvesting. These orchard fruit crops already have mechanical harvesting systems, semi-automated human-assisted systems, and robotic applications. Most robotic systems are designed for picking isolated fruits, which is possible and can be improved by using multiple arms. Figure 15.4 shows the multi-arm robotic systems for harvesting kiwi fruits, which have been developed up to commercial level (Jones et al., 2019; Williams et al., 2019).

The development of state-of-the-art detection networks combined with machine learning has recently enabled multi-arm robotic systems to manipulate each robotic

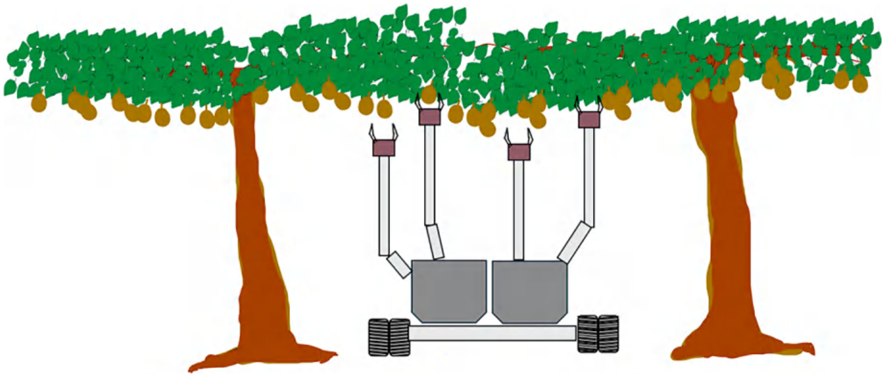

Fig. 15.4 Kiwi fruit harvesting multi-arm robotic system

arm independently, reaching the target and localizing fruit separately. Table 15.2 illustrates the recently developed multi-arm and single-arm applications for orchard applications.

Similar to the arrangement and development of greenhouse plant architecture, the orchard canopy was developed to reduce complexity. However, since the orchard has a large cultivation area, managing the canopy requires considerable effort. Figures 15.5 and 15.6 show the strawberry and apple field architecture arrangement for higher production. Outside environmental conditions are different and change quickly, leading failure of robotic applications. Moreover, these failures are basically due to detection and localization coordinate errors from 3D cameras. The deep learning algorithms are trained based on the color and shape of the harvestable fruits, and variations of lights and shadows cause False positives/unripe fruit to be considered harvestable.

The developed canopy architectures give robotic arms more unique ways of approaching the target fruits, one of the key features of orchard architectures that helps to develop custom robotic arms. Most of the developed robotic systems are based on industrial-grade manipulators, which require additional application strategies. Another key development is the use of a soft-gripping mechanism to avoid bruising to the fruit surface. Silicon finger-based grippers can grip the fruit without damaging it, and pressure sensors and tactile sensors help identify the amount of force exerted on the fruit surface.

The application of vacuum-based suction grippers showed promising results, where a single suction gripper can hold fruit and rotate and drag it toward the harvesting robot for easy pickup. Most of the orchard harvesting robotic research has used custom gripping mechanisms after studying fruit surface characteristics. Consequently, while developing multi-arm robotic systems, the gripper plays a key role in detaching the fruit at different angles. Orchard robotic systems need high-speed fruit picking to keep their productivity. Figures 15.7 and 15.8 show the application of a multi-arm robotic application for strawberries and papaya harvesting.

Table 15.2 Summary of some of the orchard fruit harvesting robots

Fruit	Mechanisms	Reference
Kiwifruit	Multi-arm (four robotic arms), 3-DoF custom manipulators, soft two-finger gripping mechanism, for pergola-style orchards, 51% success harvesting rate.	Williams et al. (2019)
Kiwifruit	The gripping mechanism consists of bionic fingers with fiber sensors, a 3-DoF manipulator (CF3-3), and a 94.2% success rate in picking.	Mu et al. (2019)
Apple	Applied to the orchard planar canopy, a 7-DoF harvesting system, attached with a three-finger gripper, achieved an 84% success harvesting rate.	Silwal et al. (2017)
Apple	Dual-arm, 8-DoF kinematically redundant picking system, 3-finger gripper with catching device, implemented pick-and-catch harvesting method to reduce harvesting time.	Davidson et al. (2017)
Apple	5-DoF custom manipulator, 3D-printed pneumatic soft-robotic end-effector for apple separation, 67% detachment successes.	Hohimer et al. (2019)
Apple	6-DoF UR3 manipulator, 4-finger gripping mechanism, Single Shot MultiBox Detector for detecting the position, 90% fruits were detected.	Onishi et al. (2019)
Apple	Analyzed basic picking patterns—horizontal pull, vertical tension, picking model dynamic simulation, horizontal and vertical velocity forces based on response surface methodology, using a bowl-shaped gripper.	Bu et al. (2019)
Grape	7-DoF manipulator, Jaco 2 Kinova, two-finger gripper with cutter, consists of three units: an aerial unit, a remote-control unit, and an autonomous grape harvesting robot, multi-purpose.	Vrochidou et al. (2021)
Orange	6-DoF ARC Mate manipulator, a hybrid multi-gripping apparatus, gripping based on four finger grippers with vacuum and tactile forces, rotational and pulling mechanisms, up to 95% harvesting success.	You and Burks (2016)
Citrus	6-DoF AUBO-i5 robotic arm, Bite mode snake head mechanism gripper, optimal harvesting posture 46° in natural environmental conditions, up to 89% average cutting success.	Wang et al. (2019)

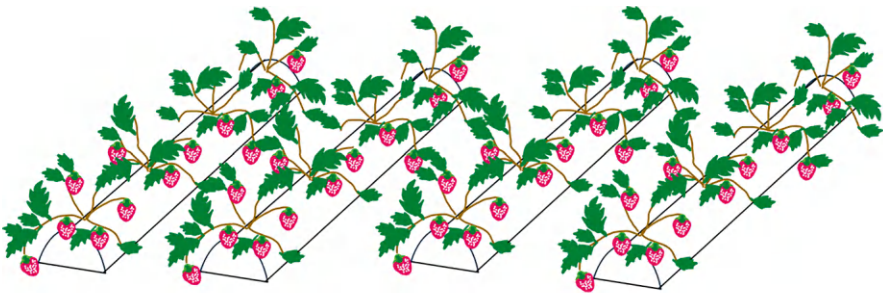

Fig. 15.5 Strawberry field arrangement for harvesting robots

Papaya, pineapples, oranges, and bananas are grown in a row manner for easy management, where harvesting can be automated. As some of these fruits need special robotic arms to handle heavy loads, handling them safely is critical. These areas

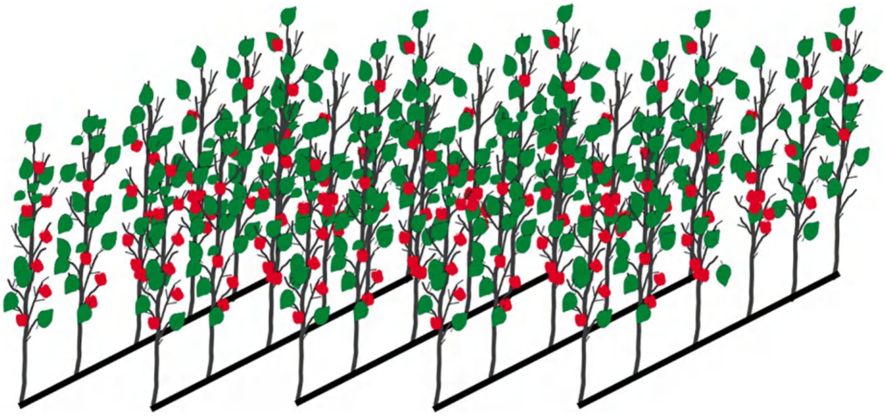

Fig. 15.6 Approaches of smaller DoF robots for manipulating fruit canopies

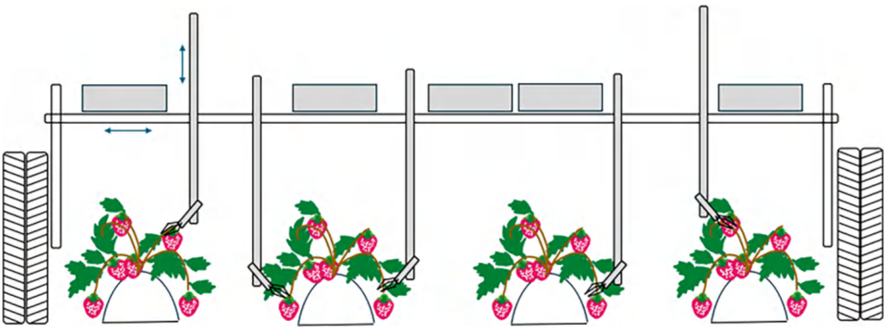

Fig. 15.7 Multi-arm strawberry harvesting system

of research need more attention and development of deep learning applications to improve productivity by reducing pre-harvest and post-harvest losses.

15.4 Discussion

Skill labor shortage and harvesting operational cost create the necessity for the application of mechanical harvesting operations, followed by the robotic application for automation. The development of robotic systems has become reliable over time, significantly due to the development of orchard systems and greenhouse crop growing patterns. Over the past few decades, robotic systems have been developed to fit existing plant growing patterns, which was a massive challenge due to the unstructured plants. The design and development of algorithms focused on finding target fruits and navigation of fruit detaching mechanisms. As this chapter indicates,

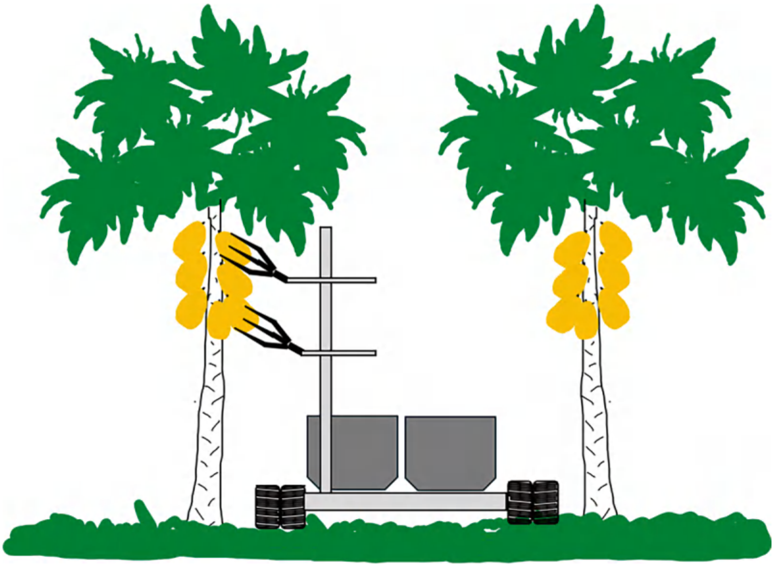

Fig. 15.8 Multi-arm papaya harvesting system

developing novel plant growing patterns plays a massive role in developing automated fruit harvesting systems.

Robotic applications' vision systems play a significant role, with the development of 3D cameras and LiDAR features creating an application of real-time data in a destructive environment, more clearly paving the way to designing robotic applications toward automating farming activities. Moreover, with the support of the sensors and actuators, novel deep learning applications are becoming more reliable and transferring the farm management application into more autonomous ones, especially the harvesting applications. Variation of lights and shadows from fruits, leaves, and branches is the key problem faced by the detection system. However, with the development of computational power and sensor integration, new concepts can be applied to field robotics.

One of the key technologies is the digital twin, where a simulated environment is created based on sensor data. It especially updates the system with real environmental changes. The farmers can make their decisions based on a simulated environment, and for the field and greenhouse harvesting robotics can plan the trajectory operations more precisely (Fig. 15.9).

The digital twin concept can be linked with virtual reality, where farmers and researchers can see the simulated field conditions in real time. In addition, another key update is to use the dual-arm concept to address occluded fruits and fruit clusters, which single robotic arms cannot or fail to address (Fig. 15.10).

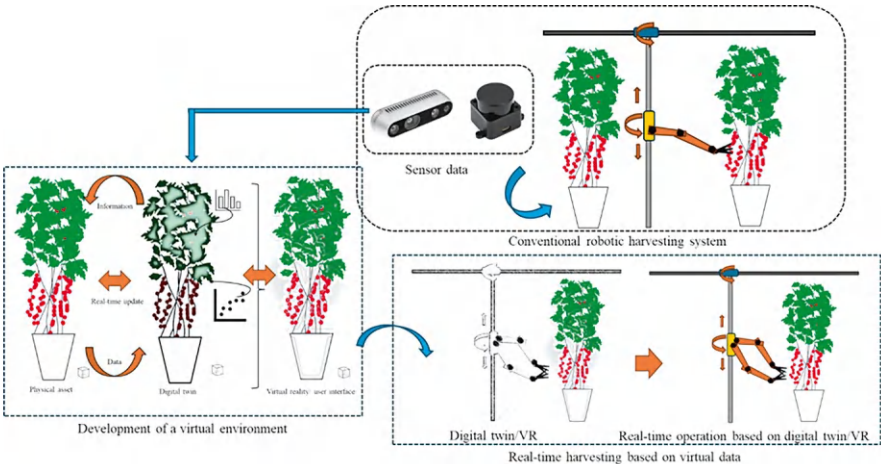

Fig. 15.9 Application of digital twin and virtual reality for greenhouse cherry tomato harvesting

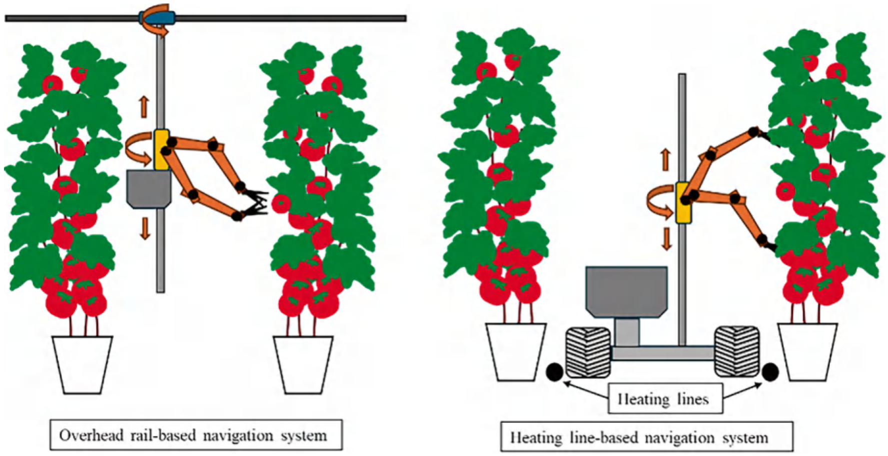

Fig. 15.10 Application dual-arm system for occluded fruits and handling fruit clusters

15.5 Conclusion

Greenhouse and field robotics are challenging, and the development of novel visual perception sensors and other sensors changes the way robotic applications. Shortage of skilled labor and a seasonal workforce, demand for fruits, and the requirement for quality fresh products stress the need for robotic applications. Conventional robotic designs consist of a single robotic arm with a custom-made gripping mechanism, which face challenges while handling occluded fruits and fruit clusters, and also have concerns with the efficiency of the system. These factors lead to the development of a multi-arm robotic system with lower degrees of freedom, custom-made manipulators with a gripping mechanism, especially for newly developed fruit canopy architectures. Moreover, dual-arm robotic systems that mimic human hand behavior are one of the key features to address fruit clusters and avoid occlusions. The digital twin concept integrated with virtual reality can lead to a new era of robotic system development.

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Chapter 16
Small-Scale Automatic Seed and Fertilizer Broadcasting Machinery: Perspective and Future

Arkar Minn and Tofael Ahamed

Abstract Fertilizer application in agriculture is one of the essential operations, not only for open-field cultivation but also for orchards and indoor cultivation. Broadcasting techniques can be used not only for seeding but also for fertilizer applications. Small-scale farmers in developing countries need to develop their farming operations through mechanization. Moreover, the agriculture sector faces difficulties such as climate change and skill-labor shortage, so farming operations need to be done promptly and skillfully. To solve these problems, machinery and automation have become important in the modern era. Therefore, this chapter explores the development of small-scale seed and fertilizer broadcasting machinery with the scope of automation. The current and prospective seed broadcasting technologies were also discussed to highlight the gap between existing machinery and the appropriate seed broadcasters required by small-scale farmers in developing countries to enhance agricultural productivity.

Keywords Small-scale · Seed and fertilizer broadcasting machinery · Automation · Design · Modification · Development

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16.1 Introduction

Planting and sowing applications in agriculture are essential operations, not only for open-field cultivation but also for orchards and indoor cultivation. In these applications, direct seeding methods can be done with less labor and used in dryland and wetland fields (Minn et al., 2023). Several types of direct seeding techniques exist, such as drilling, dribbling, broadcasting, banding, etc. Broadcasting is a popular technique because of its advantages and is widely used, especially in Southeast Asian countries (Minn et al., 2023). Broadcasting techniques can be used not only for seeding but also for fertilizer applications. Manufacturers still produce fertilizer broadcasting machines globally, which are intended for a wide range of area coverage. Smallholder farmers, especially in developing countries, must establish their farming operations through mechanization. Moreover, the agriculture sector faces difficulties such as climate change and skill-labor shortage, so farming operations need to be done promptly and skillfully. To solve these problems, machinery and automation have become important in the modern era. For that reason, this chapter explores the development of small-scale seeds and fertilizer broadcasting machinery with the scope of automation.

16.2 Seed and Fertilizer Broadcasting Machinery: Present and Perspective

Broadcastseeding is used with equipment-mounted seed broadcasters, aerial broadcasting, and hand-broadcasting (Shaw et al., 2020). Seed broadcasting machinery has led to a 30% increase in crop productivity and a 20% reduction in the input cost by the farmer globally (Mordor Intelligence, 2018). Enhancement of these advantages, from large-scale farmers to small-scale farmers in the mature market, such as North America and Europe, has been significantly adopted on seed drills and broadcast seeders, but still low demand in emerging markets such as Asia-Pacific and Africa (source: Mordor Intelligence). That information shows that most countries in the Asia-Pacific and Africa regions are developing countries, and farmers still use their operations manually. Some of the following inventions were collected during the development of broadcast seeders globally. As the fertilizer broadcast machinery, there were many choices according to the size of cultivated areas, planning types, etc. A wide range of seed and fertilizer broadcasting machinery is available, catering to different farm sizes and needs. The following are the different broadcast spreaders available in the markets.

16.2.1 *Manual-Type Broadcast Spreader*

Hand-Held Broadcast Spreader
This type of broadcaster is portable, easy to use, and suitable for small-scale plots. It is mainly used in small lawns, tight spaces, or spot treatments. Some are operated manually, as cranked, while others are battery-powered (Fig. 16.1a, b).

Wheel Burrow-Type Broadcast Spreader
This type of broadcaster is known as a lawn broadcaster and is widely used in lawn and home gardens (Fig. 16.2). These are pushed by hand and are suitable for medium- and large-sized lawns.

16.2.2 *Equipment-Mounted Broadcast Seeder*

Tractor-Mounted Type
Tractor-mounted broadcasters are developed and widely used in agriculture. Farmers use this broadcaster not only to spread fertilizer but also to broadcast the seeds. Many categories and size selections depend on the needs of the operations. The following are the types of tractor-mounted broadcast seeders that are widely used in agriculture.

(a) ***Spinner Type***

This type of broadcaster is widely used in agriculture (Fig. 16.3). The advantages of this type are that it is simple to operate, easy to maintain, and cheaper than others. Many selections are available according to the operations, such as hopper shape, single or dual spinner, agitating mechanism, vane shape, deflector, disc size and shape, etc. The tractor's PTO shaft drives spinners, and some of the broadcasters come with an ISOBUS system, which can use Variable Rate Application (VRA)

Fig. 16.1 (**a**) Cranked-type hand-held broadcaster. (**b**) Battery-powered hand-held broadcaster

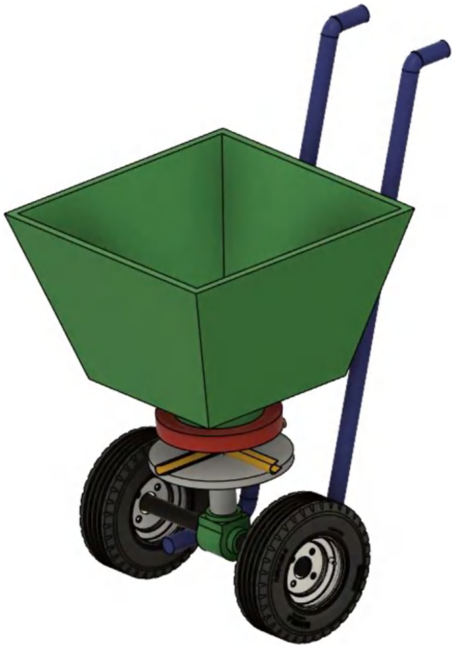


Fig. 16.2 Lawn broadcaster

Fig. 16.3 Spinner-type tractor-mounted broadcaster

with the combination of Real-Time Kinematic Differential Global Positioning System (RTK-DGPS) for precise operations.

(b) ***Pendulum Type***

Pendulum-type broadcasters, also known as pendulum spreaders or swinging spout spreaders (Fig. 16.4), are known for their balanced patterns, with minimal skewing from side to side (Parish, 2004). These types of broadcasters are valued for their even spread patterns, application versatility, and ability to handle various granular materials effectively, often with less sensitivity to wind. They are common choices in agricultural settings, particularly for tasks requiring precision and adaptation.

(c) ***Self-propelled Type***

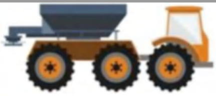
Self-propelled seed and fertilizer broadcasters have become popular in the market, and size and power sources can be selected according to the operations. This type of spreader has its own engine or motor to provide movement, eliminating the need for manual pushing or towing by a separate vehicle. These are typically used for larger areas or when consistent speed and application are critical.

Self-propelled spreaders come in various forms (Table 16.1), often categorized by their size and application:

(i) Walk-Behind Self-Propelled Spreaders: These are larger and more robust versions of walk-behind spreaders, featuring a motor to drive the wheels. This

Fig. 16.4 Pendulum spreader

Table 16.1 Various types of self-propelled spreaders

Walk-behind	Stand-on	Ride-on	Agricultural self-propelled spreaders
			
Larger and more robust versions Motor drive Easy and more consistent Uneven terrain Adjustable speed settings	Stand on a platform Can perform with liquid spraying functions	Large machine Suitable for very large turf areas Higher capacity hoppers Wider spread widths	Large, specialized vehicles designed GPS guidance VRA technology

makes spreading easier and more consistent over medium to large lawns, especially on uneven terrain. They often have adjustable speed settings.

(ii) Stand-On Self-Propelled Spreaders/Sprayers: These units allow the operator to stand on a platform, while the machine moves and spreads material. They often combine spreading capabilities with liquid spraying functions, making them versatile for lawn care professionals.

(iii) Ride-On Self-Propelled Spreaders: These are larger machines with seats for the operator and are suitable for very large turf areas like golf courses, sports fields, and expansive commercial properties. They offer higher capacity hoppers and wider spread widths.

(iv) Agricultural Self-Propelled Spreaders: These are large, specialized vehicles designed for the broad-acre application of fertilizers, seeds, and other granular materials in farming. They often feature sophisticated GPS guidance, Variable Rate Application (VRA) technology, and high-capacity hoppers. These can be either spinner (rotary) or pendulum type broadcasters.

The following are the key features and advantages of self-propelled broadcasters:

Reduced Labor: Eliminates the physical effort of pushing a spreader, making the job easier and less fatiguing, especially over large areas.

Consistent Speed: The motorized drive ensures a more uniform walking or driving speed, which is crucial for accurate and even application of materials.

Larger Capacity: Self-propelled units often have larger hoppers, allowing more material to be carried and reducing the frequency of refills.

Wider Spread Widths: Many self-propelled models offer wider spread patterns, covering more ground in each pass and increasing efficiency.

Precision Application: Features like adjustable speed, precise flow rate controls, and sometimes GPS integration allow for more accurate material application, reducing waste and improving results.

Versatility (in some models): Some self-propelled units, particularly stand-on models, can combine spreading with other functions like liquid spraying.

Operator Comfort: Ride-on and stand-on models improve operator comfort, especially during long periods of use.

Self-propelled broadcasters offer a significant advantage in efficiency, ease of use, and accuracy for spreading granular materials over larger areas. The specific type of self-propelled broadcaster will depend on the scale of the job and the features required.

16.2.3 Aerial Seed and Fertilizer Broadcasting

This method has been developed by attaching seed or fertilizer boxes and distributors to unmanned aerial vehicles (UAVs). Currently, UAVs are widely used in agriculture to monitor and control plants and distribute seed and fertilizer applications (Qi et al., 2022). Several significant advantages of UAVs usage in agriculture, such as reducing hard work, costs, and resource requirements, give these techniques potential in agriculture, especially in developing countries (Jibon et al., 2023).

16.3 Considerations for the Development of Small-Scale Autonomous Seed and Fertilizer Broadcasting Machinery

Most machinery markets in agriculture are not intended for small-scale farmers (Minn & Ahamed, 2023). To develop the livelihood of the small-scale farmers, their farm productivity needs to increase. Small-scale farmers cannot reach modern farm machinery, so local production of farm machinery is the best way to fill these gaps. Thus, the main goal of this development is to fulfill the need for efficiency, cost-effectiveness, and adaptability for small-scale farmers. Here are some considerations for developing small-scale autonomous broadcasting machinery in agriculture.

16.3.1 Platform Design

Drive System Wheeled or tracked platforms can be chosen depending on the soil conditions and environment. Rubber tires are the common choice in the wheeled platform, but narrow wheels or lug wheels are also selected, especially on inter-row or sticky soil conditions. Rubber track platforms are the type that should be chosen in terrain environments, sticky or muddy fields, and orchards. All-Wheel Drive (AWD) systems, such as Omni-wheel, are a suitable choice for vehicle path-planning and control, especially in small electric UGVs (Unmanned Ground Vehicles), because of their holonomic motion planning (Ahamed et al., 2014). Most of the vehicles in agriculture are Two-Wheel Drive (2WD) and Four-Wheel Drive (4WD); non-holonomic motion planning can be used on those machines for unmanned transformation or modification (Ahamed et al., 2014).

Inter-Row Operations and Short-Turning Radius Platform design should consider all field conditions. Automatic or mechanical lifting systems can be chosen on the variable-height inter-row design development (Fig. 16.5). For the short-turn, four-wheel steering can reduce the turning radius of the machine (Singh et al., 2014). Regarding car-like steering, rear-wheel steering enables a vehicle to achieve a tighter turning radius than front-wheel steering (Kasliwal, 2019), regardless of whether it was a front-axle or rear-axle drive vehicle.

Compact and Lightweight Platform designs should be compact and lightweight for easy maneuverability and transport.

Modular Design Implement a modular design to allow for easy attachment and detachment of different seed and fertilizer dispensing units. Three-point linkage is one of the options for the rear attachment system, and P.T.O (power take-off) functions and auxiliary hoses for electric or hydraulic power should be incorporated for rear implements. If the design follows the global standard, such as ISO 11783 (commonly referred to as "ISOBUS"), the vehicle can serve as a prime mover (Paraforos et al., 2019).

16.3.2 Autonomous Navigation

GPS-Based Navigation Precise positioning and navigation can be enhanced by integrating a GPS module. Global navigation satellite system (GNSS) integrated modules with higher accuracy and lower cost are available globally (Minn & Ahamed, 2023).

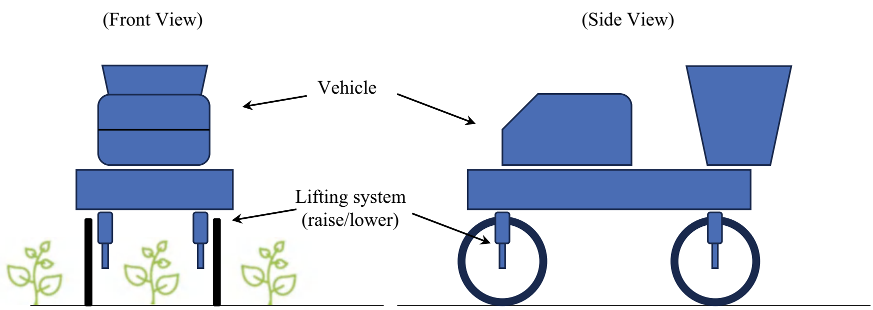


Fig. 16.5 Adjustable height system for inter-row machine operation

Obstacle Avoidance One of the goals of farm automation is to ensure safe operation. Obstacle detection and avoidance can be made by incorporating sensors such as cameras, ultrasonics, LiDAR, etc. (Ahamed et al., 2014).

Pre-programmed Paths Pre-programming of field boundaries and desired patterns and paths can reduce machine time and increase productivity (Bai et al., 2023). This is a good adaptation not only to create the path but also to analyze the machine operations. By planning the optimal route and operation sequence, machinery can operate more efficiently, minimizing wasted movement and maximizing coverage (Höffmann et al., 2023).

16.3.3 Seed and Fertilizer Dispensing

Adjustable Dispensing Rates Design mechanisms for adjusting seed and fertilizer dispensing rates to suit different crops and soil conditions.

Uniform Distribution Ensure uniform seed and fertilizer distribution across the field to maximize yield.

Seed and Fertilizer Separation The design needs to consider separate hoppers and dispensing mechanisms for seed and fertilizer to allow simultaneous or individual applications.

16.3.4 Power Source

Modification of the existing design is the proper solution for small-scale farmers. Selection of the battery is a suitable solution for a new design, but battery life and charging time need to be considered for continuous operations. Integrating solar power to supplement battery power is an alternative solution.

16.3.5 User Interface

Simple and intuitively designed machines can get higher demand from small-scale farmers. Design needs a user-friendly interface for program editing, repair, maintenance, and machinery control.

Remote Control In existing machine development, incorporating remote control capabilities for manual or adjustment is particularly beneficial for small-scale farmers.

16.3.6 Cost-Effectiveness

Locally Sourced Materials Utilization of locally sourced and readily available materials for machine development can reduce costs.

Simple Design To minimize production costs, keep the design simple and easy to manufacture. Simple substitution and modification methods should be selected with low-cost, high-performance products in modifying the existing design.

16.3.7 Adaptability

Versatility Design a mechanism system adaptable for different types of seeds and fertilizers. If the system uses specific mechanisms for specific types of seeds or fertilizers, interchangeable mechanisms should be adapted.

Terrain Adaptability The design should ensure the machine can operate on various terrains and field conditions. Depending on the region and field conditions, such as hillside (Fig. 16.6) or narrow-field conditions, adjustable or articulated chassis is the option for structure design.

16.3.8 Safety Features

Safety instructions for the machine and emergency procedures must be included in the machine manual. Additionally, warning signs must be clearly displayed on the machine. Covers and protective materials must be fitted, especially in rotating mechanisms such as universal joints.

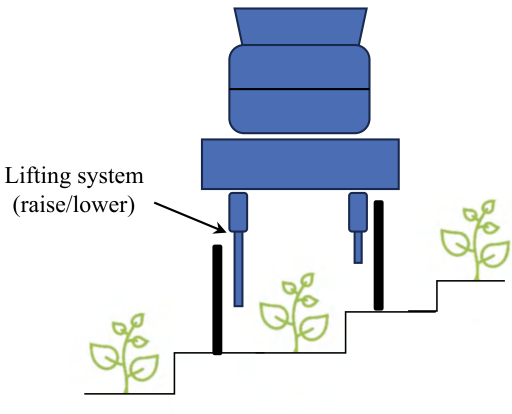


Fig. 16.6 A vehicle adjustable lifting system for hillside operations

Fig. 16.7 Warning light tower implemented small-scale autonomous seed broadcasting vehicle (University of Tsukuba, Ibaraki, Japan)

Emergency Stop Implement an emergency stop mechanism for immediate halting of the machinery in case of any issues.

Safety Sensors Integrate sensors to detect potential hazards and prevent accidents. Additionally, warning and alarm systems such as warning siren lights, light towers (Fig. 16.7), and buzzers must be considered for complete design features.

16.3.9 Testing and Validation

Field Trials Conduct thorough field trials to test the performance and reliability of the machinery under real-world conditions.

User Feedback Gather feedback from farmers to identify areas for improvement and make necessary modifications.

16.4 Challenges in the Development of Small-Scale Seed and Fertilizer Broadcasting Machinery

Developing small-scale autonomous seed broadcasting machinery presents several challenges, especially in making these technologies accessible and practical for farmers in developing regions. Here are some of the key hurdles.

16.4.1 Technical Challenges

- Precision Control: Achieving uniform seed distribution across different terrains and crop types requires sophisticated mechanisms and sensor integration.
- Sensor Calibration: Accurate calibration of positional sensors like RTK-GNSS is essential for reliable operation but can be complex for small-scale applications.
- Multi-crop Compatibility: Designing systems that can handle various seed sizes and shapes (e.g., green peas, cowpeas, chickpeas) without jamming or inconsistent flow is technically demanding.

16.4.2 Economic Barriers

- *High Initial Costs*: Many existing broadcasting seeders are too expensive for small-scale farmers, limiting adoption despite their potential benefits.
- *Limited Local Manufacturing*: A lack of locally available components and fabrication facilities can drive up costs and reduce accessibility.

16.4.3 Knowledge and Training Gaps

- *Low Technical Literacy*: Farmers may lack experience with automation, sensor systems, and data transmission, making it difficult to operate and maintain these machines.
- *Need for Customization*: Machines often require region-specific adjustments based on soil type, crop variety, and farming practices.

16.4.4 Design and Fabrication Issues

- *Durability* vs. *Cost*: Balancing low-cost materials (like 3D printed components) with durability and field-readiness is a persistent challenge.
- *Power Supply Management*: Ensuring consistent power for motors and sensors, especially in remote areas, can be problematic.

16.4.5 Socioeconomic and Policy Constraints

- *Limited Infrastructure*: Poor rural infrastructure can hinder the deployment and servicing of autonomous machinery.

- *Policy Support*: Lack of government incentives or subsidies for small-scale automation slows innovation and adoption.

16.5 Future Perspectives and Conclusion

The future of seed and fertilizer broadcasting machinery is closely linked to the advancements in precision agriculture, automation, and sustainable farming practices. Here are some key perspectives.

Enhanced Precision and Variable Rate Technology (VRT) Future broadcasters will likely see even more sophisticated integration of sensors, GPS, and data analytics (Alahmad et al., 2023). This will enable real-time monitoring of soil conditions, nutrient levels, and seeding density, allowing for precise, variable-rate application of seeds and fertilizers (Bixapathi Nayak et al., 2024). VRT will optimize resource use, reduce waste, and improve crop yields by tailoring application to specific needs within different field zones.

Autonomous Operation The trend towards autonomous farm equipment will extend to broadcasting machinery (Wei et al., 2024). Self-driving spreaders and robotic swarms could operate with minimal human supervision, increasing efficiency and reducing labor costs.

Improved Material Handling and Metering Future designs will focus on more accurate and consistent metering systems to handle a wider variety of seed and fertilizer types, including those with irregular shapes or flow characteristics. This will ensure uniform distribution and prevent clogging.

Integration with Digital Farming Platforms Broadcasting machinery will be increasingly connected to farm management information systems (FMIS) and cloud-based platforms (Fountas et al., 2015). This will allow seamless data sharing, task planning, record-keeping, and performance analysis.

Sustainability Focus Development will focus on machinery that supports sustainable farming practices. This could include features that minimize soil disturbance, reduce energy consumption, and improve the efficiency of fertilizer and seed use to lessen environmental impact. Electric or hybrid-powered broadcasters might become more common.

Drone Technology While currently used for spraying, drones could see expanded use in granular material broadcasting, especially for smaller or irregularly shaped fields or for targeted application in specific areas.

Lighter and More Durable Materials Advanced materials will lead to lighter yet more robust machinery, reducing soil compaction and increasing fuel efficiency.

User-Friendly Interfaces and Calibration Future machines will likely feature more intuitive interfaces and simplified calibration processes, making them easier for farmers to operate and maintain.

In conclusion, the present landscape of seed and fertilizer broadcasting machinery offers a range of solutions for different scales of operation. The future will be driven by precision agriculture technologies, leading to more innovative, efficient, and sustainable ways of distributing essential crop inputs. This evolution will empower farmers to optimize their resource use, be efficient, cost-effective, adaptable to the needs of small-scale farmers, improve yields, and minimize their environmental footprint.

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Chapter 17
Design and Fabrication of an Autonomous Weeder for Agricultural Fields

Nay Lin Tun, K. S. H. Nimanthi, Parwit Chutichaimaytar, Arkar Minn, and Tofael Ahamed

Abstract The escalating global warming and shifting temperatures necessitate the implementation of advanced technologies in agriculture to increase farmland productivity. Agricultural systems worldwide depend on seasonal rainfall and other environmental factors contributing to food production. However, crop production requires careful management of intercultural operations such as weed management, spraying, fertilizer application, and monitoring at the preharvest stages. Weed management is one of the most laborious and challenging tasks in both drylands and wetlands. Furthermore, applying herbicides has become problematic due to environmental concerns and limited resources. Therefore, this study aimed to design and fabricate an autonomous weeder to improve productivity while ensuring sustainability in the agriculture sector. A 12-m path was used to evaluate deviation values from the straight direction. The average deviation values on one side were measured as 25 cm, while on the opposite side were 22 cm, respectively. The field experiment was performed on the grassland at the Tsukuba Plant Innovation Research Center (TPIRC). The weeder was driven on two sides with three replications on each side, totaling six times. The deviation values on one side were measured as 3.4 m, while on the opposite side, they were 3.5 m, respectively. The grasslands had slippage, and the weeder constantly deviated from the marked track. Subsequently, experiments were conducted to turn left and right. The turning was conducted at 40° with a 5-degree deviation from the designed trajectory for turning.

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The weeding components were designed with fabricated models: first for the dry land using an L-shaped blade for drylands, wetland rotating blades with an I-shape powered by a DC motor using a Raspberry PI controller.

Keywords Autonomous weeder · Design · Fabrication · Dryland · Wetland · Weed management · Myanmar

17.1 Introduction

Adopting advanced agricultural technologies is crucial to enhancing farmland productivity by addressing the challenges posed by global warming, changing rainfall patterns, and labor shortages. Traditional agricultural systems that widely rely on seasonal rainfall and environmental factors are increasingly facing significant obstacles. Farmers are struggling with a labor shortage as many workers migrate to industrial sectors for better employment opportunities, while the remaining labor force demands higher wages due to increased demand (Jiao et al., 2022). Modern agricultural practices require substantial labor and machinery for intercultural operations such as weeding, spraying, and fertilizer application during crop growth periods. Weeding is the most labor-intensive, necessitating efficient machinery, skilled labor, and intensive effort throughout various crop growth stages. Using chemical herbicides presents environmental concerns and resource limitations, underscoring the need for effective alternatives in weed management.

While precise and free of chemical use, manual weeding is highly labor-intensive and costly. Chemical weeding, though effective and swift, requires skilled labor and poses environmental and health risks. Mechanical weeding offers a promising solution by reducing dependency and being environmentally friendly, efficient, and precise (Fujita & Okamoto, 2006). Nevertheless, the high initial costs, limited availability, and affordability of mechanical weeding technologies present challenges, especially for small-scale farmers. Addressing these issues requires investment in research and development for affordable, scalable solutions, financial support through subsidies and incentives, comprehensive training programs, collaborative efforts among stakeholders, and a pilot to demonstrate the benefits and efficiency of mechanical weeding. By addressing these aspects, mechanical weeding can significantly enhance agricultural productivity, sustainability, and resilience amidst evolving environmental conditions and labor market dynamics.

17.2 Problem Statements

The low level of mechanization during land preparation, cultivating (seeding, planting), weeding, and harvesting, coupled with higher labor costs and a high turnover of youth, poses a challenge in achieving maximum production rates and high-quality products, ultimately leading to a lower income. At present, farmers are facing extreme weather conditions and fluctuations in rainfall. Labor shortages, elevated costs, and intensive work discourage the next generation of farmers, posing a significant threat to agricultural production. Weed management costs the maximum labor in developing countries, and Myanmar is one of the countries where the subtropical climate influences much for weeds in the dry field and wet fields throughout the year. Therefore, removing weeds is one of the most prioritized tasks for weed management in agriculture at the early stages.

In the agricultural field, weeds compete against the crop, restricting its capacity to attain maximum productivity. Moreover, further contamination from weed seeds can negatively impact harvest quality and the final product, requiring additional processing measures. Currently, in Myanmar, farmers predominantly utilize traditional methods such as hand weeding and conventional chemical weeding due to their accessibility and affordability. There are detrimental effects resulting from applying herbicides, including air, water, and soil pollution. Sometimes chemical weeding also causes chronic food poisoning in consumers and acute poisoning due to herbicides. The initial expense for a mechanical weeding method is greater than that of other operations. As a result, many farmers are unable to implement this approach widely. Therefore, it is crucial to investigate low-cost, intelligent autonomous weeding methods that need minimum labor involvement to enhance crop productivity, increase income, ensure labor safety, mitigate environmental impact, and develop the agricultural sector in Myanmar.

17.2.1 Weed Management Techniques

17.2.1.1 Manual Weeding

Historically, weeding has been performed manually, requiring significant labor and time. Most of the farmers used traditional tools and equipment to control weeds (World Bank, 2021). Manual weeding, though precise, is labor-intensive and expensive, especially given the rising labor cost and the migration of workers to industrial sectors (Fig. 17.1).

17.2.1.2 Chemical Weeding

Farmers have increasingly turned to chemical weeding (Fig. 17.2), which involves the application of herbicides. While effective in reducing weed population, chemical weeding poses substantial environmental risks, including soil degradation, water pollution, and adverse health effects on humans and wildlife. The application of herbicides poses health risks to farm workers and rice consumers. It contaminates the groundwater as well (Thura, 2010). Further studies have found that chemical weeding significantly reduces the yield compared to mechanical weeding (Guru et al., 2018).

Fig. 17.1 Manual weeding method in paddy field

Fig. 17.2 Chemical weeding method in paddy field

Fig. 17.3 Mechanical weeding method in paddy field

17.2.1.3 Mechanical Weeding

Mechanical weeding is done using powered tools and an engine to remove weeds (Fig. 17.3). This method is suitable for large paddy fields as it reduces weeds more effectively than manual weeding. It kills or suppresses weeds by physically disrupting them through pulling, digging, plowing, and mowing. The operational cost is reduced by saving time and labor through mechanical weeding. The modernization of the weeder began with the invention of the powered weeder (Guru et al., 2018). Mechanical weeding, such as a rotary weeder, was used in the paddy field and grain yields significantly increased. The plant density significantly increased when using a mechanical weeder compared to manual methods such as hand weeding or using chemicals. In recent years, mechanical weeding has become the primary method for removing weeds due to its environmentally friendly nature, ability to increase soil aeration, and improved soil temperature.

17.2.1.4 Physical and Biological Weeding

Physical weeding uses plastic film or sheets to suppress the growth of weeds. This method is one of the rarely used wedding methods. This method is recommended solely for small-scale rice farmers. It requires a significant amount of time and investment. It is important to remove any plastic sheets after harvesting. Plastic pollution from sheets can cause a gradual decrease in soil quality (Lv et al., 2019). Biological weeding involves using ducks and geese to remove weeds in paddy fields. This organic method of pest and weed control involves ducks' consumption of weeds, snails, bugs, and slugs, whose waste also improves soil quality and increases rice yields. However, it may result in the loss of rice plants due to trampling by the ducks' feet. It is a less common method and is more suitable for farmers who own small paddy fields. Ducks can reduce the need for manual labor, but they must be released into the field on time and kept carefully to avoid any damage to the rice plants.

17.3 Materials and Methods

The design of an autonomous weeder incorporates rice transplanter wheels, which are suitable for wetlands (Fig. 17.4). The initial specifications focused on determining the blade spacing for the weeder. The rice planter model used as a reference featured seven within-row spacings and one inter-row spacing. Consequently, the weeder's design matched the inter-row spacing of the planter to prevent plant damage (Tang et al., 2021). Additionally, it is adaptable for the early stages of maize cultivation, which shares a similar inter-row spacing suitable for dryland conditions.

The rice transplanter has a row spacing of 300 mm, so the width of the four-row weeder was set to 900 mm. The distance between the front wheels was then set to 840 mm based on the row spacing, with these two wheels positioned at the outer two rows of the weeder. The distance between the rear wheels was 390 mm, with these two wheels positioned at the inner two rows. The distance between the front and rear wheels was 1145 mm. The servo motor was positioned 362.5 mm from the front wheels, while the blade was 455 mm from the front wheels. The 24-V DC

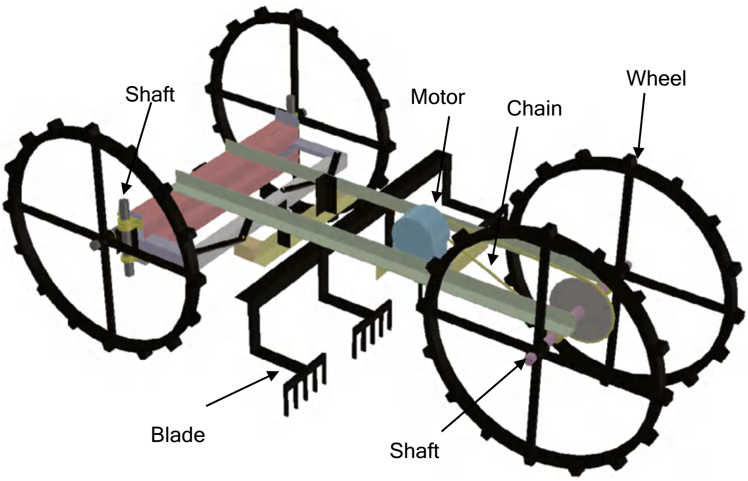

Fig. 17.4 Isometric view of the autonomous weeder

motor was placed 417 mm from the rear wheels, and the DC motor was connected to the rear wheels via a chain to drive the weeder.

17.4 Materials Used for the Autonomous Weeder

Materials selection was divided into two parts. The first part was for the frame construction, and the second was for the vehicle's power system. The materials fabricating the weeder are listed, including the autonomous weeder, which can operate in drylands and wetlands. The wheel's width was 90 mm, allowing for driving within the 300 mm row spacing. The wheel diameter was 660 mm, which reduced damage to rice plants. As the autonomous vehicle operates in the field, it must be lightweight. Therefore, the vehicle has opted for a 2 mm thick, 40 mm wide L-channel iron. Blades from orchard spike harrows were selected as the blades for autonomous weeders to remove the weeds. A 25 mm aluminum rod was selected for the shaft, as the wheel's inner diameter was 25 mm. Bearings with a 25 mm inner diameter were chosen to be used with the aluminum rod. The ball rolling bearings were 112 mm in length and 62 mm in width. The pillow block bearings were made of aluminum and zinc alloy materials to provide sufficient strength while being lightweight. Two bicycle sprockets were combined to be used in the fabricated weeder. The resulting sprocket was connected to the motor gear using a bicycle chain.

17.4.1 Motor for the Weeder and Designing the Driving Mechanism

As the model also caters to designing for paddy land, the power supply must be sufficient to drive the machine. Therefore, a 500 W, 24-V DC motor was selected to provide higher torque at a reasonable speed. The material used to make the vehicle was aluminum, which made it highly durable and resistant to abrasion. The motor could rotate clockwise and counterclockwise. The motor and other devices required a power source. The CTECHi GT200 portable power battery with a capacity of 75,000 mAh was used to supply power to these components. Its lightweight design is made for easy transport. This portable power battery serves as the basic power source for the autonomous weeder. The portable battery required an AC power source to operate the DROK switching power supply. The power supply could convert the AC power to DC power and adjust the output to 48 V.

The Raspberry Pi 4 Model B was used to serve as the primary control component for the autonomous weeder. With 4GB of RAM, the controller can control a DC motor, two servo motors, and a LiDAR sensor. The steering mechanism of the weeder utilized two RDS5160 2-axis servo motors to turn the front wheels. These servo motors have a working angle of 270° and can move up to 60 kg in weight.

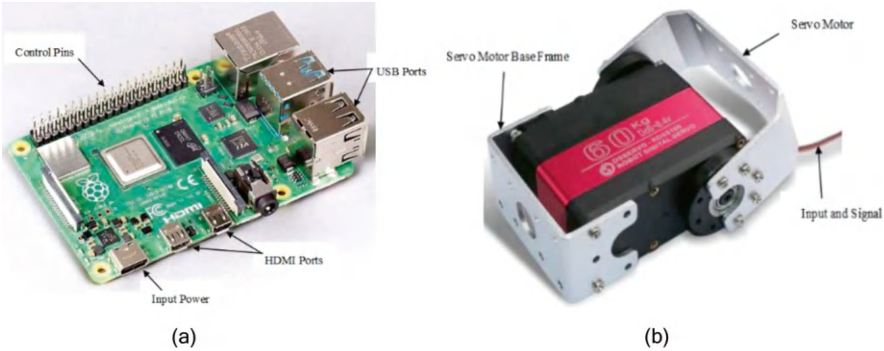

Fig. 17.5 (**a**) Raspberry Pi-4 Model B and (**b**) RDS5160 2-axis servo motor

Figure 17.5a displays the Raspberry Pi 4 Model B, while Fig. 17.5b shows the RDS5160 2-axis servo motor.

A portable and small car battery was used to source power for the autonomous robot. The power supply changed the AC power from the portable battery to DC power. Then, the power supply supported two servo motors for the steering of the autonomous robot. A microcomputer (Raspberry Pi 4) took the power from a power supply. The Raspberry PI controls the two servo motors, and the BTS 7960 motor driver drives the DC motor. The BTS7960 motor driver was used to drive the DC motor for driving the robot. This motor driver needed a stable voltage and current because it is a high-current DC motor. Therefore, a DROK buck converter was used to get a stable voltage and current from the small car battery. The BTS7960 motor driver took voltage and current from the DROK buck converter to drive the 24 V DC motor. This DC motor was the primary device for driving the robot. Figure 17.6 shows the electronic connection of power for the movement of the autonomous weeder. The pseudocode and Python code can also be seen in the appendices.

17.5 Fabrication of the Weeder

The weeder's fabrication can be divided into three sections, including the fabrication of blades. The second section involves assembling the rear wheels. The fabrication of the front wheels is discussed in the third section.

When considering the wetlands, there are three types of blades: J-shaped, C-shaped, and L-shaped. J-shaped blades are used for tilling hard and wet soils, as they loosen the dense soil surface, destroying it and providing good soil aeration. With their greater curvature, C-shaped blades penetrate the soil in hard fields and perform well in heavy soils. L-shaped blades are frequently used to remove weeds and crop residue in fields. The weeder was equipped with an L-shaped blade, with a 300 mm distance between the two centers of the blades. For the four-row weeder, 900 mm of L channel was cut. The blades were made of spikes commonly used in

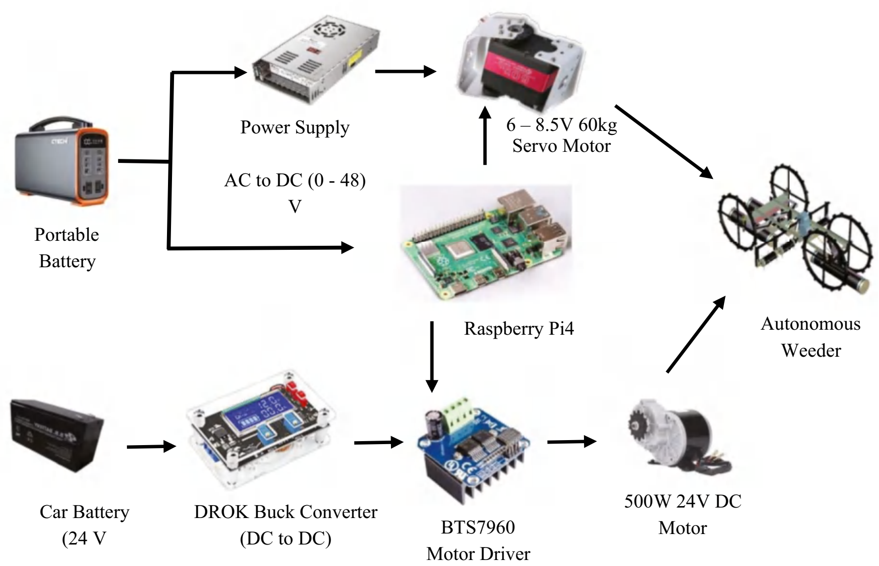

Fig. 17.6 Electronics connection of power and forward and turning of the designed autonomous weeder

orchards, with a width of 160 mm, allowing for effective forward movement between rows spaced 300 mm apart. The blades were assembled 200 mm above and 150 mm away from the main frame of the weeder.

The fabrication part of the blades for the wetland field used the rotation blades. The PVC pipes were used to make the float and blade. Pipes with 80 mm outside diameter were used to make the blades. The pipe was cut into four pipes at a length of 20 cm. Then, a 6 mm drill was used to make the hole on the surface of the pipe. After cutting an 18 cm length of the 6 mm diameter iron rod, these rods were installed in these holes.

The weeder's rear wheels were connected by two wheels commonly used for rice transplanters with an axle, each with a width of 390 mm. The body of the weeder was made up of two L-channel iron plates, each with a width of 290 mm, connected to the rear and front parts. The main frame of the weeder was attached to the shaft using two bearings. These two bearings were used to rotate the shaft and wheels. The sprocket was positioned at the center of the rear of the two wheels. A bicycle chain connected the motor and sprocket. The distance between the motor and the shaft was 417 mm.

The distance between the two front wheels was 840 mm for front wheel fabrication. These wheels were used for steering the weeder. Before selecting the final steering mode, four modes were taken into consideration. The weeder could be steered using a caster wheel by placing two bearings on the shaft of the rear wheels. The caster wheel was placed onto the bearings. This configuration enables the

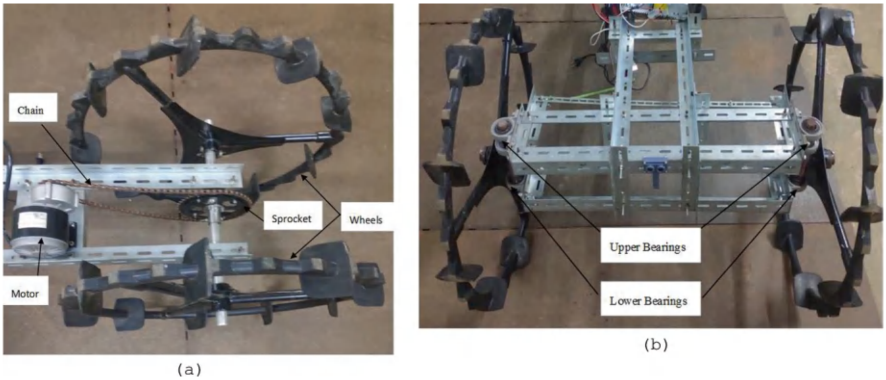

Fig. 17.7 (**a**) Assembly of the rear part and (**b**) Assembly of the front wheels

steering to operate at the rear wheel. However, when the weeder was in operation, the frame and wheels encountered each other, limiting its turning radius.

The second method involved using a caster wheel, however, with a modification to its position. The position of the caster wheel was changed from behind to the front. First, place the two bearings onto the shafts of the front wheels. Then, place the caster wheel onto these two bearings. The front and rear parts were connected using the frame. One limitation of this mode was the inability to connect the front and back parts seamlessly, as the front part was not attached to the weeder frame, leading to potential instability and falls. Figure 17.7 shows the assembly of the front and rear wheels.

Two iron pipes were used to steer the weeder thirdly. Two short shafts for each front wheel and each wheel shaft were connected to the iron pipe. Each wheel was connected to an L-shaped iron plate. The limitation of this method was that the bend in the iron pipe was not strong enough to allow the wheels to move sideways. Finally, the steering for the weeder was made by welding two short shafts and an L-shaped iron plate. The wheels were mounted on the horizontal shaft of the steering frame. The bearings are also mounted on the vertical shaft of the steering frame. Two L-channel iron frames supported the bearings on each vertical shaft.

17.5.1 Installation of Motors and Connection of Rear Axle and Front Axle

Two servo motors turned the two front wheels. Each motor and wheel was connected to iron plates. The controls were installed on the weeder for testing before fixing the arrangements. Figure 17.8 shows the assembly of the autonomous weeder for dryland and wetland fields. After transplanting, three locally available floats were used for the wetlands and shallow waters.

(a) (b)

Fig. 17.8 (**a**) Assembly of the autonomous weeder for dryland fields and (**b**) assembly of the autonomous weeder for dryland fields

Motor Power, Torque, and Force

A 500 W, 24 V DC motor powered the weeder. Calculations were necessary to determine the force and torque of the motor and assess its capability to drive the weeder. Therefore, the force and torque of the motor for the weeder are calculated as follows.

$$P = V \times I \tag{17.1}$$

$$P_{\text{losses}} = \frac{P_{\text{actual}}}{P_{\text{theory}}} \tag{17.2}$$

$$\tau = \frac{P_{\text{actual}}}{N} \tag{17.3}$$

$$F_{\text{m}} = \frac{\tau}{r_{\text{shaft}}} \tag{17.4}$$

where P is motor power (W), V is the electrical potential required for the operation (V), I is the amount of electrical charge flowing through the system during its operation (A), τ is the torque (Nm), N is the rotational speed (rpm), r_{shaft} is the radius of the shaft (m), and F_{m} is motor force (N). Therefore, a motor with a power rating of 500 W, operating at a speed of 2800 rpm, shaft diameter of 10 mm, and running on 24 V with a current of 28.5 A, was calculated to have a theoretical power of 684 W, losses of 73.1%, torque of 10.71 N·m, and force of 2142.86 N.

17.5.2 *Weeder Force and Torque*

The weeder's mass was assumed to be 50 kg. The torque and force of the weeder were calculated using the following equations.

$$F_{\text{weeder}} = m \times g \tag{17.5}$$

$$\tau_{\text{weeder}} = F_{\text{weeder}} \times r_{\text{sprocket}} \tag{17.6}$$

where F_{weeder} is the force of the weeder (N), τ_{weeder} is the torque of the weeder (Nm), and r_{sprocket} is the radius of the sprocket (m). Therefore, assuming a weeder mass of around 50 kg, the calculated force and torque were 490.5 N and 41.69 Nm.

17.5.3 Gear Ratio

Gear ratio is a method used to increase speed or torque. There are two methods of gearing. They are the gear reduction method and the overdrive situation method. The gear reduction method is where a small gear drives a large gear. This method reduces speed but increases torque. The overdrive method is the opposite of the first method. In overdrive, a large gear drives a small gear. The overdrive method increases speed but reduces torque. The gear reduction method must be applied to meet this requirement. This is because it is necessary to obtain high torque for the motor. The gear ratio can be calculated using the number of gear teeth, torque, and speed. The following formula is the gear ratio formula used for the calculation.

$$\text{GR} = \frac{t_{\text{out}}}{t_{\text{in}}} = \frac{\tau_{\text{out}}}{\tau_{\text{in}}} = \frac{N_{\text{out}}}{N_{\text{in}}} \tag{17.7}$$

where GR is gear ratio, t_{out} is the number of teeth of the output gear, t_{in} is the number of teeth of input gear, τ_{out} is the torque of the output gear (Nm), τ_{in} is the torque of the input gear (Nm), N_{out} is the number of rotations of the output gear per minute (rpm), and N_{in} is the number of rotations of the input gear per minute (rpm).

17.5.4 Calculation for Gear Ratio

The gear ratio formula shown in Eq. (17.7) was used to calculate the gear ratio of the number of teeth, torque, and rpm. Both the number of gear teeth of the motor and sprocket are used to calculate the gear ratio. As you know, we used two sprockets. The number of teeth on the gear attached to the motor shaft was 11, while the number of teeth on the sprocket was 69. The input torque was 14.66 Nm, and the rpm output was 2800 rpm. Therefore, based on calculations, the teeth ratio was 6.27 and the output torque was 91.92 Nm.

The motor's new torque was 91.92 Nm, while the weeder's torque was 41.69 Nm. Thus, the motor can drive the weeder due to its higher torque than the weeder. Finally, the speed of the weeder was calculated using the gear ratio equation, and the speed of the weeder was 447 rpm.

17.6 Results and Discussion

17.6.1 Weeder Driving Test on the Concrete Road

The experiment involved testing and driving the motor and servo motor in a testing room and then carrying out a straight-ahead test on a concrete road using a grid to guide the deviations. This experiment was done to get the value of the deviation distance of the steering of the servo motor and another to know whether the DC motor could drive the weeder.

Figure 17.9 shows the deviation from the weeder testing on the concrete road for driving straight ahead from Side A. However, the path had an uneven surface with potholes in real conditions. Therefore, the deviation from the straight line occurred. The figure indicates that the weeder has less deviation on path two, while the deviation was more significant on paths one and three. Deviation values were lower before they reached the potholes and increased thereafter.

Figure 17.10 shows the deviation from the weeder testing on the concrete road for driving straight ahead from Side B. The deviation also occurred in the test. Both figures clearly show that path two was less than the other two. Even the motor was able to drive the autonomous weeder. Since the weeder speed was fast, the motor speed was reduced, but the weeder was not running. This is because the motor used in the weeder was a high-speed motor with low torque.

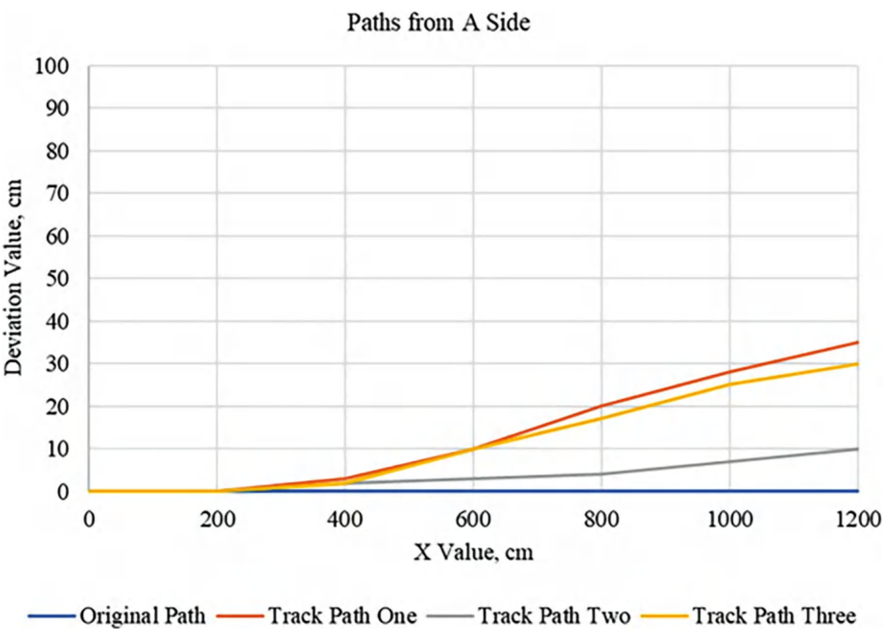

Fig. 17.9 Average deviation results from side A

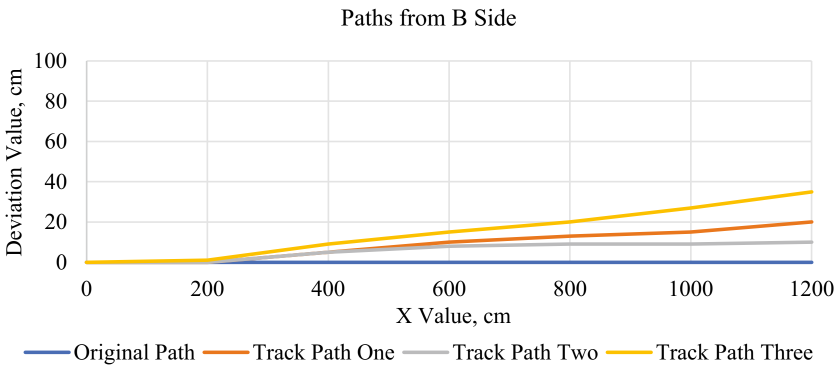

Fig. 17.10 Average deviation results from side B

17.6.2 Testing Weeder on the Grassy Field

The autonomous weeder was tested in a straight direction on the grassy road at the TPIRC. The driving area was increased compared to before. The area of the grass field was 20 m long and 6 m wide. Driving on the grass is very different from driving on concrete roads. As the road length increased, the deviation value also increased. The necessary facts of the autonomous weeder were also becoming more apparent. The autonomous weeder needed more torque since grass adds more friction to the wheels than concrete roads. The weeder speed was further reduced in some areas with thick grass.

17.6.3 Turning Testing on the Grass Field

The autonomous weeder was driven on the grass field to test turning right, left, and U-shaped turning. Coding was done in the program to navigate the weeder automatically. The autonomous weeder was driven in a straight line for 2 s. At this stage, the angle of the servo motors was at a 90-degree position. Then it was driven in the turning right direction for 5 s. The turning angle of the servo motor is set to 60° in the program. After that, the angle of the servo motor was set to a straight-line direction again to move the weeder in a straight line for 3 s. The actual result of the autonomous weeder was the following. The autonomous weed moved 3.7 m in a straight line in 2 s. Then, it turned 45° to the right within 5 s. It moved 4.9 m in a straight line in 3 s. The autonomous weeder was then driven to turn left by the exact dimensions. The results for turning left and turning right remained the same. The autonomous weeder was driven by turning right in a U shape. The program for the U-shaped turn was coded as follows. At first, the weeder was driven in a straight line in 2 s. The time was set to 16 s to complete a U-shaped turn. The degree of the servo motors was set to 60° for turning right.

Finally, the degree of the servo motor was put in a right-angle position to go in a straight-line direction. The weeder moved in a straight line in 2 s. While running the weeder under this programming, the weeder moved 3.8 m in a straight line in the first 2 s. Then, the weeder turned 45° to the right in 16 s. Finally, the weeder traveled 3.8 m straight in 2 s. The distance from the weeder's start to the endpoint was 6 m. Therefore, if the weeder is to drive back and forth in a U shape, the distance between the two lines will be 6 m.

17.6.4 Limitations

The weeder has not yet been equipped with a reliable navigation system. Therefore, it cannot run properly on the desired path, resulting in deviation during testing. Moreover, the vibration from the motor on the weeder's body is still quite significant because the frame was made of L-plate iron. This material caused the frame to bend when the wheels ran on uneven surfaces and high friction.

17.7 Conclusion

This research was focused on designing and fabricating an autonomous weeder for agricultural fields that can move forward and turn to the left and right. This paper comprises a design, fabrication, and evaluation part for the fabricated weeder in dryland and wetland fields. The following points summarize the design, fabrication, and experimental results.

Design The design of the autonomous weeder was completed using the AutoCAD software and Autodesk Fusion 360 software. The design is considered for both dryland and wetland fields. At first, a four-row weeder was designed for dryland fields. The row spacing of many rice transplanters is 300 mm. Therefore, the distance of the two adjacent blades was set at 300 mm for both dryland and wetland fields. The shaped blades for the dryland field were referred to as L-shaped blades, and the wetland had rotating shaped blades. The distance between the two adjacent blades was considered 300 mm. All dimensions were the same for the wetland field as the weeder designed for the dryland field, but the main difference lay in the blade design. Another difference was the inclusion of three floats due to the presence of water in the wetland field. The two front floats were positioned between the two front wheels, while the rear float was positioned between the two rear wheels.

Fabrication After completing the design of two weeders, fabrication was completed with locally available materials for the weeder designed for dryland and wetland fields. When choosing materials for the weeder, there were two primary concerns: lightweight to facilitate operation in low-land cultivation and the use of low-cost materials to reduce machinery expenses. Because most farmers in

Myanmar have low incomes and limited purchasing power, the weeder was fabricated in three stages after materials selection. The fabrication part of the blades for the wetland field used the rotation blades. The PVC pipes were used to make the float and blade.

Fabrication of the Blades Two types of weeders were constructed: dry land blades and wetland blades. The materials were made of iron plates. Dryland blades were used as L-shaped blades for dry land. At the same time, wetland blades were rotating blades with an I-shape. The blade can be changed based on the purpose and land conditions. Dryland blades are utilized by attaching the L-shaped blades to the connector on the main frame, while wetland blades need to be connected to a controlled DC motor.

Fabrication of Rear Wheel Components The rice planter wheels with a diameter of 660 mm and an axle hole of 25 mm were used for the rear wheels. The wheels were placed on a 500 mm long, 25 mm diameter axle, spaced 390 mm apart. A sprocket was positioned at the center of the two rear wheels. 150 mm diameter PVC pipes were utilized for the floats, with a 50 cm float installed between the rear wheels.

Fabrication of the Front Wheel Components The front wheel was constructed using an iron rod and an L-channel iron plate. Two iron rods were welded into a 90-degree-shaped two-axle configuration to address movement and turning. The front wheels were mounted on the horizontal axle, and the vertical axle was equipped with a bearing, facilitating steering. Two L-channel iron plates connected the front and rear wheels. The distance between the front wheels was nearly 900 mm. Two floats were placed between the front wheels, each measuring 40 cm long.

Installation of Motors and Power Train A 500 W 24 V DC motor was installed to drive the weeder. A bicycle chain connected the motor and sprocket at the rear shaft. Two 60 kg servo motors were used for steering the robot. The box housing the electronic devices for controlling the system is installed on the body frame of the weeder. The box contained the microcontroller (Raspberry Pi 4), LCD monitor, motor driver, power supply, portable battery, and two small car batteries.

Evaluation DC motor and servo motor tests were made inside the laboratory after fabrication. The outside experiments were done three times on the concrete road and the grass fields. The autonomous weeder drove on the concrete road to determine the deviation values. The weeder drove three times from one side and three times from another. The weeder drove 1200 cm long on the concrete road. The average deviation values from one side to another were 25.3 cm and 21.6 cm, respectively.

The weeder drove on the grass fields in the second experiment and took the deviation values as in the first experiment. But the length of the road was more than the first path. The weeder drove 2000 cm across the grass field, making three passes from one side and then repeating the process from the other three more times. The average deviation values from one side to another were 340 cm and 350 cm, respectively.

Finally, the turning left, turning right, and U-shaped turning were performed on the grass fields. The degree of the servo motors was set to 60° in the program. Moreover, the weeder drove the turning left and right conditions to this degree. However, the servo motor could turn about 45° under left and right turning conditions. In the U-shaped turning test, the servo motor could only turn about 45°. However, the distance between the start and end points was 600 cm. This value was significant because the servo motor could not externally turn the whole degree in the program. Therefore, the weeder needed a width of 600 cm to drive the opposite way again.

17.7.1 Future Improvements

An autonomous weeder can move in straight lines and can be driven both forward and backward with ease. However, the weeder must have the best navigation system for detecting obstacles. Therefore, the vehicle will be implemented by adding the RTK GNSS, LiDAR, and camera to avoid the barriers and provide a sound navigation system.

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Chapter 18
Weeding Techniques in Tropical Places for Cassava Plantations

Opasatian Ithiphat and Tofael Ahamed

Abstract This comprehensive review paper provides a detailed overview of weeding techniques available for cassava plantations in tropical areas. It covers mechanical, organic, and chemical methods for weed control, including the weed time and density available in those areas. The paper also thoroughly examines the weed management efficiency in the tropical area's chemical, organic, and mechanical aspects and summarizes the most appropriate methods of weeding in Cassava plantations. Moreover, it underscores the potential of current innovative technologies for intelligent Cassava weeding technologies, offering a promising glimpse into the future of weed management. These advancements in innovative technologies hold the potential to revolutionize weed management, reducing the reliance on manual labor and significantly increasing efficiency in Cassava plantations, instilling a sense of optimism for the future of weed management.

Keywords Cassava (*Manihot esculenta* Crantz) · Weeding methods · Weeding machinery

18.1 Introduction

Cassava (*Manihot esculenta* Crantz) is a widely consumed tuber crop worldwide. Cassava produces a lot of starch and can thrive in challenging environments where other plants cannot survive. Cassava is often grown in tropical climate areas, such as in Africa, Southeast Asia, and South Asia. It is a primary source of carbohydrates and provides a significant portion of daily caloric intake in many tropical countries (Montagnac et al., 2009). Though primarily a source of carbohydrates, cassava can

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be processed to enhance its nutritional value, such as through biofortification to increase its vitamin and mineral content. Cassava is highly drought-resistant and can thrive under prolonged drought conditions for 6 months (El-Sharkawy, 2003). This plant can grow in poor, nutrient-deficient soils where other crops might fail. Weeds pose a significant problem for cassava farmers as they compete with cassava plants for important resources such as nutrients, water, and light, leading to substantial yield losses and reduced productivity (Ekeleme et al., 2019). Therefore, effective weed management is essential for cassava during the first three to 4 months after planting (Pv et al., 2016). This was done to maintain the growth of its tubers within the growing period.

The paper will explain different weeding techniques, such as mechanical, chemical, and organic methods, and emerging technologies like precision agriculture and robotics. Additionally, it will assess the factors influencing the adoption of these technologies, such as economic viability and environmental sustainability. Combining the latest research and developments in this field, the review paper provides valuable insights and recommendations for cassava farmers and researchers to make informed decisions and promote sustainable cassava production in tropical regions.

Furthermore, the review will highlight the importance of integrated weed management strategies tailored to tropical regions' specific agroecological conditions. Effective weed control enhances cassava yield and productivity, improving food security and environmental conservation in these regions. This emphasis on integrated weed management will give the audience valuable insights and recommendations for best practices in cassava production.

18.2 Weed Challenges in Tropical Cassava Plantations

Weed is an undesirable plant that impacts cassava growth (Fig. 18.1). Three categories of weeds are mutual in cassava fields: grasses, sedges, and broadleaf weeds (International Institute of Tropical Agriculture, 2024). The grass-type weeds in Tropical areas are Cogon grass (*Imperata cylindrica*) and Bermuda grass (*Cynodon dactylon*). The specific sedge type of weeds is Java grass (*Cyperus rotundus*). The broadleaf-type weeds are the Siam weed (*Chomolaena odorata*) and the Giant sensitive plant (*Mimosa invisa*). These perennial weeds have the potential to dominate the cassava plantation and cause significant problems for cassava plants (Ekeleme et al., 2019). Cassava is a vital tropical crop, ranking third in carbohydrate content among plants in tropical climates, followed by rice and maize. However, weeds, as pests, significantly reduce the production of crops. Weeds extract nutrients, water, and moisture from the soil, competing with cassava plants for light and air, which negatively affects the cassava plants. Moreover, weeds limit crop yield by limiting plant-food resources from which plants receive energy for their growth and development (Jahan Leghari et al., 2015). Cassava yield significantly suffers from weed invasion in the tropical climate. These weeds are commonly regarded as unwanted

Fig. 18.1 Weeds grow in the cassava planting groove

plants that grow in cultivated fields. This issue concerns cassava farmers in Southeast Asian tropical agriculture, including Thailand, Malaysia, Indonesia, and Vietnam. Weeds reduce cassava root yields significantly. During the initial weeding, cassava yields ranged from 11 to 26 tons per hectare. Without any weeding, yields drop to about 4 tons per hectare, a 15% decrease compared to regular yields. Conversely, if weeding is performed three times, the potential yield increases to 22.7 and 36.6 tons per hectare.

18.3 Overall Cycle of Cassava Plantation

18.3.1 Land Preparation

Lack of proper land preparation leads to increased weed growth in cassava fields, which decreases cassava tubers' yield (Nedunchezhiyan et al., 2014). Plowing, harrowing, and ridging using manual labor or tractor-drawn machines before planting can control weeds in the cassava field. Proper land preparation enhances soil structure, aids root penetration, boosts microbial activities, and assists in weed management (Chiona et al., 2016). Appropriate land preparation involves cleaning cassava seedbeds of weed rhizomes, stolons, and tubers to reduce weed pressure from root weeds (Research Institute of Organic Agriculture FiBL, 2022). In tropical regions, it is common for medium to large-scale farmers to employ tractor-drawn

Fig. 18.2 Cassava plantations were prepared by using tractor-drawn bed ridging machines in the Northeast region of Thailand

implements such as plows and harrows to prepare the land for planting cassava (Fig. 18.2). These mechanized tools facilitate soil tillage and create optimal conditions for cassava cultivation. Conversely, small-scale farmers typically utilize manual tools like shovels and spades to prepare the cassava field for planting meticulously. This hands-on approach enables them to tend to smaller plots with precision and care, ensuring an ideal environment for cassava growth.

For land previously under cultivation, use a combination of slashing and tilling to prevent weeds from interrupting cassava growth. However, if spear grass (*Imperata*) is present, herbicides can kill it. Incorporate the cover crop into the soil for short fallow periods by plowing. Cut the vegetation for land under long fallow or forest and perform selective, controlled burns of wood materials before tilling.

18.3.2 Cassava Planting

Collect 20- to 30-cm-long stem cuttings from the central portion of the healthy brown stems when the Cassava cuttings are around 12 months old. Harvest the stems roughly a week before planting to promote consistent growth and keep them in a well-ventilated space. Take the cuttings during planting or the day before, ensuring each has five to seven dormant buds (Kouakou et al., 2016). Then, transplant those cuttings into the row by placing them into the soil upright with one node (the point where a leaf was attached to the stem) above the soil level (Johnstone, 2024). Weeds affect cassava planting stages by competing with cassava for essential resources, including moisture, nutrients, space, and light. This competition is particularly detrimental during the first 3–4 months due to the slow initial development of cassava stem cuttings and sprouts (Research Institute of Organic Agriculture FiBL, 2022).

18.3.3 Weed Management

After planting, farmers need to remove weeds from the cultivation area, as these can have long-term adverse effects on the growth and development of cassava. Farmers in Thailand use various weed management techniques, choosing methods that suit their preferences. Typically, Thai farmers apply herbicides to eliminate grasses shortly after planting the stems, which can effectively control weeds for approximately 1 month. Furthermore, they often employ a walking tractor equipped with weeding implements or continue spraying herbicides three to five times until the cassava reaches 5 months of age. At this stage, the cassava plants will have expanded their stems and leaves enough to cover the entire planting area, thereby preventing weeds from growing and competing with the cassava.

18.3.4 Fertilizer Application

Farmers apply fertilizers when the soil is moist following one or two rain showers. Urea and NPK 15:15:15 should be split into two to four equal doses, with the first application occurring 1 month after planting. Subsequent splits should be applied, as rain allows, over the next 2–3 months (National Root Crops Research Institute, 2020). While cassava can grow in nutrient-poor soil, its growth rate may slow, and yields may be low-quality. To enhance the cassava crop, farmers must apply fertilizers that provide the essential nutrients lacking in the soil (Sike-Ezo, 2024). Weeds significantly impact the fertilizer application stage by affecting both the effectiveness of the fertilizers and the overall crop performance. Weeds compete with cassava plants for the applied fertilizers, reducing the nutrients available to the crop. Fertilizers can stimulate weed growth, further exacerbating the competition for resources. Weeds reduce fertilizer efficiency as they may absorb a significant portion of the nutrients intended for cassava plants, leading to suboptimal cassava growth and development (De Souza Cardoso et al., 2022; Cio et al., 2016).

18.3.5 Harvesting

Cassava plants are typically harvested 12–18 months after they are planted. Before harvesting, the plants' stems are trimmed back, leaving about 30–50 cm above the ground. These stems can be used to help pull the tubers from the soil. If the soil is too rigid or compacted during harvesting, it is advisable to loosen the soil around the plants using a garden fork (Caribbean Development Bank (CDB) et al., 2021). However, manual harvesting can be a time and labor-intensive operation that causes severe root injury, especially during the dry season, leading to yield loss (International Institute of Tropical Agriculture, 2024). Therefore, farmers adopt mechanized

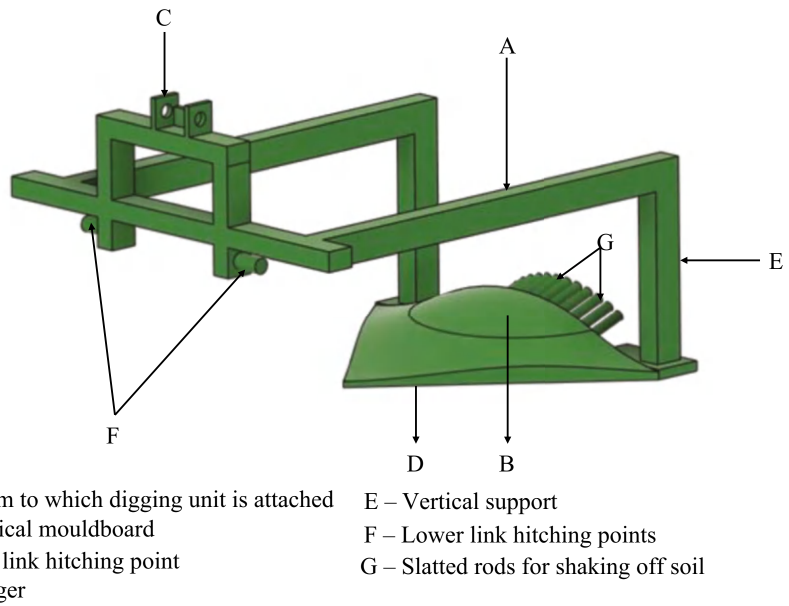

Fig. 18.3 The tractor-drawn type mechanical cassava harvester developed by the TEK company

cassava harvesting technology by using tractor-mounted harvesters. For example, the TEK cassava harvesters are operated by the dig-and-pull principle (Fig. 18.3). The digger moves through the soil, bringing roots to the surface for collection and removal, aided by the slanted conical mouldboard (Amponsah et al., 2018). Weeds can considerably impact the harvesting stages in several ways. Uncontrolled weed growth throughout the cassava life cycle can lead to 40–90% yield losses. The presence of weeds can interfere with the manual or mechanical extraction of cassava roots because weeds, especially Cogon grass (*Imperata cylindrica*) and Guinea grass (*Panicum maximum*), can make the harvesting process more challenging and time-consuming. Also, weeds work as hosts for pests and diseases that may affect the cassava crop until harvest time. This potentially reduces root quality or yield during harvest (Ekeleme et al., 2019). Weed competition throughout the growing season can potentially delay cassava maturity, affecting the optimal timing for harvest and potentially reducing overall yield (Ekeleme et al., 2021).

18.4 Weeding Timeline

To promote the establishment of young plants, farmers actively manage weeding on their plantations for around 3 months because it is the critical period for weed removal (Fig. 18.4). On many small-scale farms, delaying the first-hand weeding

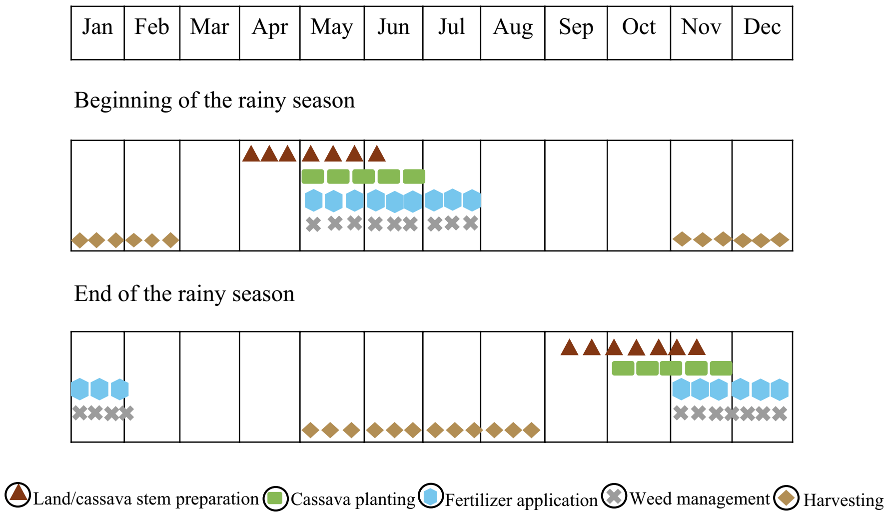

Fig. 18.4 Weeding timeline for cassava farmers in tropical countries

for up to 2 months after planting can reduce cassava root yield by 20–50% (Ekeleme et al., 2019, 2021). As cassava plants grow taller, they can block weeds from accessing sunlight. Consequently, very little light is available for weeds or grasses to thrive, allowing the cassava plants to grow more vigorously without interference from unwanted vegetation. This approach effectively enhances the yield and overall health of the cassava crop.

18.5 Traditional Weeding Techniques

The traditional weeding methods are hoeing and hand-weeding, which can be time-consuming on each cassava plantation (Onasanya et al., 2021). Farmers typically walk between the cassava planting rows to hoe and hand-weed, helping to uproot the weeds (Fig. 18.5). Additionally, farmers use grass-cutting knives or machetes to slash and chop down large shrubs and broad weeds to eliminate them. Small-scale farmers could weed their cassava fields several times throughout the growing season. However, hoeing and hand-weeding are labor-intensive tasks suitable only for small-scale farms, which makes it challenging for commercial farms to effectively eliminate weeds throughout their cassava plantations due to the significant labor requirements. Also, Cassava plants could get damaged if misconduct occurs during cassava weeding operations. The grass-cutting knives and machetes could cut or slash the cassava tree stems or leaves, directly affecting the cassava plants.

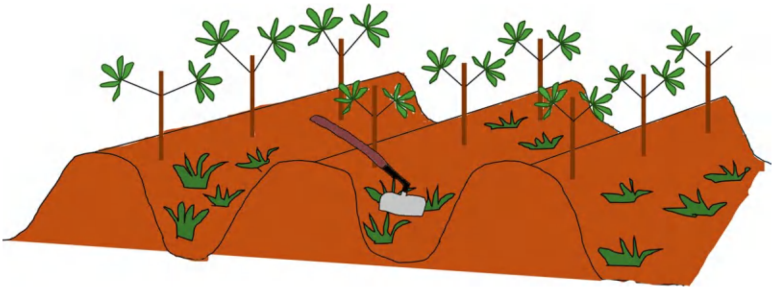

Fig. 18.5 The example of Hoe-weeding in the cassava plantations

18.6 Modern Weeding Techniques

18.6.1 Organic Weeding

Organic weeding is a technique for minimizing the impact of weeds in plantations without resorting to synthetic herbicides (Gramig, 2018). Farmers use organic weeding methods when they cannot afford chemical herbicides on an individual, small-scale farmer (Vissoh et al., 2004). Organic weeding consists of intercropping and crop rotation to create unfavorable environments for weeds to grow. This method can eliminate weeds without using chemicals, which causes less harm to the surroundings near the cassava planting field. The following paragraph explains the research and development of organic weeding in tropical cassava planting fields, which gives insights into the practices of organic weeding in cassava plantations.

The intercropping method is a natural way of controlling weeds in cassava plantations (Fig. 18.6). This technique involves planting two different crops in the same field, which helps to reduce weed growth in cassava fields. A study by Padmapriya et al. (2008) used groundnut (*Arachis hypogea*), vegetable cowpea (*Vigna sinensis*), and black gram (*Vigna mungo*) to compare various weed control practices. Intercropping impacted the population of grasses, sedges, and broadleaf weeds and the total dry matter produced by weeds. Effective weed management improved cassava growth, yield, and economic returns. The most outstanding results were achieved by intercropping vegetable cowpeas with the pre-emergence application of Fluchloralin at 0.75 kg/ha, followed by one round of hand weeding 4 weeks after planting and the application of alachlor at 1.5 kg/ha, along with another round of hand weeding 4 weeks after planting.

The research, which was conducted in Ibadan, Nigeria, evaluated two types of planted fallow: alley cropping with leucaena and live mulch with tropical kudzu, in comparison to natural bush fallow over 3 years and various land-use intensities (Ekeleme et al., 2003). The results indicated that the weed seed bank was 55% lower in plots with tropical kudzu and 43% lower in Leucaena plots when compared to natural bush fallow. A 23% difference was also noted between the leucaena and natural fallow. The seed bank primarily consisted of annual broadleaf weeds,

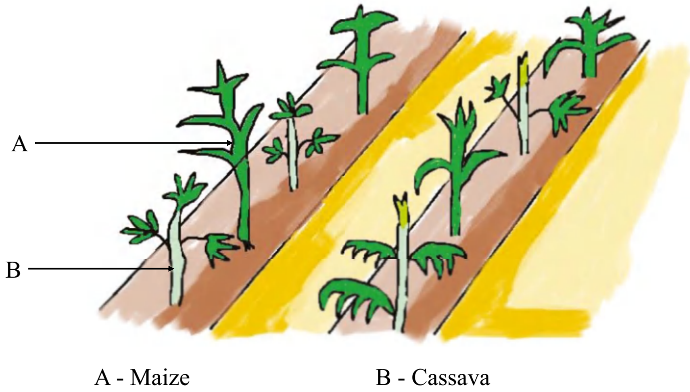

Fig. 18.6 Cassava plants intercropped with maize to reduce weeds

whereas sedges were more common in continuously cultivated areas. Furthermore, lower land-use intensity was associated with higher densities of perennial broadleaf weeds. In conclusion, tropical kudzu demonstrated greater effectiveness in reducing the weed seed bank than Leucaena or natural bush fallow after 2–3 years of implementation.

18.6.2 Chemical Weeding

Chemical weeding is an agricultural strategy that uses chemicals to kill weeds in each plantation. Chemical weeding is a simple, efficient, dependable, and cost-effective method of weed control (Iqbal et al., 2019). Chemical weeding in cassava plantations is widely used among tropical farmers because it is easy to apply, saves farmers from labor scarcity during weeding operations, and effectively eliminates weeds, which can gain more profit (Manisankar et al., 2022). This method is particularly helpful for headland-less cassava planting fields, which are unsuitable for any tractor-drawn weeding machines (Fig. 18.7). Consequently, farmers must manually spray chemical herbicides to eliminate weeds in this field, which is a labor-intensive task.

The chemical weed control study was conducted, which showed that several herbicides were tested for weed control in cassava plantations. The data suggests that Metobromuron, Prometryn, Fluometuron, Atrazine, Diuron, and Gramuron (diuron + paraquat) were effective and economical for weed control in cassava. Similar results were found in Colombia for fluometuron, diuron, and diuron plus paraquat. Farmers typically apply chemical herbicides in cassava plantations by spraying the liquid using a handheld herbicide sprayer directly on weeds (Fig. 18.8). The efficiency of herbicide application for weed control relies on climatic and belowground ecosystem factors, weed flora, application rate, crop variety, and management

Fig. 18.7 Headland-less cassava plantation in northern Thailand

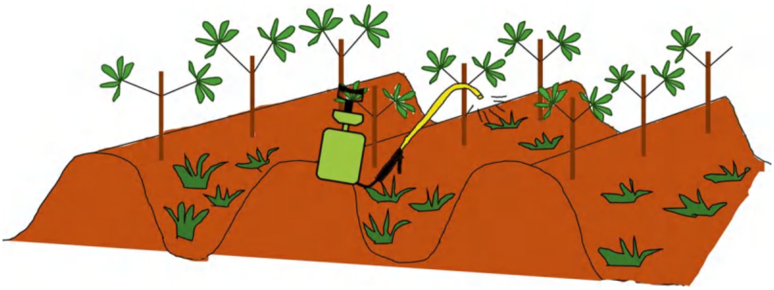

Fig. 18.8 Herbicide application in the cassava plantation

practices (Jugulam et al., 2018). Besides being economical, chemicals were inexpensive, convenient, and attractive. However, herbicide implementation became difficult because of a lack of skills and an unreliable supply of herbicides from abroad. Moreover, chemical herbicides were hazardous to cassava farmers and polluted nearby areas. Also, tight-budgeted farmers could not purchase herbicides for their use. These challenges in chemical weed management underscore the need for a comprehensive understanding of weed management techniques

Fig. 18.9 Farmers using mechanical weeders for weeding in cassava plantations

18.6.3 Mechanical Weeding

Mechanical weed control methods in cassava farming systems involve various innovative approaches such as full-width, inter-row, and intra-row cultivators. These are designed to target specific weed issues and improve weeding operations directly (Melander & McCollough, 2022). Farmers typically use handheld weeding machines for inter-row weeding or tractor-drawn machines for weeding cassava fields, which can reduce fatigue in weeding operations (Fig. 18.9). Recently, more advancements in agricultural machinery development have been made to allow for the easy conduct of weeding jobs, which will be explained in the following paragraph.

A Kenyan researcher conducted a study on using the Backpack weeder for weed control in cassava fields in Busia County (Susan & Wawire, 2021). The research compared the efficiency of a mechanical backpack weeder with manual weeding in four cassava fields. The results demonstrated that machine weeding was highly effective, resulting in lower fuel consumption and operational costs, particularly in sandy loam soil. The operational cost of manual weeding remained consistent, with slightly higher costs for test plot three due to increased fuel consumption. These findings underscore the potential of mechanical weeding in cassava plantations and emphasize the importance of considering soil texture and fuel consumption during operations. The specialized power weeder for hilly terrains, designed explicitly for mound-cassava cultivation, was developed by Selvan et al. (2015). The innovative weeder includes a petrol engine, main and offset weeding rotors, a depth control lever, ground wheels, a transmission assembly, a frame, and a handle. The main rotor removes weeds in furrows, while the offset rotor handles weeds on mounds without causing damage to the surrounding soil tubers. The experiment indicated efficient fuel consumption at 27 L/ha. The machine achieved a weeding efficiency of 92.8%, with minimal damage to the rhizome (0.7%). It boasted a 0.16 ha/day

Table 18.1 Mechanical cassava weeding research analysis

References	Weeding efficiency (%)	Field efficiency (%)	Fuel consumption (L/ha)	Plant damage (%)	Operational cost (USD/ha)
Susan and Wawire (2021)	98	n/a	0.4	n/a	10.48
Selvan et al. (2015)	92.8	79	27	0.7	n/a
Sangphanta et al. (2015)	90–97	83	9.38–10.63	n/a	n/a
Sabaji et al. (2014)	91.37	83.93	n/a	2.66	n/a
Techasen (2022)	85–90	n/a	15.63	n/a	n/a

field capacity and 79% field efficiency. Moreover, complications during weeding were minimized by strategically attaching the lateral rotor ahead of the central axis with a 20 mm offset. This power weeder was well-suited for medium-sized cassava farms in India. Further research and development of the mechanical cassava weeder aimed to reduce farmers' burdens and increase their work efficiency. Table 18.1 below summarizes cassava weeders' current and up-to-date development in tropical and subtropical regions.

18.7 New Technologies

Recently, there have been some advancements in research and developments in cassava weeding technology. Both use cutting-edge technology and new automatic vehicles to eliminate weeds in cassava plantations, which continue to develop to help farmers work without much effort and solve the labor shortage problem (Fig. 18.10). The following paragraph will describe the recently developed innovative technologies for cassava weeding.

A cassava detection system using UAV images was developed with the YOLOv5 model to help control weeds in cassava fields (Nnadozie et al., 2022). The study used two YOLOv5 versions, YOLOv5n and YOLOv5s, to assess cassava detection as an initial step toward real-time weed identification. Both models were trained on aerial images of cassava plantations to build the detection system. Their performances were tested across different image resolutions, in various conditions such as changes in lighting, weed density, and crop growth stages. YOLOv5s achieved the highest accuracy, while YOLOv5n was faster in inference. When trained with the exact resolution, YOLOv5s outperformed YOLOv5n, but YOLOv5n trained on higher resolutions could surpass YOLOv5s trained on lower resolutions. Both models handled field variability well. The speed vs. accuracy analysis provided insights into the trade-offs, assisting in deploying these models for real-time cassava detection.

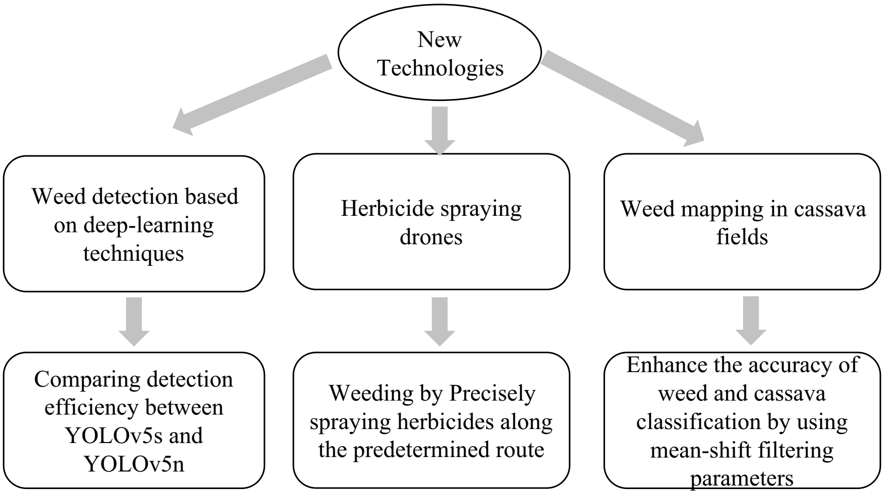

Fig. 18.10 New technology for cassava weeding diagram

XAG, an agricultural robotics and AI company, has introduced cutting-edge technologies that utilize drones for spraying herbicides on cassava farms in Cambodia (Claver, 2022). Drones can be effortlessly transported and deployed to the fields, offering a more convenient alternative to large agricultural machinery. These drones use fewer chemicals and reduce the workload on farms. The developed herbicide-spraying drone can autonomously weed by flying over ridges of cassava plants, precisely spraying along predetermined routes, and covering eight hectares within just 1 h using a single agricultural drone. In addition to these capabilities, the farm drone helps bridge the yield gap and protects farmers from herbicide exposure. XAG's drone sprays from the air to avoid direct contact with large ground machinery on cassava crops, ensuring the pesticides penetrate the plants and prevent crop damage. Moreover, these drones can save eight to ten American dollars per hectare, typically spent on manual spraying, and reduce the use of chemicals by 10–30%.

A group of researchers from Thailand researched the application of mean-shift filtering parameters for mapping weeds in cassava fields using UAV images (Boonrang et al., 2021). The study identifies effective parameters, such as spatial size and color value, to enhance the accuracy of weed and cassava classification. The RGB images captured by the UAV were utilized as the input dataset for the mean-shift process. The filtered images were then classified using a Support Vector Machine (SVM), resulting in detailed maps of weeds and cassava. The findings indicated that using mean-shift filtering could improve accuracy by up to 4.22% compared to traditional pixel-based classification through parameter adjustments. The classification accuracy ranged from 78.38% to 82.60%. The study demonstrated that mean-shift filtering can significantly enhance classification accuracy when applied with suitable parameters.

At present, research on automated and innovative weeding technologies specifically for cassava cultivation is quite limited. Despite this, there is significant potential for these technologies to be further developed and demonstrated in upcoming agricultural practices. Improving weeding efficiency is crucial for cassava farmers, as effective weed management can enhance crop yields and reduce labor costs. Therefore, there is an urgent need for more comprehensive research and development efforts focused on creating and implementing such weeding technologies. By focusing on this area, we can help cassava farmers achieve better productivity and sustainability in their farming practices.

18.8 Integrated Weed Management

Integrated weed management (IWM) combines effective chemical, organic, and biological practices to improve crop yield economically (Gupta et al., 2021). Integrated weed management is essential for its long-term effectiveness in weed elimination. Relying on a single tactic over an extended period may not sufficiently counter the impact of a dynamic weed population due to weeds' environmental adaptation, which makes the weeds gain more resistance to single weed elimination methods (Casimero et al., 2022).

The research compared various weed management practices for cassava plantations (Pv et al., 2016). These practices included pre-emergent herbicides such as Oxyfluorfen, Pendimethalin, and Imazethapyr, as well as directed Glyphosate application, hoeing, earthing up, growing cowpeas, and unweeded control. The results indicated higher tuber yields for treatments involving hoeing and earthing up to 30 and 60 days after planting, Pendimethalin with hoeing and earthing up at 60 DAP, and Glyphosate with hoeing and earthing up at 60 DAP. The study also observed that earthing at 60 DAP increased weed control efficiency. Additionally, the best benefit-cost ratio was achieved with the pre-emergence application of Pendimethalin combined with hoeing and earthing up.

The study examined the impact of integrated weed management on cassava tuber yield (Nwagwu & Asukwo, 2019). The experiment involved 12 treatments, including individual and combined weed control methods. The results showed that weeding significantly reduced weed density and biomass compared to unweeded conditions. The fusion of Atrazine and Metolachlor herbicides with Egusi melon and hand-weeding suppressed considerable weeds. The study also found that integrating hand weeding with mixed solution herbicide and Egusi melon reduced weed dry matter significantly. The highest fresh tuber yield was achieved in plots treated with mixed solution herbicide and hand-weeding twice. The study suggests that three hand-weeding sessions optimize cassava tuber yield, but integrating mixed solutions can effectively replace primary hand-weeding.

18.9 Comparison and Considerations for Choosing a Weeding Technique

Weeding techniques in cassava plantations include chemical, organic, integrated weed management, and computer vision technologies. Each weeding technique has its advantages for eliminating weeds in cassava planting fields. Organic weeding uses intercropping methods by planting legume crops to limit the weed growth in cassava planting grooves, which reduces the use of chemical herbicides. Chemical weeding uses chemical herbicides to eliminate weeds, which is fast and effective. The mechanical weeder uses machines to dig up and uproot weeds, which can kill the weeds in each part of the cassava planting field. The IWM method combines organic, chemical, and mechanical weeding to create sustainable weeding practices in the cassava field. The factors for choosing a weeding technique for specific cassava plantations depend on farm size, weed pressure, budget, and readiness of labor and machinery. Farmers with a larger budget will most likely adopt the machinery method to eliminate weeds in their plantations. Farmers who cannot afford the weeding machines will likely adopt chemical methods that quickly and easily kill weeds. In the case of Organic and IWM weeding, farmers who cannot afford chemical herbicides would implement this method in their field. Most new technologies for weeding in the cassava field are currently being developed, such as intelligent robots and vision-based technologies, which have the potential to be demonstrated soon.

18.10 Solution

AI-driven automation and robotic technologies have advanced to assist people in nearly every sector, including agriculture. Farmers are now utilizing these innovative technologies, integrating AI, computer vision, and deep learning to support various tasks, particularly in weeding. Advanced robotic systems can address labor shortages and enhance safety for cassava farmers. Robotic weeding machines can efficiently and accurately remove weeds by combining AI and deep learning for weed detection in cassava fields. Additionally, weed mapping technologies enable robots to identify the location of weeds within the field, facilitating more effective weed management processes. Future developments in cassava weeding technologies promise further improvements in the industry.

18.11 Conclusion

Weeding is necessary for cassava farmers to remove weeds in cassava plantations. Farmers need to weed their fields regularly for the first 3 months because it is a critical period for weed removal to prevent suboptimal growth issues. Weeds affect every cassava planting cycle by reducing their growth and development, which leads to yield loss and interferes with the manual or mechanical extraction of cassava roots. Various methods for weeding in the cassava field were developed to promote better methods for farmers. Before cassava planting, farmers must prepare the land to reduce weed growth and increase cassava yield. At first, farmers utilized traditional weeding methods to minimize weeds in cassava planting fields. Then, when the size of farmland increased, farmers changed their methods from conventional to mechanical and chemical methods to reduce their weeding burden. Organic weeding methods were also considered an alternative for weeding in cassava plantations, as they would not jeopardize the nearby environment and reduce expenses for chemical herbicides. The advancement of research in organic, chemical, and mechanical methods was conducted to test the efficiency of each technique and determine which one can be implemented in each cassava plantation. Future advancements in cassava weeding technology, including AI, computer vision, and robotics, have gradually developed and can be applied to automatic weeding techniques in cassava plantations.

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Chapter 19
AI Agent System for Agricultural Water Resources Management

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Abstract Agricultural water resources face increasing pressure due to climate variability, rising food demand, and limited water availability. Efficient and adaptive management strategies are essential to maintain agricultural productivity while preserving environmental sustainability. This chapter introduces an AI agent system to support agricultural water resources management by integrating environmental monitoring, hydrological simulation, crop water demand modeling, and policy evaluation. The system utilizes multiple specialized agents, each responsible for a specific task, and is coordinated by a Large Language Model (LLM) interface that interacts with users, interprets queries, and delegates actions to appropriate agents. This modular and intelligent system offers a powerful decision support tool for farmers, policymakers, and researchers aiming to achieve sustainable water use in agriculture.

Keywords Agricultural water resources management · AI agent · Decision support

19.1 Introduction

Agricultural water management is a multifaceted challenge, particularly under the combined threats of climate change, extreme weather events, and competing water demands from industrial and domestic sectors (Krishnan et al., 2022; van Oel et al., 2010). Recent advances in artificial intelligence (AI) provide new opportunities to enhance decision-making in water resource systems (El Fartassi et al., 2025). Among these, AI agent systems—comprising task-specific, semi-autonomous computational agents—offer a structured and adaptable framework to automate and

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coordinate complex tasks. When coupled with a Large Language Model (LLM) interface, such systems can bridge the gap between user intent and technical implementation, enabling non-technical stakeholders to interact effectively with high-performance computational tools.

This chapter presents an AI agent system for agricultural water resources management, featuring a network of agents responsible for environmental data collection, hydrological modeling, crop water demand simulation, and water policy analysis. These agents deliver accurate simulations, forecasts, and policy insights through collaboration and communication, empowering stakeholders to make informed and timely decisions.

19.2 Method: AI Agents for Agricultural Water Resources Management

The AI agent system is composed of four core agent modules, coordinated through an LLM interface:

LLM-Coordinated User Interaction
At the heart of the system is a Large Language Model that serves as the communication interface between users and AI agents. Users—ranging from farmers to government planners—can pose questions in natural language. The LLM interprets the request, identifies relevant tasks, and delegates them to the appropriate agents. For instance, a user asking "How much irrigation water is needed for rice next month in District X?" triggers a chain of actions involving environmental data retrieval, crop simulation, and hydrological assessment.

Environmental Data Collection Agent
This agent continuously gathers and updates environmental datasets, including rainfall, temperature, humidity, solar radiation, and evaporation. Data sources include weather stations, satellite observations, and remote sensing APIs. The agent preprocesses raw data (e.g., gap filling, interpolation, outlier removal) and supplies them to downstream modules in standardized formats. Real-time monitoring enhances the system's responsiveness to short-term weather variations.

Hydrological Modeling Agent
This agent simulates surface and groundwater dynamics using physical and data-driven hydrological models. It integrates rainfall-runoff models, groundwater recharge-discharge models, and water balance equations to estimate available water resources at multiple spatial and temporal scales. Advanced modules use machine learning (e.g., LSTM or hybrid models) to improve prediction accuracy under changing climatic conditions.

Crop Water Demand Simulation Agent

This agent estimates irrigation requirements based on crop type, growth stage, soil moisture, and weather conditions. It uses models like FAO's CROPWAT or machine learning algorithms trained on regional crop data. The agent adjusts estimates dynamically with real-time weather inputs and supports multi-crop and multi-season simulations. It enables scenario analysis, such as estimating water needs under alternative planting schedules or drought conditions.

Agricultural Water Management and Policy Simulation Agent

The final agent models agricultural water allocation strategies under various policy and infrastructure constraints. It evaluates trade-offs between productivity, water use efficiency, and environmental protection. Simulation tools (e.g., optimization algorithms, agent-based models) help design policy instruments such as water pricing, subsidy schemes, or crop zoning. The agent can simulate policy change outcomes and provide long-term planning recommendations.

19.3 Conclusion

Integrating AI agents with a natural language interface offers a transformative approach to agricultural water resources management. The system supports adaptive and evidence-based decision-making by combining real-time environmental monitoring, robust hydrological simulation, and dynamic policy modeling. The LLM interface ensures accessibility for non-specialists, while modular agents provide specialized, high-performance computations. This AI agent system has the potential to become a cornerstone technology for achieving water sustainability, enhancing agricultural resilience, and informing policy in the face of climate and socioeconomic uncertainties.

As agriculture continues to evolve in the twenty-first century, intelligent, responsive, and data-driven systems like this one will play a critical role in shaping the future of global food and water security.

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Chapter 20
An IoT-Assisted Dual Supply Solar Food Drying System for Tropical Agricultural Conditions

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Abstract The world's population is expanding and is estimated to reach 9.1 billion by 2050, necessitating a 70% increase in food production. Post-harvest losses (PHL), estimated at 20–60% of food products, exacerbate the food demand-supply gap, especially in developing countries. PHL is a key issue in worldwide farming, undermining efforts for better food access, poverty reduction, and sustainable development. PHL results in considerable losses in both food quantity and quality, affecting not only the ready accessibility of food for consumption but also the sustained financial health of farmers. Agricultural food processing has been recognized as a potentially practical approach to post-harvest loss (PHL), whereby direct agricultural products are modified to consumable processed goods, thereby adding value. This approach innovatively preserves spoilable food and, at the same time, develops product diversity. Also, beyond the reduced crop waste, it enables farmers, particularly smallholders, to access new markets and improve their earnings and well-being. Traditional preservation techniques like canning, pickling, freezing, fermenting, smoking, salting, and drying have long been used to reduce such losses. Drying, particularly solar drying, offers a sustainable, low-energy alternative vital for tropical and subtropical regions. Solar drying systems, cabinet, tunnel, and hybrid types have evolved by integrating solar collectors, such as parabolic troughs, dishes, and solar power towers. This chapter discusses the development of an Internet of Things (IoT)-assisted dual-supply solar food drying system, integrating a flat-plate collector and a parabolic dish, with IoT-based real-time monitoring and automated temperature control. Performance evaluation showed that the hybrid system (combined flat-plate and parabolic dish) achieved the highest drying efficiency. Moisture content of ash plantain (*Musa paradisiaca*) reduced from 72% to 15%,

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and *Moringa* (*Moringa oleifera*) leaves from 73% to 6% within 450 min, outperforming single-source systems by reducing drying time by 100 min compared to flat-plate and 50 min compared to dish systems. Traditional methods in Sri Lanka face issues of weather dependency, contamination, and inefficiency. The proposed system, leveraging dual solar sources and IoT, ensures improved drying quality, energy efficiency, and reduced spoilage risks, offering a scalable solution for sustainable food preservation. The architecture combines solar concentration techniques with flat-plate heating, Arduino-based temperature control, and real-time data monitoring, providing a reliable method to enhance food security while minimizing environmental impacts.

Keywords Post-harvest loss · Food security · Food preservation · Solar drying · IoT-assisted

20.1 Introduction

According to the Food and Agriculture Organization (FAO, 2009), the world's population will reach 9.1 billion, increasing the demand for food. The estimated food demand increase is 70%, and this is challenging. The key to achieving this challenge is improving productivity and reducing food loss, which will be a plus point (FAO, 2011). Research findings suggest that food loss in the developed world is critical at the consumption stage and is severe throughout the value chain in developing countries (Chegere, 2018). A considerable volume of fresh food, including fruits and vegetables, is lost and wasted at various phases of the agricultural value chain. These post-harvest losses widen the gap between food demand and supply. It is estimated that 20–60% of food products are lost before they reach the consumer (Anand & Barua, 2022).

Food preservation is an action or method used to increase the shelf life of a perishable or semi-perishable product, assuring edibility for later use. Preservation methods can be classified into three classes based on the principle used; they reduce chemical and microbial decay, neutralize harmful organisms, and prevent recontamination throughout the process (Ariyamuthu et al., 2022). Several conventional and modern methods exist for this purpose, such as canning, pickling, freezing, fermenting, smoking, salting, and drying.

Canning is placing food in a jar or a can under sterilized conditions and sealing it to prevent contamination and oxidation. Pickling involves preserving food through anaerobic fermentation in a brine or vinegar solution, adding salty or sour flavor. Pickling medium can be vinegar, alcohol, olive oil, or brine (Ariyamuthu et al., 2022). Under the freezing technique, food is kept at a freezing temperature to prevent microbial activity, and the water inside the food changes from liquid to ice crystals. This completely inhibits biochemical, bacterial, and fungal activity. The biochemical change of sugars into ethanol is known as fermentation. This process is used to manufacture a variety of fermented drinks, including wine, cocktails, and apple juice. Smoking is one of the earliest ways of food preservation, appearing soon after the discovery of fire cooking, and was used for fish and meat preservation. Smoking temperatures range from 42 to 72 °C, and time also varies based on the type of food. Salt is used to cover the food that needs to be preserved. This accelerates the water inside the food, which is removed by osmosis. This reduces the overall water activity of the food and prevents the biochemical, enzymatic reactions and microbial growth that cause food rot (Udomkun et al., 2020).

The drying process removes excess moisture from food items, which has been identified as a significant contributing factor in the deterioration of food products. It is a fundamental step in food preservation and prolongs storage time for a wide range of fruits and vegetables (Salehi, 2020). The food's water level affects its perishability; the higher the water, the lower the shelf life. While drying, water is removed from the food to increase its shelf life. The process of drying has been improved over time to preserve food. Recently, there has been a notable advancement in this field. Diverse drying techniques have been pivotal in preventing food wastage throughout history. Sun drying has been used for centuries in tropical countries (Naliyadhara & Trujillo, 2025).

Solar drying of food is more sustainable than other energy-consuming methods. Solar drying systems need a chamber to dry food, a heating system or a solar heat collector, and an airflow system. The drying chamber should also be able to save the food from rain, insects, and rodents. Solar dryers depend on the design; these systems utilize either natural convection, based on rising hot air, or forced convection, where fans actively push air through the drying area (Green & Schwarz, 2001).

The Internet of Things (IoT) has become a highly valuable application across various fields, including agriculture, home management, traffic control, autonomous vehicles, environmental monitoring, and industrial sectors. Its application in food production and processing is noteworthy, offering significant benefits by enhancing operational efficiency (Seyar et al., 2023; Hamidon et al., 2023). The availability of low-cost sensors for easy measurement of temperature and other parameters, combined with using existing communication technologies with minimal configuration, makes IoT-based food drying systems an affordable solution. These systems enable remote monitoring and regulation, further improving process management.

This chapter highlights the integration of solar concentration techniques with traditional food drying methods and the application of IoT technologies to minimize maintenance time while enhancing quality, particularly in tropical and subtropical regions.

20.2 Importance of Solar Energy

The sun, the largest object in our solar system, holds about 98% of the system's total mass. Its outermost visible layer, the photosphere, reaches temperatures of approximately 6000 °C. Humans have harnessed solar energy for everyday activities like drying clothes and food for centuries, but only recently has this abundant resource been tapped for generating power. Positioned around 150 million kilometers from Earth, the sun is a potent energy source (Lang & Zirin, 2024). Interestingly, the tiny fraction of solar energy that reaches our planet, roughly one hundredth of a millionth of a percent, is more than enough to meet global energy demands many times over. Solar energy is commonly utilized through four primary methods: solar cells, solar water heating, solar drying, and solar furnaces. As a renewable energy source, solar power is inexhaustible, consistently replenished by nature as long as the sun shines. It also produces no greenhouse gas emissions during operation, making it an environmentally friendly option that helps lower carbon footprints and mitigate climate change. Adopting solar energy reduces dependence on fossil fuels and imported energy, enhancing energy security and independence. Moreover, its applications are vast, ranging from electricity generation and water heating to agricultural drying and providing power to remote areas and satellites in space.

20.3 Overview of Traditional Solar Drying Techniques

20.3.1 Solar Dryer (Cabinet Type)

A cabinet-type solar dryer is a specialized device designed to utilize solar energy for drying various materials, primarily agricultural products, in a controlled and efficient environment. The dryer consists of a cabinet-like structure that encloses the drying chamber, creating a contained space for the drying process. Within this chamber, multiple trays or racks are arranged in tiers to hold the materials, ensuring adequate air circulation around each layer to promote uniform drying. Attached to the cabinet is an air heating unit, which plays a crucial role in generating the necessary heat for the process. This unit typically features a transparent top cover, made from glass or clear plastic, allowing sunlight to penetrate the chamber. Beneath the cover, a black-colored absorber plate captures the incoming solar radiation, converting it into heat. As the air within the chamber warms, it rises, creating a natural convection current that carries moisture away from the drying materials. Figure 20.1 illustrates the arrangement of these key components in a cabinet-type solar dryer, showcasing how the integration of solar energy and airflow mechanisms results in a sustainable and energy-efficient drying method.

20.3.2 Solar Dryer (Tunnel/Box Type)

A tunnel-type solar dryer is a large-scale drying system that utilizes solar energy to dry agricultural products efficiently. It features a long, tunnel-shaped structure covered with a transparent material, such as glass or plastic, which allows sunlight to

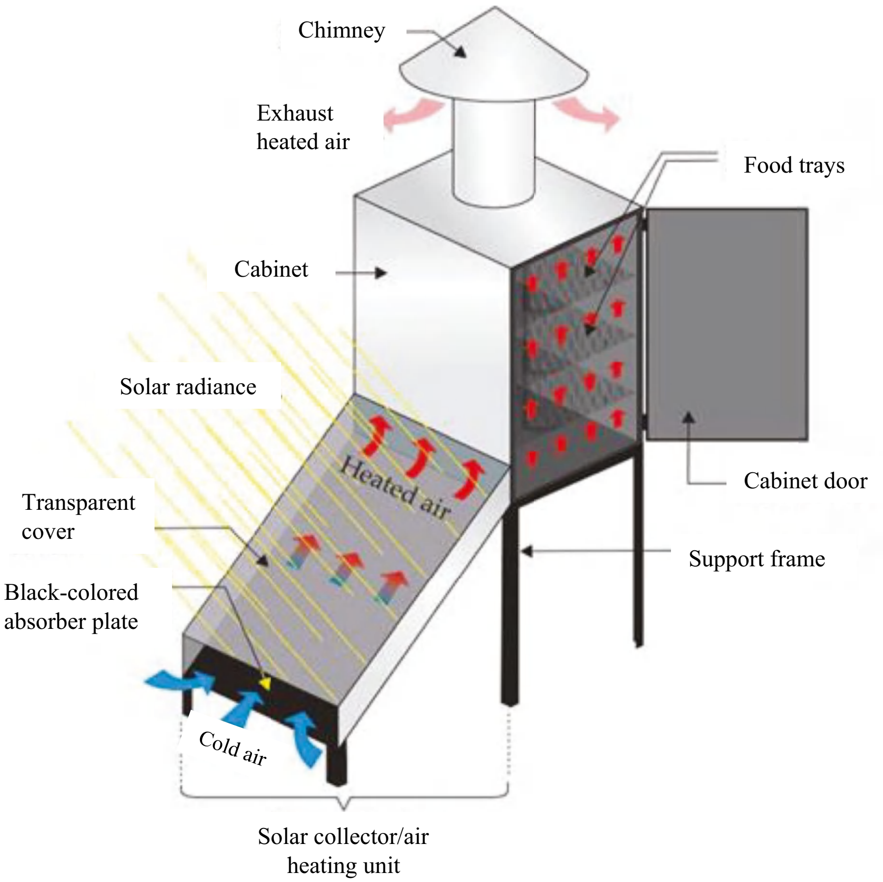

Fig. 20.1 The configuration of the main components in a cabinet-type solar dryer

penetrate and heat the air inside the tunnel. Figure 20.2 gives a schematic diagram of a tunnel-type solar dryer.

20.3.3 Hybrid Solar Dryers

A solar hybrid dryer is an advanced system designed to enhance the efficiency and sustainability of drying processes by integrating an additional energy source, such as biogas or biomass, alongside solar energy. Solar thermal collectors, like flat plate or evacuated tube collectors, capture solar radiation and convert it into heat, which is then used to warm the drying air. Solar tracking mechanisms can be incorporated to maximize solar energy capture, adjusting the collectors' orientation throughout the day (Kumarasiriwardhana et al., 2020). In solar-biogas hybrid systems, organic

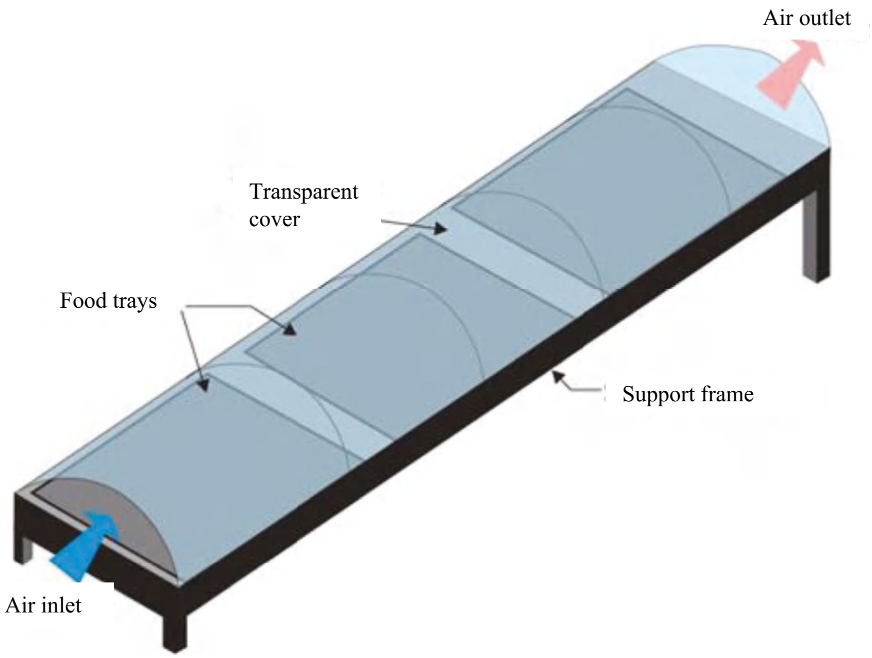

Fig. 20.2 A tunnel-/box-type solar dryer

materials such as agricultural residues, food waste, or animal manure undergo anaerobic digestion, producing biogas through microbial fermentation. The biogas is then burned to generate heat, either supplementing solar energy or acting as a backup during periods of low solar radiation. Conversely, solar-biomass hybrid systems utilize biomass, such as wood chips or agricultural residues, burned in a biomass burner or boiler to produce heat. Rice husk is an abundantly available biomass residue in most paddy-growing countries and is a suitable energy source for various agricultural operations (Piyathissa et al., 2023). This heat can be applied directly to drying or combined with solar energy to maintain optimal drying temperatures. The drying chamber is carefully designed to ensure efficient heat transfer from these energy sources to the air, creating a reliable and sustainable drying environment. Figure 20.3 explains the arrangement of a solar hybrid dryer.

20.4 Solar Concentration Techniques

Solar thermal energy can be harnessed by employing interconnected systems that capture and transfer. The process begins with specialized solar collectors that concentrate sunlight onto a receiver. The captured heat is then transferred to a working fluid, typically synthetic oil or molten salt, with excellent thermal properties for

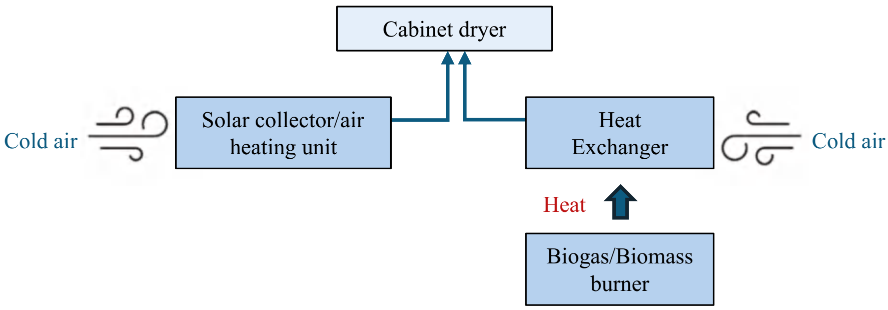

Fig. 20.3 Air heating process in solar hybrid drying

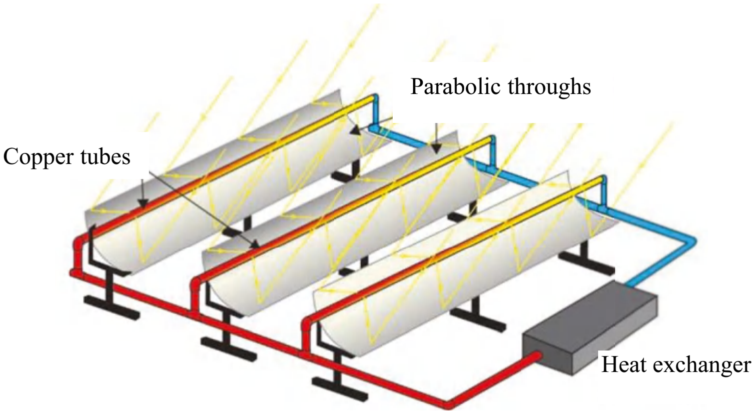

Fig. 20.4 Parabolic trough collector

retaining and transporting heat. This heated fluid passes through a heat exchanger, transferring its thermal energy to water, converting the water into steam. To complete the cycle, a cooling system condenses the steam back into water, allowing it to be reused.

These plants employ different types of solar collectors, each with unique characteristics. Parabolic trough collectors consist of long, curved mirrors that focus sunlight onto a receiver pipe along the trough's focal line (Fig. 20.4).

Parabolic dish collectors use dish-shaped mirrors to concentrate sunlight on a central receiver at the dish's focal point (Fig. 20.5).

Solar power towers take a different approach, using an array of movable mirrors known as heliostats. These heliostats track the sun's movement and direct sunlight toward a receiver at the top of a central tower (Fig. 20.6).

Each collector type is crucial in optimizing solar energy capture, making solar thermal energy harnessing an efficient and sustainable solution for thermal applications.

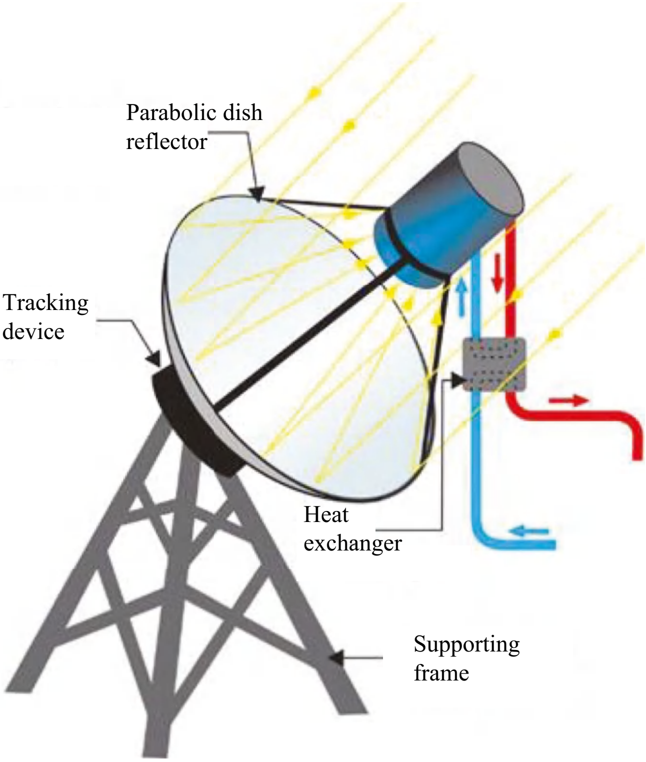

Fig. 20.5 Parabolic dish collector

20.5 Development of an IoT-Assisted Dual Supply Solar Food Drying System

A cabinet-type solar dryer is a device that harnesses solar energy to dry various materials, primarily agricultural products, in a controlled and efficient manner. The main component is the cabinet structure, providing a contained environment for drying. Inside the cabinet, trays or racks are arranged to hold the materials to be dried, allowing air to circulate them (Kumarasiriwardhana et al., 2020). An air heating unit is attached to the cabinet structure to provide heated air. This unit has a transparent top cover, often made of glass or clear plastic, that allows sunlight to enter. Inside, a black-colored absorber plate absorbs sunlight and converts it into heat. The applications of this type of dryer extend to agricultural products such as drying fruits, vegetables, herbs, spices, and grains. It is also used for drying medicinal plants, fish, meat, and other materials, and extending the shelf life of perishable food items.

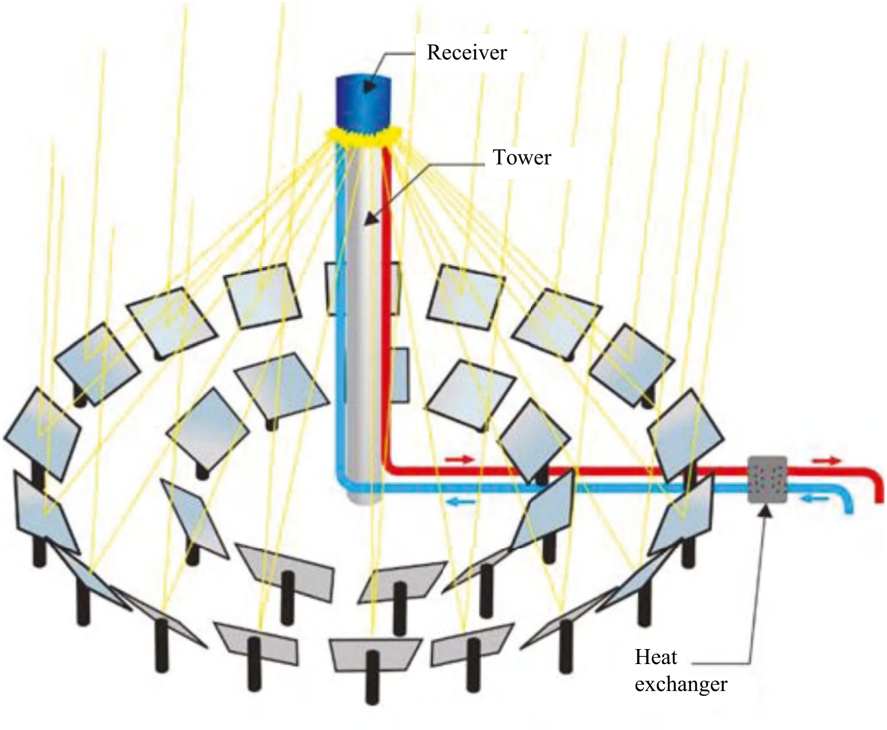

Fig. 20.6 Solar power towers

In Sri Lanka, food drying predominantly relies on traditional sun drying and rudimentary techniques like open-air drying. While these methods are low cost and culturally ingrained, they face several challenges. First, they are highly dependent on weather conditions, which can lead to inconsistent drying and increased susceptibility to spoilage, especially during the monsoon season. Quality control is another issue, as traditional methods often result in uneven drying and contamination from dust, insects, and microorganisms, compromising the safety and marketability of dried foods. Moreover, the lengthy drying times required by these methods contribute to inefficiencies in production and can lead to significant post-harvest losses due to spoilage.

Additionally, space constraints and environmental concerns related to waste disposal further limit the scalability and sustainability of traditional drying practices. Addressing these challenges requires modernizing drying techniques by adopting technologies like solar dryers, which offer controlled environments that enhance product quality, reduce drying times, and improve overall efficiency in food processing. The basic architecture of the IoT-assisted dual supply solar food drying system is shown in Fig. 20.7.

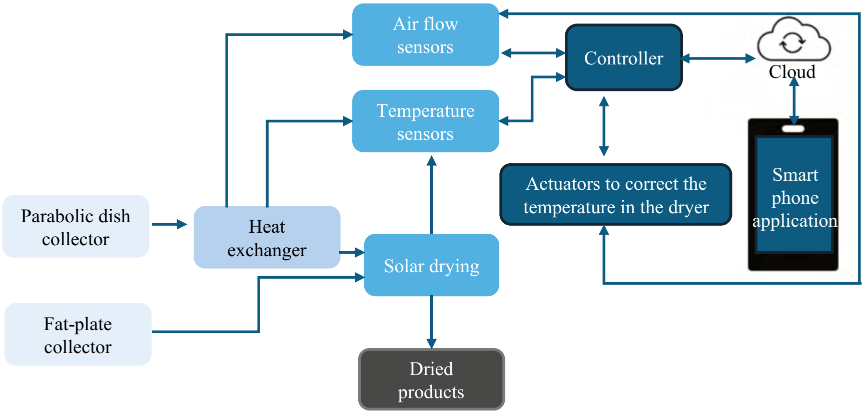

Fig. 20.7 Basic architecture of the IoT-assisted dual supply solar food drying system

Despite these limitations, a cabinet-type solar dryer with a concentrated solar-cum-flat-plate collector, which operates by dual solar power sources, represents a significant advancement over traditional drying methods and is suitable for various climatic conditions and food types. By combining conventional drying methods with modern technology, leveraging solar energy and IoT, this study seeks to provide a reliable and sustainable solution for food preservation and create a highly efficient and environmentally friendly drying system that can be adopted in various regions, especially in areas with high solar irradiance. Figure 20.8 illustrates the arrangement of components of the proposed drying system.

20.5.1 Temperature Controlling System

The temperature control system was operated using Arduino programming. The main components included temperature sensors (DHT22 and thermocouples), an Arduino UNO board, an LCD, 12 V DC fans, a Real-Time Clock (DS1302), and a relay module. The temperature sensors measured the middle layer temperature, providing input data to the system. Based on this input, the output signal was sent to the relay, which controlled the connection and disconnection of the current supply to the DC fans. The Real-Time Clock (DS1302) tracked the time and date displayed on the LCD screen along with temperature and humidity readings. The captured data was also stored on an SD card to ensure data preservation. Figure 20.9 illustrates the process block diagram of controlling the temperature and humidity.

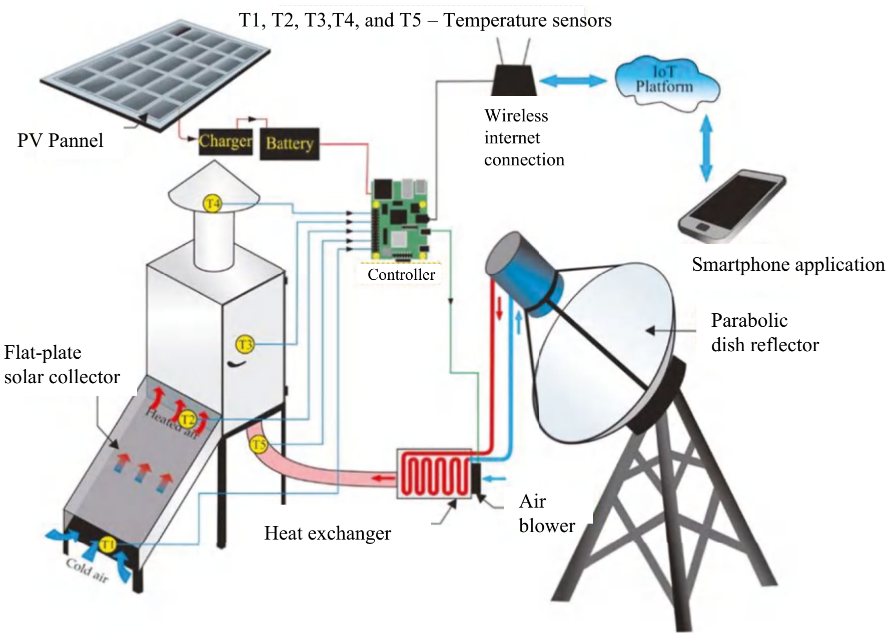

Fig. 20.8 Proposed drying system with IoT and dual solar power

20.5.2 Specifications of the Fabricated Dryer

Figure 20.10 shows the fabricated IoT-assisted dual solar supply dryer designed for tropical conditions, while Table 20.1 presents the dryer's key specifications.

Performance Evaluation

The dryer's performance was compared with a conventional cabinet-type solar dryer under no-load and loaded conditions. Experiments were conducted with three replicates for each treatment. The three treatments were defined as follows: T1: Flat-plate collector configuration; T2: Parabolic dish configuration; and T3: Combination of both flat-plate collector and parabolic dish configuration.

20.5.3 No-Load Test

The no-load test measured the dryer's temperature and relative humidity without any products inside. This test helped identify the basic operational characteristics, such as the dryer's heating capacity and energy extraction efficiency. Measurements recorded at 20-min intervals included the following: the inlet air temperature from the flat-plate collector, the inlet air temperature to the cabinet, the outlet air temperature at the exhaust chimney, the inlet and outlet water temperatures at the heat

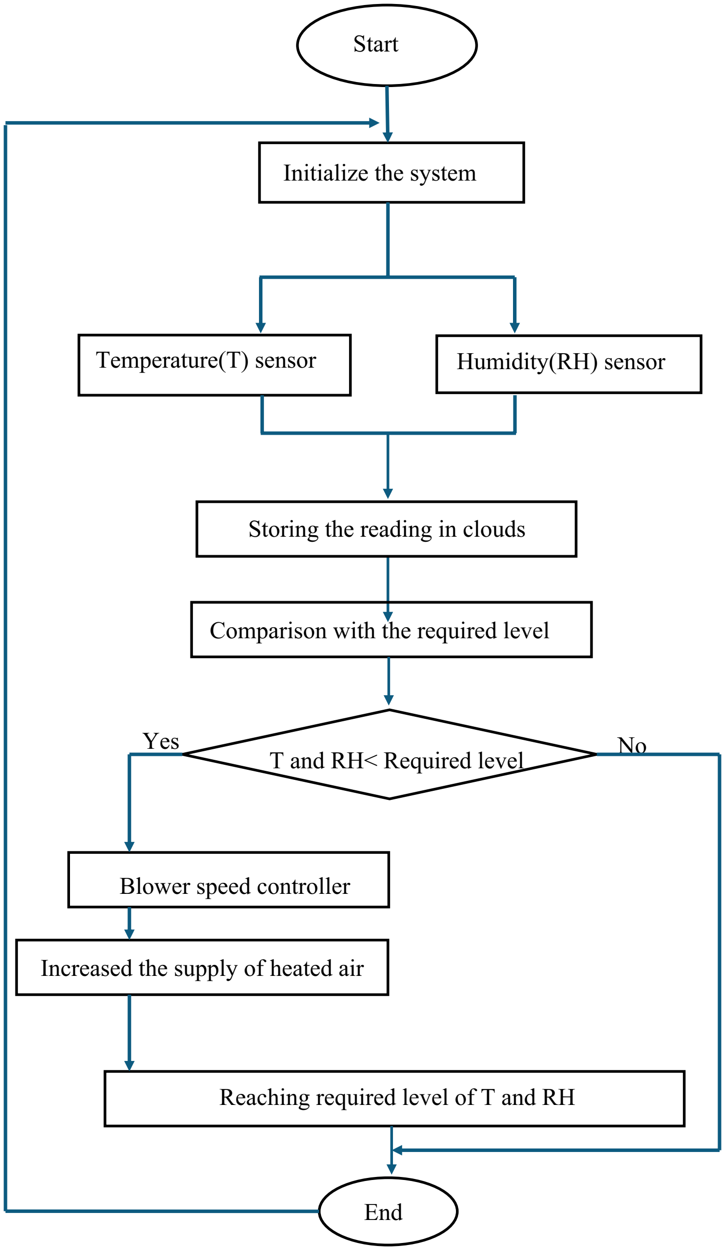

Fig. 20.9 Process block diagram of the system

Fig. 20.10 Fabricated IoT-assisted dual solar supply dryer

Table 20.1 Specifications of the IoT-assisted dual solar supply dryer

Components	Description	Dimension
Parabolic dish	Diameter Rim angle	1 m 45°
Flat-plate collector	Length Width Height Tilt angle	1.7 m 0.6 m 0.2 m 27°
Tray	Length Width Gap between trays	0.5 m 0.45 m 0.15 m
Chamber	Length Width Height	0.5 m 0.45 m 0.65 m
Heat storage unit	Capacity	8 L
Heat exchange unit	Length Width Height	0.2 m 0.1 m 0.08 m

exchanger, the inlet air temperature from the heat exchanger, the time taken to reach the maximum temperature, the airflow rates through the flat-plate collector and the heat exchanger, and the ambient temperature. In the no-load test, temperature variations in the cabinet chamber over 7 h from 9.00 am to 4.00 pm are shown in Fig. 20.11.

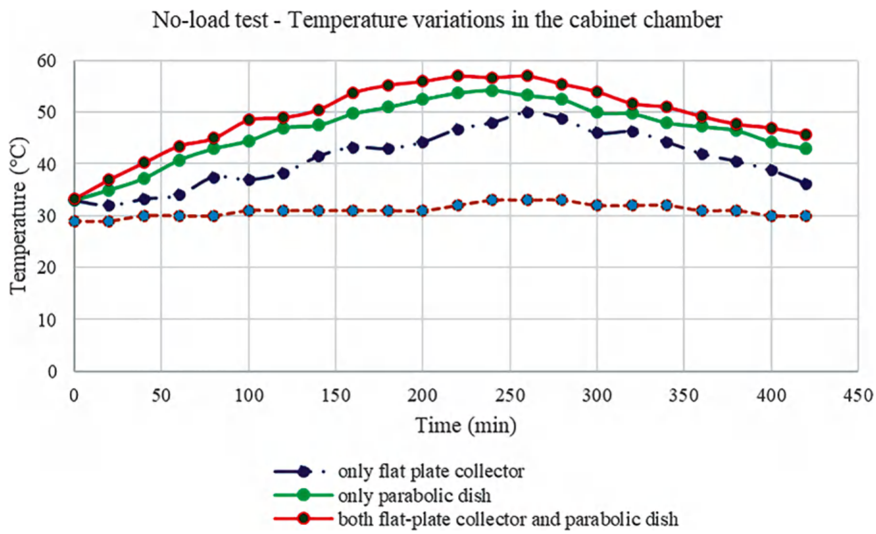

Fig. 20.11 Temperature variations in the drying chamber during the no-load test

The ambient conditions were monitored throughout the testing period, with temperatures between 28 and 33 °C. Minimal fluctuations were observed, confirming that controlled testing conditions were achieved. These ambient measurements served as the baseline for evaluating the system's performance.

An initial temperature of 32 °C was recorded in the flat-plate collector configuration. The temperature gradually increased, reaching a maximum of 50 °C 300 min into the testing period. A moderate heating rate was observed, and the temperature profile exhibited a characteristic sigmoid curve. Following the peak period (300–450 min), performance degradation was noted, with the final temperature recorded at 37 °C at the 450-min mark.

20.5.4 Drying Curves for Moringa *Leaves and Ash Plantain*

Moringa leaves (*Moringa oleifera*) and ash plantain (*Musa paradisiaca*) were sourced from the local market in the Anuradhapura area. The average initial moisture content was 0.75% for *Moringa* leaves and 0.73% for ash plantain.

Mature, unripe ash plantains were washed, peeled, and sliced to an approximate thickness of 5 mm for drying. *Moringa* leaves were also washed, and the ribs were removed. Pre-treatment was carried out using hot water blanching: ash plantain slices were dipped in hot water at approximately 72 °C for 2–3 min, followed by immediate cooling in ice water to enhance color retention and reduce drying time. The prepared produce was then arranged in a single layer on the trays to prevent

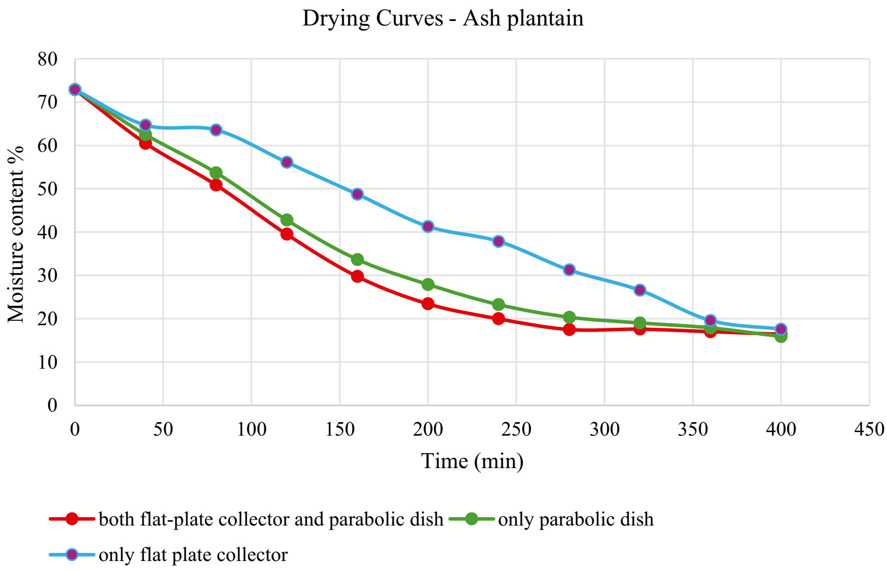

Fig. 20.12 Variation in moisture content over time for ash plantain

moisture accumulation in the lower layers. Figure 20.12 illustrates the variation in moisture content over time for ash plantain under the three treatments.

The moisture content variations in ash plantain samples were investigated under three distinct drying configurations, and the following observations were recorded and analyzed. At the beginning of the drying process, all samples exhibited an initial moisture content of approximately 72%, ensuring consistency and experimental validity across all three configurations. Drying behavior was monitored over a 450-min period, during which notable differences in moisture reduction rates were observed among the configurations:

Flat-Plate Collector Configuration A relatively gradual moisture reduction was observed. Moisture content decreased from 72% to 64% within the first 50 min, followed by a steadier decline. By the end of the 450 min, a final moisture content of 18% was achieved, representing the slowest overall drying rate among the three setups.

Parabolic Dish Configuration The dish recorded a faster initial drying rate than the flat-plate collector. Moisture content dropped to 58% within the first 50 min, and a final moisture content of 16% was achieved. This setup demonstrated intermediate drying performance.

Combined Flat-Plate Collector and Parabolic Dish Configuration The combined system exhibited the most efficient drying characteristics. Within the first 50 min, an initial moisture reduction to 60% was observed, followed by the steepest overall drying curve. A final moisture content of 15% was achieved, indicating the highest drying efficiency.

Comparative analysis revealed that the combined system enhanced the initial moisture reduction rate by 25% compared to the flat-plate collector and by 15% compared to the parabolic dish configuration. Additionally, the time required to reach the desired final moisture content was significantly reduced: approximately 100 min less than the flat-plate collector and 50 min less than the parabolic dish system. Toward the final phase of drying (350–450 min), convergence of all three drying curves was observed, with similar equilibrium moisture contents reached across the configurations. This convergence was attributed to reduced moisture availability in the samples and the decreased influence of drying mechanisms at lower moisture levels. The variation in moisture content over time for *Moringa* leaves under the three treatments is presented in Fig. 20.13.

At the commencement of the drying process, an initial moisture content of approximately 73% was recorded across all *Moringa* leaf samples. Uniformity in initial moisture content was maintained to ensure experimental consistency across the three drying configurations. Moisture reduction patterns were monitored and analyzed for each configuration:

Flat-Plate Collector Configuration (T1) The slowest drying rate was observed in this configuration. Moisture content decreased to approximately 60% within the first 50 min, followed by a gradual decline throughout the drying period. A final moisture content of 8% was achieved at the 450-min mark, and the most moderate drying curve was recorded.

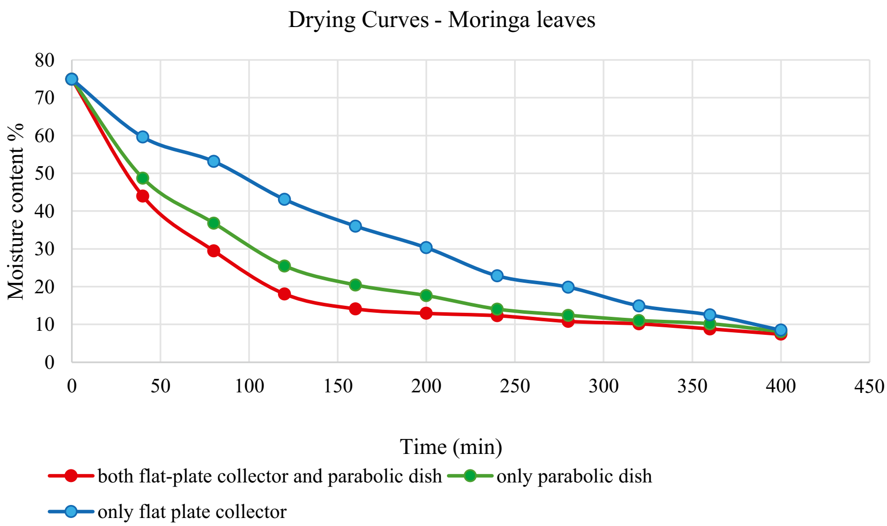

Fig. 20.13 Variation in moisture content over time for *Moringa* leaves

Parabolic Dish Configuration (T2) An intermediate drying rate was documented. Moisture content dropped to approximately 48% within the first 50 min. A steeper drying curve compared to the flat-plate collector was observed, with a final moisture content of 7% achieved, indicating enhanced drying performance.

Combined Flat-Plate Collector and Parabolic Dish Configuration (T3) The combined system recorded the most efficient drying characteristics. Moisture content was reduced to approximately 43% within the initial 50 min, and the steepest drying curve was observed throughout the process. A final moisture content of 6% was achieved, reflecting the highest drying efficiency.

The drying curves converged during the final phase (350–450 min), when similar equilibrium moisture contents were attained across all configurations. This convergence was attributed to the reduced moisture availability in the *Moringa* leaves and the diminished effectiveness of the drying mechanisms at lower moisture levels. A final moisture content range of 6–8% was achieved across all configurations, which falls within acceptable limits for *Moringa* leaf preservation. However, the time required to reach these moisture levels varied significantly between the different drying systems.

20.5.5 Determination of Efficiencies

Efficiency of the Flat-Plate Collector

The efficiency of the flat-plate collector (η_{fc}), which indicates how effectively it converts incident solar energy into useful heat, was calculated using Eq. 20.1 (Duffie & Beckman, 2013).

$$\eta_{fc} = \frac{V_{afc}\rho_{\mathrm{a}}C_{pa}\Delta T_{\mathrm{a}}}{I_{\mathrm{c}}A_{fc}} \times 100\% \tag{20.1}$$

Where, V_{afc} = volumetric flow rate of air (m^3/s), ρ_a = air density (kg/m^3), ΔT_a = air temperature elevation (°C), C_{pa} = air specific heat capacity (J/kg/°C), I_c = insolation on collector surface (W/m^2), A_{fc} = area of the flat-plate collector (m^2).

Efficiency of the Heat Exchanger

The efficiency of the heat exchanger ($\boldsymbol{\eta}_{he}$), representing how effectively it transfers heat from the collector to the drying air, was calculated using Eq. 20.2 (Fakheri, 2014).

$$\eta_{he} = \frac{V_{ahe}p_a\Delta T_{whe}C_{pa}}{V_{wse}\rho_{\mathrm{w}}C_{pw}\Delta T_{wse}} \times 100\% \tag{20.2}$$

Table 20.2 Efficiencies of main components of IoT Assisted Dual Solar Supply Dryer

Component	Symbol	Efficiency (%)
Flat-plate collector	η_{fc}	25.54
Heat exchanger	η_{he}	46.94
Solar energy extractor (parabolic dish)	η_{se}	80.53

Where, V_{ahe} = volumetric flow rate of air at heat exchanger (m^3/s), V_{wse} = volumetric flow rate of water (m^3/s), ρ_w = water density (kg/m^3), ΔT_{wse} = water temperature elevation in solar energy extractor (°C), ΔT_{whe} = water temperature elevation heat exchanger (°C), C_{pw} = water specific heat capacity (J/kg/°C).

Efficiency of the Solar Energy Extractor (Parabolic Dish)
The efficiency of the solar energy extractor (η_{se}) was determined by combining the efficiencies of the flat-plate collector and the heat exchanger. The efficiency of the parabolic dish ranged from 23% to 33% (Sivalingam et al., 2024); therefore, an average efficiency of 28% was considered for calculations. Overall efficiency was calculated using Eq. 20.3.

$$\eta se = \frac{V_{wse}\rho_w C_{pw}\Delta T_w}{I_c A_{pd} E_{pd}} \times 100\% \tag{20.3}$$

Where, I_c = insolation on collector surface, A_{pd} = total area of glued mirrors (m^2), E_{pd} % = efficiency of parabolic dish.

Table 20.2 presents the efficiencies of the flat-plate collector, heat exchanger, and parabolic dish

20.6 Conclusion

As global food demand rises, innovative, efficient, and sustainable food preservation methods become increasingly critical. Traditional drying techniques, while historically significant, are often inadequate in meeting the modern challenges of quality assurance, efficiency, and food security. Solar energy, a clean and abundant resource, provides a sustainable foundation for advanced food drying systems, minimizing environmental impact while reducing reliance on fossil fuels.

Integrating Internet of Things (IoT) technologies into solar food drying systems represents a transformative advancement in food preservation. IoT enhances the drying process's operational efficiency, consistency, and reliability by enabling real-time monitoring, precise temperature and humidity control, data recording, and system automation. As outlined in this study, developing and evaluating an IoT-assisted dual supply solar food drying system demonstrates significant improvements over conventional drying methods, particularly in drying speed, energy utilization, and final product quality.

Incorporating IoT into solar-powered drying ensures optimal drying conditions. It reduces labor, maintenance time, and post-harvest losses, ultimately supporting the agricultural sector's development toward more innovative, resilient practices. Especially in tropical and subtropical regions like Sri Lanka, where solar energy is abundant, this approach offers a scalable and environmentally friendly solution for enhancing food security and economic development. Moving forward, widespread adoption and further innovation in IoT-based agricultural technologies will be vital in addressing the pressing global challenges of food preservation, sustainability, and climate resilience.

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Chapter 21
Technological Transitions in Thermal Drying: Integrating Microwave and Heat Pump Technologies with AI and IoT to Enhance Productivity in Food and Agricultural Systems

A. J. Fernando

Abstract Thermal drying is a crucial method in food preservation; however, conventional approaches often compromise product quality and consume significant amounts of energy. This chapter examines the technological advancements in thermal drying, with a focus on microwave and heat pump drying systems that are enhanced by Artificial Intelligence (AI) and the Internet of Things (IoT). By integrating these Industry 4.0 technologies and the concept of Industry 5.0, food drying processes are being transformed into intelligent, adaptive systems that minimize nutrient losses, retain sensory attributes, and improve energy efficiency. This chapter reviews key developments, highlighting AI's extensive application in predictive modeling and process optimization, particularly through Artificial Neural Networks (ANNs), while emphasizing the potential of IoT for real-time monitoring and control. A bibliometric analysis further illustrates AI's dominance in research and the underutilization of IoT despite its industrial scalability. Beyond technical gains, the integration of AI and IoT directly supports multiple Sustainable Development Goals (SDGs), including Zero Hunger, Good Health and Well-Being, Affordable and Clean Energy, and Responsible Consumption and Production, by fostering food security, reducing resource consumption, and promoting sustainable automation. In alignment with Society 5.0, this chapter positions these innovations as enablers of human-centered, resilient, and sustainable food systems, paving the way for next-generation drying technologies in agriculture and food processing.

Keywords Artificial Neural Networks (ANNs) · Predictive modeling · Process optimization · Society 5.0 · Sustainable Development Goals (SDGs)

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21.1 Introduction

Food drying is one of agriculture's oldest and most vital preservation techniques. Reducing postharvest losses, extending shelf life, enhancing food safety, and ensuring year-round food availability are essential.

With the growing global population, increasing climate variability, and limited natural resources, improving drying technologies has become critical for enhancing food security and agricultural sustainability. Given that most food items contain between 75% and 90% moisture, considerable energy, approximately 2.8 kJ per kilogram of water, is required to reduce this to below 10%. Starch-based products are particularly energy-intensive, as their processing involves multiple thermal steps that add and remove water (Roos et al., 2016).

Traditional drying methods in the food industry are often characterized by excessive energy consumption, inconsistent drying performance, and compromised product quality, underscoring the need for technological advancements. Over 85% of industrial thermal dryers exhibit low energy efficiency, averaging around 30%, contributing to as much as 90% of total processing costs (Gremmen et al., 2009). Additionally, 35% to 45% of the input energy is typically lost as hot exhaust gases, resulting in considerable energy inefficiency and elevated greenhouse gas emissions (Atuonwu et al., 2011).

Among food drying techniques, microwave and heat pump drying are increasingly utilized in various food processing sectors due to their efficiency and ability to retain quality. Microwave drying is a process that employs microwave energy to evaporate moisture from materials, generating heat within the material's volume. Microwaves penetrate the material, exciting water molecules and causing them to vibrate, generating heat and driving moisture's evaporation. Compared to conventional drying, microwave drying can reduce the drying time by up to 50% (Guo et al., 2023). Meanwhile, heat pump drying operates at low temperatures with high energy efficiency by recycling latent heat, making it particularly suitable for drying heat-sensitive, high-value agricultural commodities with minimal environmental impact (Fernando & Rosentrater, 2023).

Artificial Intelligence (AI) and the Internet of Things (IoT) are revolutionizing agriculture by enabling precision, automation, and data-informed decisions throughout the value chain. AI is applied in yield forecasting, pest and disease identification, crop growth monitoring, and the optimization of agricultural processes. Meanwhile, IoT technologies, including sensors, drones, and intelligent controllers, collect real-time data on soil health, weather conditions, crop status, and equipment performance. When combined, AI analyses the vast datasets gathered by IoT devices to generate actionable insights, enabling farmers and processors to make informed, timely decisions that enhance productivity, reduce resource consumption, and increase sustainability. This lays the foundation for innovative farming systems that are efficient, adaptive, and aligned with contemporary sustainability goals.

Integrating AI and IoT into thermal drying systems aligns seamlessly with the vision of Society 5.0, a concept introduced by Japan to create a super-smart society where digital transformation addresses societal challenges and promotes well-being. In this paradigm, innovative food drying technologies serve as key enablers, utilizing data-driven insights and intelligent control to optimize drying operations. These systems can autonomously adjust drying parameters based on real-time inputs, predict equipment maintenance needs, and ensure consistent product quality. Such innovations reflect the essence of Society 5.0, where advanced technologies harmonize with human needs to achieve inclusive growth, food security, and environmental stewardship.

Moreover, innovative thermal drying technologies contribute directly to several United Nations Sustainable Development Goals. By reducing postharvest losses and improving food preservation, they advance SDG 2 (Zero Hunger), ensuring greater food availability and agricultural sustainability. Their efficient energy use and compatibility with renewable sources support SDG 7 (Affordable and Clean Energy) by minimizing the carbon footprint of drying operations. In addition, optimized resource utilization and reduced waste align with SDG 12 (Responsible Consumption and Production), promoting circular economy practices in the food processing sector. Collectively, these contributions demonstrate the crucial role of innovative drying technologies in establishing a more resilient and sustainable agricultural and food system.

This chapter examines the technological transitions in thermal food drying, with a focus on integrating AI and IoT into microwave and heat pump drying systems. It explores how these innovations enhance agricultural productivity and support the broader goals of sustainable agriculture and Society 5.0.

21.2 Historical Perspective: Industrial Revolutions and Food Industry Transformation

The evolution of industrial revolutions has continuously reshaped the food processing sector, driving significant technological advancements over time (Hassoun et al., 2023). Figure 21.1 illustrates a chronological overview of the key developments in food drying technologies across different phases of industrialization.

The onset of the industrial revolution in the late 1700s marked a transition from manual and natural energy sources, such as human, animal, wind, and water power, to steam-driven machinery for repetitive operations. This transformation significantly advanced thermal processing methods. Further, Louis Pasteur introduced the pasteurization method in the 1860s, and by 1876, he and Charles Chamberland had developed the earliest version of the autoclave (Misra et al., 2017).

The late nineteenth century marked the second industrial revolution, characterized by the transition from steam to electrically powered machinery. This period witnessed notable innovations, including juice extraction equipment, vacuum sealing technologies, early advancements from batch to continuous pasteurization, and the introduction of refrigeration systems (Hassoun et al., 2023). These technological improvements significantly boosted industrial efficiency and processing capabilities.

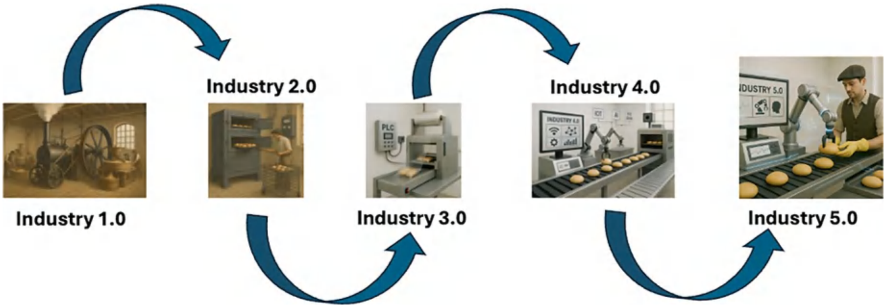

Fig. 21.1 Evolution of the industrial revolution and its influence on the food processing sector

During the 1970s, the third industrial revolution emerged, introducing the digitalization of food processes through advancements in microchip technology and enhanced control of food processing operations (Teixeira & Shoemaker, 1989). The advent of digitalization in process control enabled precise and uninterrupted food processing through automated and programmable computer systems (Goff & Griffiths, 2006). This phase also introduced robotics into food manufacturing (Nayik et al., 2015). It led to the development of irradiation techniques, including ionizing radiation and microwave-based systems (Farkas & Moh´acsi-Farkas, 2011).

The shift from Industry 3.0 to Industry 4.0, which began around 2011, marked a transformative phase in manufacturing, as it adopted advanced digital and automated technologies. While Industry 3.0 emphasized electronics and automation to enhance production, Industry 4.0 integrates innovations such as the IoT, AI, and big data analytics. These technologies enable real-time communication between machines, allowing autonomous decision-making and process optimization. This evolution enhances efficiency, adaptability, and innovation across various manufacturing sectors, including food processing, where smart sensors, robotics, AI, and IoT play increasingly vital roles (Hassoun et al., 2022a, b). Figure 21.2 illustrates the key components of Industry 4.0.

In 2021, the European Commission introduced the concept of Industry 5.0, signaling a new phase of industrial evolution. This framework emphasizes a human-centric vision that integrates advanced technologies, including Artificial Intelligence, augmented reality, and decentralized systems. Unlike previous industrial revolutions, Industry 5.0 prioritizes collaboration between humans and machines, aiming to combine technological innovation with human intuition, creativity, and emotional intelligence. The approach seeks to enhance personalization, sustainability, and resilience across industries. By aligning technological advancements with human values and well-being, Industry 5.0 envisions a more inclusive and sustainable industrial landscape (Breque et al., 2021).

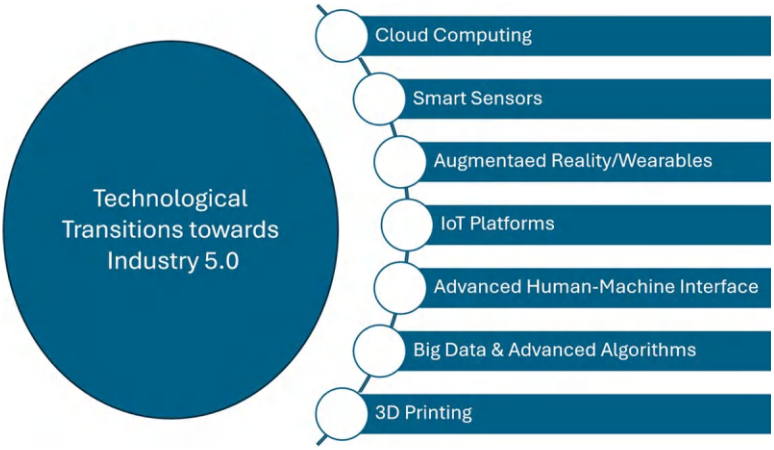

Fig. 21.2 Technological transitions toward Industry 5.0

21.3 Overview of Thermal Food Drying Methods

21.3.1 Principles of Food Drying

Food drying is a process that involves removing moisture from food to lower its water activity, thereby inhibiting microbial growth, enzymatic activity, and chemical reactions that cause spoilage. Three fundamental principles governed the drying process: heat transfer, mass transfer, and reduction of water activity. Heat transfer involves supplying energy, typically through conduction, convection, or radiation, to evaporate moisture from the food. Mass transfer refers to the movement of water vapor from the food's interior to its surface and into the surrounding air or vacuum. Water activity reduction decreases the availability of free water to a point where spoilage organisms can no longer survive or multiply. Several factors influence drying efficiency, such as drying temperature, humidity levels, airflow speed, pressure conditions, the food's structural properties, and the internal moisture diffusion rate.

21.3.2 Classifications of Food Drying Methods

Food drying methods can be classified based on the drying medium, energy source, operation mode, or temperature regime. The main classifications include the following:

Based on Heat Source:

- Convective Drying (Ex: Hot Air Drying, Spray Drying)
- Electromagnetic Radiation Drying: Radiative drying (Ex: Infrared Drying), Dielectric Drying (Ex: Microwave Drying)

- Conductive Drying: Drum Drying, Vacuum Contact Drying

Based on Temperature Conditions:

- High-Temperature Drying (e.g., hot air drying)
- Low-Temperature Drying (e.g., freeze drying, heat pump drying)

Based on Pressure Conditions:

- Atmospheric Drying
- Vacuum Drying

Based on Operation Type:

- Batch Drying
- Continuous Drying

21.3.3 Advanced Crop Drying Methods

Microwave and heat pump drying are among the advanced techniques that have attracted growing interest due to their potential to enhance energy efficiency, shorten drying duration, and maintain superior product quality. Microwave drying utilizes electromagnetic radiation and provides volumetric heating, which accelerates moisture removal from the inside out. This technique is ideal for uniformly drying high-moisture foods. Heat pump drying, a low-temperature technique, reuses latent heat for energy conservation and is particularly beneficial for drying heat-sensitive and high-value commodities. These methods exemplify the technological advancements driving the evolution of food drying systems toward more sustainable and precise processes.

Microwave Drying Microwaves belong to the electromagnetic spectrum with frequencies ranging from 300 MHz to 300 GHz and wavelengths between 1.0 mm and 1.0 m. When materials are subjected to microwave energy, polar molecules rapidly align and misalign with the alternating electromagnetic field, producing heat internally. This internal heating results from molecular friction and movement overcoming intermolecular forces, increasing the material's temperature (Rattanadecho & Makul, 2016). The process of molecular polarization and depolarization induced by microwave radiation is presented in Fig. 21.3.

Microwave heating operates mainly through dielectric loss, where absorbed microwave energy is converted into heat within the material. Polar molecules continuously reorient under a rapidly oscillating electric field, causing vigorous molecular motion. The friction generated by this movement produces heat internally, resulting in a rise in the material's temperature (Guzik et al., 2022). Figure 21.4 indicates the schematic diagram of the microwave drying process.

Microwave drying technology offers numerous advantages, making it a highly valuable tool in food processing. Its rapid heating, higher efficiency,

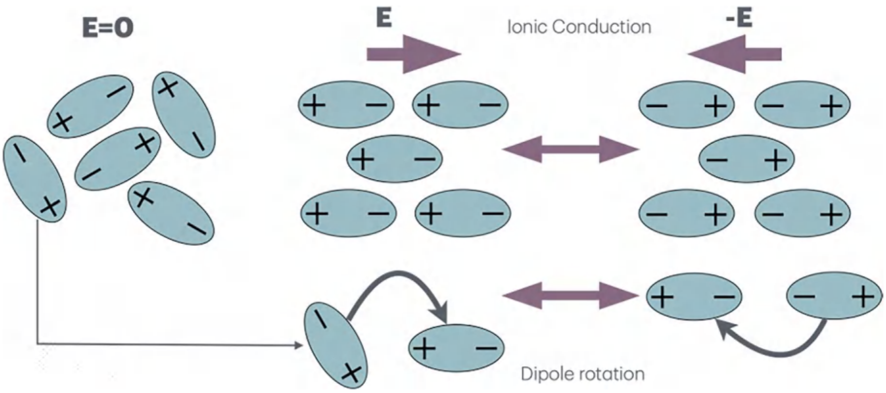

Fig. 21.3 The schematic representation of molecular polarization and depolarization under microwave radiation illustrates internal heat generation through dipole rotation and molecular friction

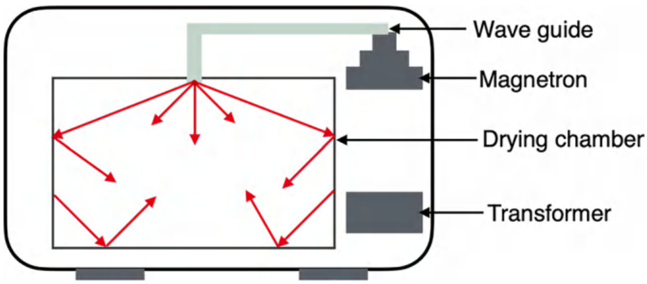

Fig. 21.4 Schematic representation of the microwave drying process, illustrating energy absorption, internal heat generation, and moisture removal mechanisms in food materials

energy-efficient operation, and ease of control contribute to its increasing application. Beyond enhancing processing efficiency, microwave heating can improve the appearance and flavor of foods, promote better nutrient absorption, and accelerate the transformation of bioactive compounds, paving the way for innovative food products. Microwaves can also alter the structural and functional properties of starches, lipids, and proteins to meet evolving market demands. Notably, microwave treatment can enhance antioxidant activity in oxidation-prone foods, reduce the risk of damage from peroxidation, and increase the content of specific amino acids. Moreover, it has been demonstrated to diminish food allergenicity while retaining more flavors and small molecular nutrients such as vitamins and minerals without raising safety concerns, making it a promising and consumer-friendly drying method (Deng et al., 2022).

Microwave drying offers high efficiency, as it generates internal heat without relying on thermal conduction, resulting in faster moisture removal and improved product quality when applied optimally. Despite these benefits, limited penetration depth remains a notable drawback, especially at the commonly used 2.45 GHz

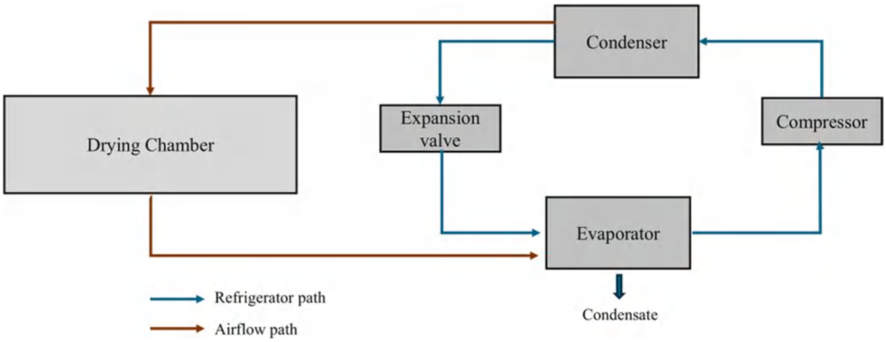

Fig. 21.5 Schematic diagram of open-loop heat pump dryer

Table 21.1 Comparative overview of heat pump drying and conventional hot air drying

Parameter	Heat pump drying	Conventional hot air drying
Specific moisture extraction rate (SMER) (kg/kWh)	1.0–5.0 (approximately three times higher)	0.2–0.6
Operating temperature (°C)	−20 to 100	40 to very high
Relative humidity (%)	10–80	Variable
Drying efficiency (%)	Up to 95	35–40
Drying rate	Faster	Moderate
Final product quality	Very good	Average
Rehydration capacity	Excellent	Average
Initial investment cost	Moderate	Low
Operating cost	Low	High
Drying duration	Relatively longer (1–1.5×)	Shorter
Energy efficiency	High (up to 70% energy savings)	Low

Sources: Fernando and Rosentrater (2023), Chua et al. (2010), Patel and Kar (2012), Minea (2015), Goh et al. (2011), Uthpala et al. (2020)

frequency. Industrial applications generally use frequencies such as 915 MHz (USA), 896 MHz (UK), 902 MHz (Australia), and 2450 MHz, with corresponding commercial systems widely available (Radoiu, 2020).

Heat Pump Drying Heat pump drying systems combine a heat pump with a drying unit to produce dehumidified air, which removes moisture from food materials. The refrigerant in the evaporator absorbs heat from the warm, moist air and dissipates to the dehumidified cold air at the condenser. The hot, dehumidified air generated at the condenser is used to dry crops in the drying chamber. The heat pump's compressor uses electrical energy to elevate the pressure and enthalpy of the refrigerant vapor. This approach is highly energy-efficient, as it recycles thermal energy within the system rather than releasing excess heat into the environment. Figure 21.5 illustrates the schematic layout of an open-loop heat pump drying system. Table 21.1 presents a comparative analysis of heat pump dryers and hot air dryers.

21.4 Fundamentals of AI and IoT in Food Processing

21.4.1 Fundamentals of AI

AI is an innovative technology replicating human intelligence by enabling machines, such as computers, robots, and digital devices, to perform intelligent functions (Patel et al., 2021). It operates through three core cognitive processes: learning (collecting data and developing algorithms to convert it into useful information), reasoning (selecting the most appropriate algorithm to achieve a desired outcome), and self-correction (continually refining algorithms to enhance accuracy) (Gharaei et al., 2019).

AI encompasses various subfields, including Artificial Neural Networks (ANNs), fuzzy logic, expert systems, and swarm intelligence (Mohd Adnan et al., 2013). ANNs are computational models inspired by the structure and functioning of the human brain. These models consist of interconnected processing elements or nodes, either linear or nonlinear, linked through weighted connections (Fig. 21.6). A typical ANN architecture comprises three fundamental layers: input, hidden, and

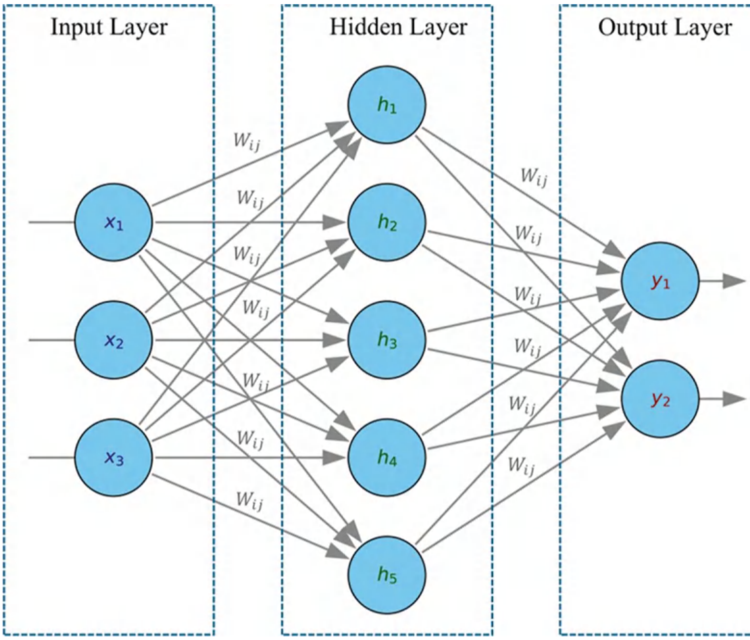

Fig. 21.6 Schematic representation of Artificial Neural Network (ANN) architecture and proceed further

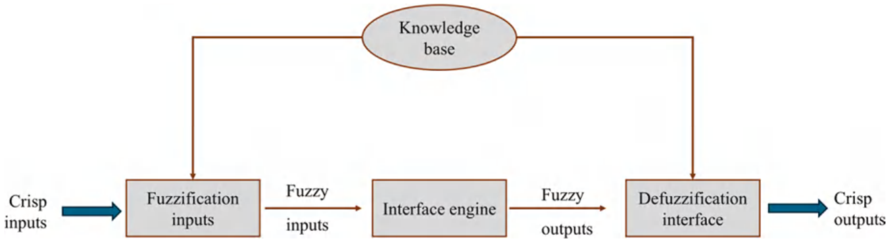

Fig. 21.7 Structural representation of a fuzzy logic system, including rule base, fuzzification, inference, and defuzzification stages

output. Based on its structure, an ANN can be categorized as either feed-forward or feedback type, and it may employ supervised (guided) or unsupervised (self-organizing) learning strategies (Shi, 2009).

Fuzzy logic is developed to emulate human reasoning and decision-making processes. It operates through key components: a fuzzy rule base, fuzzification, inference, and defuzzification (Mohd Adnan et al., 2013). As illustrated in Fig. 21.7, expert knowledge or operator experience is encoded into a set of fuzzy rules forming the rule base. Crisp input values are converted into fuzzy values through the fuzzification stage. These fuzzy inputs are then evaluated using the inference mechanism to derive fuzzy outputs, which are translated back into precise outputs through defuzzification.

21.4.2 Fundamentals of IoT

According to the European Commission Information Society, the IoT refers to identifiable objects equipped with embedded systems and intelligent interfaces that enable them to communicate and interact within specific environmental, user, or social contexts. IoT enables seamless connectivity between devices, allowing them to share data and function remotely across various locations and times (Dadhaneeya et al., 2023). Figure 21.8 illustrates the typical architecture of an IoT system.

Embedded systems integrate hardware and software components (Heriansyah et al., 2019), and IoT technology facilitates remote monitoring and control of physical assets through networked communication (Badarinath & Prabhu, 2017).

21.4.3 AI Applications in the Food Industry

The convergence of AI and the IoT is transforming the food processing industry, improving efficiency, product quality, and environmental sustainability. The global food industry is undergoing a transformation, driven by growing demand for automation, traceability, and sustainability. Traditional food processing systems are

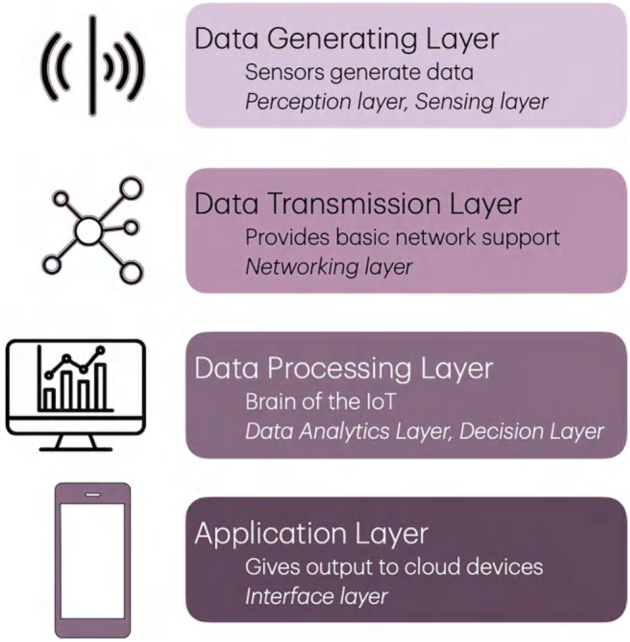

Fig. 21.8 Conceptual framework illustrating the architecture of an Internet of Things (IoT) system

being replaced with intelligent frameworks that enable real-time monitoring, data-driven decision-making, and self-optimization. Two key enablers of this transformation are AI and the IoT.

- AI provides predictive capabilities and data-driven automation through machine learning (ML), deep learning (DL), and computer vision.
- IoT enables real-time sensing, remote control, and connectivity across production nodes using embedded systems and cloud infrastructure.

Together, these technologies facilitate intelligent food systems that align with the goals of Industry 4.0 and Society 5.0, where innovation coexists with social well-being.

21.4.4 IoT Applications in the Food Industry

IoT systems typically consist of sensors, actuators, microcontrollers (e.g., Arduino, ESP32), communication modules (such as Wi-Fi, LoRa, and Zigbee), and cloud platforms (e.g., ThingSpeak, AWS IoT).

Monitoring and Data Collection

- Environmental Monitoring: Temperature, humidity, CO_2, and volatile compound sensors ensure optimal conditions for drying, fermentation, and storage.

- Process Monitoring: Load cells, flow meters, and thermal cameras measure critical parameters like feed rate, moisture content, and product temperature.

Process Control and Automation
IoT facilitates adaptive control strategies by linking sensor feedback with actuators:

- Intelligent dryers that adjust IR intensity based on moisture data collected in real time.
- Smart mixers and homogenizers that optimize speed and duration based on rheological sensors.

Traceability and Transparency
RFID, QR codes, and blockchain-integrated IoT devices enable end-to-end traceability in food chains, ensuring food safety compliance and quality assurance.

21.4.5 AI and IoT Integration in the Food Processing Industry

AI algorithms help make sense of the large volumes of data generated by IoT devices and optimize decision-making processes.

Machine Learning Applications
- Quality Prediction: ANN and SVM models predict final product quality (e.g., texture, moisture, microbial stability).
- Process Optimization: Regression and decision trees optimize drying times, energy use, or fermentation cycles.
- Fault Detection: Anomaly detection using unsupervised ML prevents equipment breakdown or product loss.

Deep Learning and Computer Vision
- Defect Detection: CNNs are widely used for identifying visual defects in fruits, vegetables, and meat cuts.
- Maturity and Ripeness Classification: Thermal and RGB images analyzed by DL models aid in sorting and grading.

Reinforcement Learning and Predictive Control
AI agents learn optimal control policies (e.g., drying schedules or energy-efficient HVAC settings) by interacting with the environment.

21.5 Smart Integration of AI and IoT in Thermal Food Drying

Thermal drying represents one of the most energy-demanding processes in food manufacturing. Key challenges include maintaining product quality, reducing energy losses, and responding to fluctuating processing conditions. Emerging technologies such as AI and the IoT have paved the way for a new generation of innovative drying systems with self-optimization and autonomous control capabilities.

An extensive review of peer-reviewed English publications was conducted, spanning the period from January 1, 2014, to December 31, 2024. Relevant articles were sourced from the Scopus database using a structured set of search keywords.

All the terms were referred to with appropriate synonyms related to the study and the search strings, and related to each publication's title, abstract, and keywords. The terms "microwave drying" and "microwave-assisted drying" have been used interchangeably, while "heat pump-assisted drying" is referred to as "heat pump drying" or "heat pump-assisted drying". The Artificial Intelligence was referred to as "Artificial Intelligence" OR "Machine learning" OR "Deep learning" OR "Intelligent systems" OR "artificial neural network" OR "Support vector machines" OR "Fuzzy logic" OR "Genetic algorithms" OR "Decision tree models" OR "Expert systems". The Internet of Things was referred to as "Internet of Things" OR IoT OR "cyber-physical systems" OR "smart systems" OR "connected devices" OR "smart sensors" OR "Wireless sensor networks" OR "Machine-to-machine communication" OR "Edge computing" OR "Industrial Internet of Things". The broader term "drying" was incorporated into all search queries to ensure comprehensive coverage, despite the primary focus on food drying. This strategy addressed the difficulty of defining "food materials" during the search process. Using more general terminology yielded a wider range of sources, which were subsequently screened and assessed for relevance in later stages of the review.

The first screening was conducted to eliminate conference papers and conference reviews, concentrating on peer-reviewed publications. Next, studies related to food and crop drying were selected. Subsequently, another screening was performed to exclude review articles, focusing on journal publications associated with AI and IoT applications in microwave and heat pump-assisted drying. Figure 21.9 presents the methodological framework employed for conducting the bibliographic analysis.

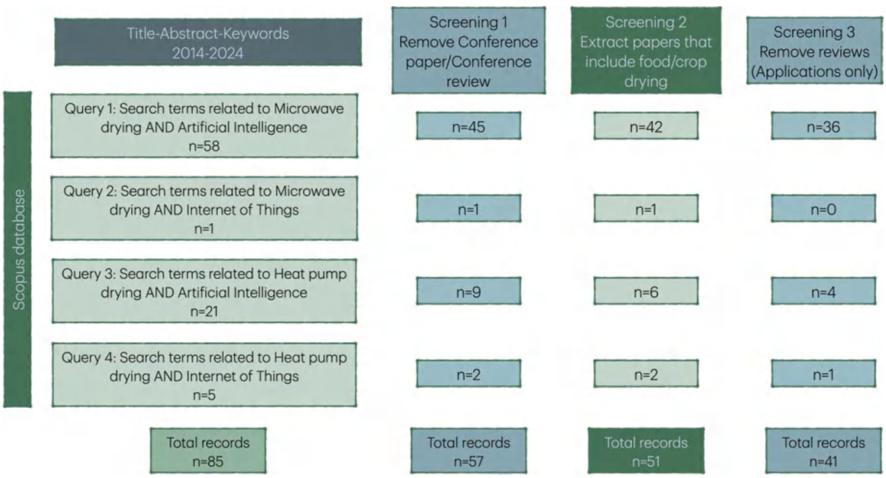

Fig. 21.9 A methodological framework was used for bibliographic analysis in the study

21.5.1 Application of AI in Food Drying

Tables 21.2 and 21.3 present the applications of various AI techniques in microwave and heat pump drying of food, respectively. Each application is also aligned with relevant Sustainable Development Goals (SDGs) and the principles of Society 5.0, highlighting their contributions to sustainable and human-centered technological advancement.

AI enables predictive and prescriptive capabilities using data-driven models. In thermal drying, AI assists in the following:

- Predicting moisture content based on temperature, air velocity, time, and sample properties.
- Modeling drying kinetics using machine learning techniques like Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests.
- Optimizing drying parameters (e.g., temperature, IR power, air speed) for product-specific quality retention.

The most commonly employed AI technique in thermal food drying is the ANN, which is primarily used to optimize the process by modeling drying kinetics. However, in many cases, these models are applied retrospectively, after the drying process has been completed, rather than being integrated in real time to guide or control the drying operation.

Integrating Artificial Intelligence into microwave and heat pump drying technologies supports several core Sustainable Development Goals (SDGs), such as SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-Being), SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). These AI-enhanced drying technologies support SDG 2 by improving food preservation, reducing postharvest losses, and strengthening food security. They contribute to SDG 3 by preserving nutritional quality and ensuring safer food products through more controlled and consistent drying conditions. SDG 9 is addressed by adopting intelligent, data-driven innovations in food processing infrastructure, while SDG 7 and SDG 12 are promoted through improved energy efficiency and the minimization of resource wastage. SDGs 2, 3, and 12 emerged as the most commonly addressed goals across the reviewed studies.

In alignment with the vision of Society 5.0, these studies demonstrate how advanced AI technologies can be integrated into smart agriculture to create efficient, productive, sustainable, and human-centric systems. By enabling intelligent control, predictive modeling, and resource-efficient drying, AI-driven microwave and heat pump systems exemplify the potential of digital innovation to solve complex societal challenges in food processing.

Table 21.2 Application of AI techniques for microwave drying of agricultural products

References	Product	Dryer type	AI method	Research Alignment with SDGs and Society 5.0
Das et al. (2016)	Aloe vera (*Aloe barbadensis* Miller)	Microwave-assisted drying	ANN	Developing a computer-simulated ANN model using the Levenberg–Marquardt backpropagation algorithm demonstrated superior predictive performance over Face-centered Central Composite Design in mapping process variables to desired outcomes. This supports SDG 9 by applying intelligent modeling techniques, and SDG 12 enables efficient process optimization. Integrating AI-based predictive tools aligns with the vision of Society 5.0, promoting smart, data-driven, and human-centered technologies in sustainable food and agricultural systems.
Sharabiani et al. (2021)	Apple	Microwave dryer	Cascade Forward Backpropagation (CFBP) Neural Network, TAN Activation Function (Tangent Sigmoid), Levenberg–Marquardt (LM) Algorithm	The study demonstrated the effectiveness of an AI-driven Cascade Forward Backpropagation (CFBP) neural network for accurately estimating the moisture ratio during convective and microwave drying of apples. Optimized with TAN activation functions and the Levenberg–Marquardt algorithm, the model achieved outstanding predictive accuracy. This application supports SDG 2 by enhancing postharvest drying efficiency, SDG 9 through advanced neural network architectures, and SDG 12 by promoting intelligent, resource-efficient food processing. Integrating AI-based modeling aligns with Society 5.0, fostering smart, data-driven, and human-centered technologies in sustainable agricultural systems.
Li et al. (2015)	Apple	Microwave Drying	Fuzzy logic	Developing a fuzzy logic controller to optimize microwave drying conditions enhanced volatile retention and prevented burning while maintaining acceptable time and energy use. This aligns with SDGs 12 and 9 by promoting intelligent, energy-efficient processing. It also reflects the goals of Society 5.0, integrating intelligent control for sustainable, human-centered food technology.

(continued)

Table 21.2 (continued)

References	Product	Dryer type	AI method	Research Alignment with SDGs and Society 5.0
Rashvand et al. (2024)	Apple	Vacuum-Assisted Microwave Drying	ML (ANN, SVR)	The superior performance of ML techniques, ANN, and SVR in predicting the moisture ratio of microwave-dried apple samples demonstrates their potential for real-time monitoring and control of drying processes. This supports SDG 2 by enhancing food preservation, SDG 9 by integrating advanced predictive systems, and SDG 12 by improving process efficiency and reducing waste. The application aligns with Society 5.0 by embedding intelligent, human-centered technologies into sustainable food processing systems.
Liu et al. (2024)	Astragalus	Microwave Drying	ANN-based predictive control	The application of advanced control strategies in microwave vacuum drying significantly improved the quality of astragalus, enhancing key bioactive compounds and flavor attributes. This aligns with SDG 3 by preserving functional compounds, SDG 9 through intelligent process control, and SDG 12 by improving processing efficiency. It reflects the vision of Society 5.0 by integrating innovative, human-centered technologies into sustainable food and herbal product development.
Li et al. (2021a)	Balsam pear	Microwave Drying	Fuzzy logic control	This study integrates fuzzy logic control with aroma detection (zNose™) to retain desirable aroma and suppress burning during drying, enhancing product quality. An industrialized control system was developed to replicate these results without sensor dependency. This aligns with SDG 9 by promoting innovative process automation, SDG 12 through improved product quality and energy efficiency, and Society 5.0 by embedding intelligent, human-centered systems into food processing for sustainable, high-quality production.
Sabzevari et al. (2021)	Banana	Microwave-hot air dryer	ANN: Feed-forward Backpropagation, Cascade Forward Backpropagation; Machine vision	This study applied two ANN models to predict moisture content and microwave power input for drying banana slices, monitoring appearance quality through machine vision. Real-time verification confirmed the models' reliability under fixed microwave power density for online drying control. This supports SDG 2 and SDG 12 by improving postharvest processing and aligns with SDG 9 and Society 5.0 by integrating intelligent, real-time, and human-centered drying technologies.

Nagvanshi and Goswami (2021)	Banana (*Musa Cavendish*)	Microwave Drying	ANN: Feed-forward neural network with backpropagation	The application of ANN modeling to predict values from a developed Computer Vision System (CVS) for assessing color changes in fresh and microwave-dried banana slices supports SDG 2 by improving postharvest quality assessment of minimally processed fruits. It also contributes to SDG 9 by integrating intelligent imaging and predictive systems in food processing. By eliminating the need for homogeneous sample requirements typical of colorimeters, the CVS enhances accessibility and efficiency, aligning with the principles of Society 5.0 by promoting smart, data-driven, and human-centered food quality monitoring technologies.
Çetin et al. (2024)	Bananas (*Musa acuminata*)	Microwave Drying	Wide Neural Network, Bilayered Neural Network, Medium Neural Network, RBF Network, Multilayer Perceptron, WiSARD	The integration of image analysis with ANN for identifying quality in dried banana slices contributes to SDG 2 by enhancing postharvest quality assurance, supports SDG 9 by implementing AI-based inspection technologies, and advances SDG 12 by enabling efficient, non-destructive assessment methods. This strategy also aligns with the principles of Society 5.0 by fostering intelligent, human-centric innovations within the agri-food industry.
Luka et al. (2024)	Cabbage (*Brassica oleracea* var. L. capitata var. L.)	Microwave Drying	Probabilistic computational intelligence modeling	Employing probabilistic computational intelligence models to estimate moisture ratio during cabbage drying improves the precision of process monitoring and optimization. This contributes to SDG 2 by preserving postharvest quality and minimizing nutrient loss, supports SDG 9 through intelligent modeling in agri-food technology, and advances SDG 12 by fostering energy-efficient and sustainable processing methods. Integrating AI-based predictions also reflects the goals of Society 5.0 by promoting data-driven, smart, and human-centric innovations in food engineering.
Zhu et al. (2023)	Cantaloupes (*Cucumis melo* var. *saccharinus*)	Microwave Drying	Online machine vision, ANN, and Extreme learning machine (ELM)	The effective operation of the system and algorithm, with ELM outperforming ANN in predictive accuracy and learning speed, supports SDG 9 and SDG 12 by advancing intelligent, efficient drying technologies. This aligns with Society 5.0 by integrating real-time AI solutions for sustainable, human-centered food processing.

(continued)

Table 21.2 (continued)

References	Product	Dryer type	AI method	Research Alignment with SDGs and Society 5.0
Wu et al. (2021)	Celery stalk	Microwave Drying	Fuzzy logic control	Implementing an integrated fuzzy logic and PID control system that adjusts drying temperature based on changes in volatile compounds improves accuracy and preserves product quality. This approach aligns with SDG 9 by advancing intelligent automation and supports SDG 12 through enhanced energy efficiency and reduced processing losses. Soft computing techniques also reflect Society 5.0 principles by fostering smart, human-centric innovations in sustainable food processing technologies.
Hashemi Shahraki et al. (2014)	French fries	Microwave Drying	Genetic algorithms (GA)	GA-optimized models showed a better, though not significant, fit than RSM models. This supports SDG 9 and 12 by improving modeling accuracy and process efficiency, aligning with Society 5.0 by integrating AI-driven optimization in sustainable, human-centered food processing systems.
Bai et al. (2018)	*Ginkgo biloba* Seeds	Domestic digital microwave oven	ANN: BP neural network model	The ANN model accurately predicted experimental data during microwave drying of *Ginkgo biloba* seeds, with a high correlation coefficient and low mean square error. Its capability for online prediction of moisture content and color changes supports SDG 2 and SDG 12 by enhancing food quality and reducing waste. It also aligns with SDG 9 and Society 5.0, promoting innovative, human-centered drying technologies.
Li et al. (2021b)	Hawthorn fruits	Microwave Drying	Fuzzy logic controller	An optimal product quality and accelerated drying speed were achieved using a fuzzy-controlled microwave drying system with real-time humidity adjustment. This aligns with SDG 2, SDG 9, and SDG 12 and supports Society 5.0 by integrating intelligent automation into sustainable agricultural processing.
Bulus (2024)	Hazelnut shells (*Corylus avellana* L.) and Olive pomace (prina)	Microwave Drying	ML (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)	The developed ANFIS and ANN models proved effective in predicting moisture levels but were unsuitable for estimating drying rates. Both models achieved high accuracy for moisture prediction. These results support the integration of intelligent modeling in sustainable drying systems, aligning with SDG 9 and SDG 12. Moreover, they contribute to the goals of Society 5.0 by incorporating advanced AI technologies into smart agriculture for improved efficiency and sustainability.

Karacabey et al. (2016)	Jerusalem artichokes (*Helianthus tuberosus* L.)	Microwave-assisted drying	Genetic algorithms (GA)	GA was successfully applied to optimize the drying process of Jerusalem artichokes, demonstrating high predictive performance with results comparable to RSM's. The findings confirm that GA models can effectively gain deeper insight into bioprocessing systems. This aligns with SDG 2 by supporting postharvest efficiency, SDG 9 through advanced optimization tools, and SDG 12 by promoting intelligent, resource-efficient processing. The integration of GA into drying optimization reflects the goals of Society 5.0, advancing sustainable and human-centered technologies in agricultural engineering.
Sarkar et al. (2021)	Mango leather	Laboratory microwave dryer	ANN	The development of an ANN-based prognostic model for optimizing mango leather production demonstrates the potential of AI in capturing complex nonlinear relationships among key process parameters, such as TSS, power level, temperature, and texture. The superior performance of the ANN model over traditional RSM supports SDG 2 by enhancing the preservation and value addition of seasonal fruits, SDG 9 (Industry, Innovation, and Infrastructure) through the integration of intelligent modeling in food processing, and SDG 12 by promoting efficient and optimized drying methods. This approach aligns with Society 5.0 by embedding innovative, human-centered, data-driven technologies into sustainable agri-food systems.
Omari et al. (2018)	Mushroom	Microwave-hot air dryer	ANN	The superior accuracy of the dynamic ANN model over the static model in predicting moisture content demonstrates its potential for real-time adjustment of microwave power during mushroom drying. This supports SDG 2 by enhancing food preservation, SDG 9 through intelligent process control, and SDG 12 by promoting energy-efficient drying. The integration of dynamic modeling aligns with Society 5.0, enabling intelligent, human-centered automation in sustainable food systems.
Azadbakht et al. (2018)	Orange slices	Microwave Drying	ANN	The application of ANN for predicting osmotic pretreatment effects based on energy and exergy analysis in microwave drying of orange slices supports SDG 7 and SDG 12. It aligns with Society 5.0 by integrating AI for energy-efficient, sustainable food processing.

(continued)

Table 21.2 (continued)

References	Product	Dryer type	AI method	Research Alignment with SDGs and Society 5.0
Taghinezhad et al. (2020)	Paddy	Microwave Drying	ANN: Multilayer feed-forward-back-propagation (FFBP) and Cascade-forward-backpropagation (CFBP) networks	The successful application of ANN to accurately predict the moisture ratio (MR) in parboiled paddy microwave drying supports SDG 2 by enhancing grain drying efficiency and postharvest quality, and SDG 12 by promoting data-driven process optimization. This aligns with Society 5.0 by integrating intelligent technologies into sustainable and human-centered agricultural systems.
Qadri et al. (2020)	Papaya	Microwave-assisted foam mat drying	ANN, SVR, and Gaussian process regression (GPR)	The practical application of machine learning models, SVR, GPR, and ANN for predicting the drying process in microwave-assisted foam mat drying supports SDG 2 by improving food preservation techniques and SDG 12 through enhanced process efficiency. The superior performance of the SVR model further demonstrates the value of intelligent modeling. This aligns with Society 5.0 by promoting smart, data-driven, and human-centered solutions in sustainable food processing systems.
Hadjout-Krimat et al. (2023)	Pea pods	Microwave Drying	ML (Support vector machine (SVM) and Dragonfly algorithm (DA)	The DA-SVM model reliably captured the nonlinear behavior of thin-layer drying kinetics of pea pods. This supports SDG 2 and SDG 9 by advancing precision modeling in agricultural drying. It also aligns with Society 5.0 by applying intelligent data-driven systems for efficient and sustainable food processing.
Shi et al. (2024)	*Penaeus vannamei*	Microwave Drying	ANN	An electronic tongue system combined with an ANN model effectively visualized taste compound variations across four dried shrimp products. This supports SDG 2 and SDG 12 by enabling data-driven evaluation of drying methods for quality improvement. Integrating AI in sensory analysis aligns with Society 5.0 by advancing intelligent, high-quality food manufacturing.
Jahanbakhshi et al. (2020)	Pistachio	Microwave Drying	ANN, and adaptive neuro-fuzzy inference system (ANFIS) methods	The ANFIS model outperformed both traditional mathematical models and ANN in predicting the moisture ratio of pistachios, contributing to SDG 2 and SDG 12 by enhancing accuracy and efficiency in the drying process. This advancement aligns with the principles of Society 5.0 by promoting intelligent and adaptive technologies in sustainable food processing applications.

Kırbaş et al. (2019)	Pomelo fruit peel (*Citrus maxima*)	Microwave Drying	ML (ANN)	The developed ANN models accurately predicted mass-dependent parameters and drying time, demonstrating high performance and a user-friendly, innovative interface, contributing to SDG 2 through enhanced crop drying, SDG 9 via AI-powered technological advancement, and SDG 12 through efficient resource use. This aligns with Society 5.0 by integrating intelligent systems into agriculture for a human-centered, sustainable, and data-driven future.
Su et al. (2020)	Potato and Sweet potato tubers	Microwave drying	Support Vector Machine Regression (SVMR), Backpropagation Artificial Neural Network (BPANN)	This study applied NIR and MIR hyperspectral imaging with AI-based models, including BPANN and LWPLSR, for real-time moisture content prediction in tubers during drying. Feature selection using regression coefficient and SPA (Successive Projection Algorithm) enhanced model simplicity and industrial applicability. The approach supports SDG 2 by improving food preservation, SDG 9 through intelligent process automation, and SDG 12 via efficient, non-destructive quality control. It aligns with Society 5.0 by promoting smart, data-driven, and human-centered technologies for sustainable food processing and monitoring.
Li et al. (2016)	Red Maple	Microwave Drying	Recurrent Self-Evolving Fuzzy Neural Network (RSEFNN)	Developing an RSEFNN-based predictive control system for microwave drying addresses process uncertainty and enhances drying efficiency through intelligent, adaptive optimization. This supports SDG 9 by advancing smart manufacturing technologies and SDG 12 by promoting energy-efficient, data-driven drying methods. Integrating self-evolving AI aligns with the vision of Society 5.0, fostering sustainable, human-centered innovations in food and material processing systems.
Kalsi et al. (2023)	*Stevia rebaudiana* leaves	Microwave Drying	Multilayer feed-forward (MLF) artificial neural network (ANN) using the backpropagation algorithm	The effective use of ANN for predicting the moisture ratio of *Stevia* leaves during microwave drying contributes to SDG 2 by improving postharvest processing efficiency and SDG 12 by enabling intelligent, non-destructive monitoring. This approach aligns with the vision of Society 5.0 by incorporating AI-based predictive models into sustainable, human-centric agricultural technologies.

(continued)

Table 21.2 (continued)

References	Product	Dryer type	AI method	Research Alignment with SDGs and Society 5.0
Fathi et al. (2016)	Tea leaves	Microwave drying	ANN Models: Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks were used, and their parameters were optimized using a genetic algorithm (GA)	The superior predictive performance of MLP and RBF neural network models over semi-empirical approaches in estimating the moisture ratio of tea leaves during various drying processes supports SDG 2 by enhancing postharvest quality preservation. It contributes to SDG 9 by applying intelligent modeling and SDG 12 by promoting efficient, data-driven drying practices. This aligns with Society 5.0 by integrating AI technologies into sustainable and human-centered agricultural processing systems.
Sarimeseli et al. (2014)	Thyme (*Thymus Vulgaris* L.)	Microwave Drying	ANN	The successful application of ANN to accurately predict the microwave drying behavior of thyme leaves supports SDG 2 by enhancing the efficiency and quality of herb preservation. It contributes to SDG 9 by adopting intelligent modeling tools in food processing and SDG 12 by promoting optimized, energy-efficient drying practices. This study aligns with the principles of Society 5.0, integrating AI-driven, human-centered technologies for sustainable agricultural and food system development.
Hussein et al. (2024)	Tomato	Microwave Drying	ANN and the adaptive neuro-fuzzy inference system (ANFIS)	The ANFIS model's superior predictive performance over the ANN model in modeling microwave drying kinetics of tomato slices supports SDG 2 and SDG 12 by improving process accuracy and product quality. It aligns with Society 5.0 by integrating intelligent, data-driven technologies in sustainable food processing.
Hussein et al. (2023)	Tomato	Microwave Drying	Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN)	Applying soft-computational models, ANFIS and ANN, to predict the quality traits of microwave-dried tomato slices enhances the precision of food quality assessment. The superior performance of the ANFIS model supports SDG 2 by improving postharvest handling and reducing losses, and SDG 12 by enabling accurate, non-destructive quality evaluation. This study aligns with SDG 9 by adopting intelligent modeling in food systems. It reflects the vision of Society 5.0 by integrating advanced, human-centered, and data-driven technologies into sustainable food processing.

Su et al. (2019)	Tuber crops	Microwave Drying	Support vector machine regression (SVMR)	The successful development of a robust SVMR model using tuber Uniaxial Compressive Strength (UCS) values fitted by an exponential function highlights the potential of AI in agricultural quality assessment. This aligns with SDG 2 by supporting efficient crop processing, SDG 9 through advanced modeling techniques, and SDG 12 by enabling data-driven optimization. It also supports the vision of Society 5.0 by integrating intelligent technologies into sustainable and human-centric agricultural systems.
Zarein and Jaliliantabar (2014)	White mulberry	Microwave Drying	ANN	Developing an ANN model trained with the BFGS algorithm for predicting moisture content, drying rate, and energy efficiency in microwave drying of white mulberry contributes to SDG 2 by improving postharvest processing and reducing losses. It supports SDG 9 by integrating advanced predictive modeling into agricultural engineering and SDG 12 through energy-efficient, data-driven drying optimization. This aligns with the vision of Society 5.0, promoting smart, human-centered technologies in sustainable food processing systems.
Bulus et al. (2023)	Zucchini (*Cucurbita pepo* L.)	Solar-assisted microwave belt dryer	ANN and Adaptive Network-Based Fuzzy Inference System (ANFIS)	The comparative use of ANFIS and ANN models for estimating drying rate and moisture content of zucchini slices highlights the practical application of AI in food process modeling. While ANFIS excelled in predicting drying rate and ANN in moisture content estimation, both models proved valuable. This supports SDG 2 through improved postharvest processing, SDG 9 by integrating intelligent modeling tools, and SDG 12 through efficient resource use. It aligns with Society 5.0 by advancing smart, data-driven agricultural systems.

Table 21.3 Application of AI techniques for heat pump drying of agricultural products

References	Product	Dryer type	AI method	Research alignment with SDGs and Society 5.0
Çerçi and Hürdoğan (2022)	Peanut	Heat pump-assisted rotary desiccant dryer	ANN	This study evaluated the performance of a heat pump-assisted rotary desiccant dryer for low-temperature peanut drying and applied an ANN to model the desiccant wheel. The ANN model demonstrated reliable predictive capability, making it a valuable tool for analyzing desiccant-based drying systems. This supports SDG 2 by improving peanut drying efficiency and quality, SDG 9 by integrating AI in drying technologies, and SDG 12 by promoting energy-efficient practices. It aligns with Society 5.0 by advancing intelligent, sustainable, and human-centered food processing systems.
Peter et al. (2021)	Chanterelle mushrooms	Heat pump dryer	1-3 ANN architecture, Support Vector Machine, Nearest Neighbors (k-NN)	Among the thin-layer models, the Midilli et al. model exhibited the least variation in moisture ratio. However, computational intelligence techniques such as ANN, SVM, and k-NN-SVM with a standardized Pearson universal kernel achieved higher predictive accuracy for modeling the drying kinetics of chanterelle mushrooms in a heat pump dryer. These findings emphasize the effectiveness of SVM in process prediction and real-time control. The study aligns with SDG 2 and SDG 12 by enhancing food quality and resource efficiency, and supports Society 5.0 by adopting smart, human-centered drying technologies.
Li et al. (2019)	Tilapia fillets	Heat pump dryer	ANN	This study applied an ANN model to optimize pulse vacuum osmotic pretreatment conditions for drying tilapia fillets using a heat pump to maximize product quality. The model demonstrated strong predictive accuracy and fitting performance for comprehensive quality scores. This supports SDG 2 by enhancing postharvest fish preservation, SDG 12 through efficient and quality-focused drying, and SDG 9 via AI-driven process optimization. It aligns with Society 5.0 by promoting smart, human-centered, sustainable food technologies.
Aktaş et al. (2015)	Bay leaves	Closed-loop heat pump dryer	ANN: Backpropagation Learning Algorithm, Levenberg–Marquardt (LM) Algorithm	This study applied an ANN model to analyze bay leaves' drying characteristics, moisture content, and thermal energy consumption in the heat pump dryer. The model demonstrated reliable forecasting performance and can support future process design. This contributes to SDG 2 by improving herb preservation, SDG 9 through intelligent process modeling, and SDG 12 by enhancing energy efficiency. It aligns with Society 5.0 by promoting smart, sustainable, and human-centered food drying technologies.

21.5.2 Integration of IoT Technology in Food Drying Processes

IoT revolutionizes drying in the food industry by introducing real-time monitoring, data-driven control, and intelligent automation. In conventional systems, the lack of continuous sensing and adaptive feedback often leads to inefficient energy use and inconsistent product quality. IoT-enabled drying systems overcome these limitations by utilizing sensor networks, wireless communication, and cloud integration.

Real-Time Monitoring
IoT systems use various sensors to monitor key drying parameters such as:

- Temperature (e.g., DS18B20, RTDs)
- Relative humidity (e.g., DHT22, SHT31)
- Moisture content (using capacitive or IR-based sensors)
- Air velocity and pressure
- Product weight (via load cells)

These sensors continuously collect data and transmit it via microcontrollers (e.g., ESP32, Arduino, Raspberry Pi) to a central system or cloud platform for processing.

Remote Control and Automation
IoT systems allow remote control of heaters, fans, and motors through:

- Mobile or web-based dashboards (e.g., using Blynk, Node-RED, or custom apps)
- Cloud platforms (e.g., ThingSpeak, AWS IoT, Firebase)
- Automated control through feedback loops and rule-based triggers (e.g., turning off a heater when the Temperature exceeds the setpoint)

This enables real-time interventions to prevent over-drying or under-drying, improving product quality and energy efficiency.

Data Logging and Predictive Maintenance
IoT-enabled systems store historical data that can be used for:

- Drying curve analysis
- Performance benchmarking
- Identifying anomalies (e.g., fan failure, temperature fluctuations)
- Predictive maintenance, using historical trends to schedule service before a failure occurs

Energy Optimization
By integrating real-time data on temperature, humidity, and drying time, IoT systems can:

- Schedule drying cycles during off-peak electricity hours
- Adjust the heating power dynamically
- Recommend optimal air velocity or drying time to reduce energy consumption

This directly supports SDG 7 (Affordable and Clean Energy) and SDG 12 (Sustainable Consumption and Production) by promoting energy-efficient technologies and responsible resource utilization.

Traceability and Quality Assurance
IoT systems contribute to traceability by:

- Logging batch-wise drying parameters
- Generating digital records for audits and regulatory compliance
- Linking with blockchain for end-to-end food quality traceability (e.g., in exports)

Integration with AI and Machine Learning
IoT acts as the data foundation for AI-based predictive models. For example:

- Moisture content predictions using ANN or ANFIS
- Quality grading using CNNs on images collected via IoT-enabled cameras
- Drying parameter optimization using fuzzy logic or genetic algorithms

The literature review identified no studies that applied IoT technologies specifically to microwave drying under the selected IoT-related search terms. However, one relevant study by Mishra et al. (2023) demonstrated the application of IoT in heat pump drying, specifically for mint and coriander leaves. In that study, the IoT system was built using a microcontroller (ESP32), programmed via the Arduino IDE, and integrated with various sensors, including a DHT22 sensor for temperature and humidity, digital temperature sensors, and an air velocity sensor. Data acquisition and cloud integration were facilitated using ThingSpeak, while data processing and visualization involved MATLAB and a connected computer interface.

The deployment of an IoT-enabled heat pump drying system for preserving the quality of delicate leafy greens illustrates the transformative role of IoT in modernizing food processing. Real-time monitoring and automated control enhance the following:

- SDG 2 (Zero Hunger) by improving postharvest shelf life.
- SDG 9 (Industry, Innovation, and Infrastructure) through the integration of smart technologies.
- SDG 12 (Responsible Consumption and Production) by advancing energy-efficient drying practices. This approach also aligns with Society 5.0's vision of smart, sustainable, and people-centric food system innovation.

21.6 Conclusions

This chapter examines the technological advancements in thermal food drying, focusing on the transition from conventional methods to modern approaches, such as microwave and heat pump drying. These advanced drying systems offer notable improvements in energy efficiency, product quality, and process control. A key enabler of this transformation is the integration of Artificial Intelligence (AI) and the Internet of Things (IoT), which facilitates real-time monitoring, predictive modeling, and adaptive process optimization.

Among the two technologies, AI, particularly Artificial Neural Networks (ANNs), has been more extensively applied, especially in microwave drying. These models are predominantly used to predict drying kinetics and optimize processing conditions. However, a significant limitation remains that, in most cases, AI is employed in post-process analysis rather than integrated into real-time control systems. In contrast, IoT presents a promising opportunity for industrial-scale deployment, enabling dynamic, sensor-driven control of thermal drying environments. Despite having fewer documented applications than AI, the real-time capabilities of IoT make it an essential complement to AI-driven models.

The combined application of AI and IoT contributes meaningfully to several Sustainable Development Goals (SDGs), including SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-Being), SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). These technologies support food security by enhancing postharvest preservation, safeguarding nutritional quality through precise drying control, and promoting industrial innovation by introducing intelligent automation. Additionally, improved energy efficiency and reduced resource consumption directly contribute to sustainable production practices. SDGs 2, 3, and 12 were most frequently addressed among the reviewed studies.

In alignment with the principles of Society 5.0, this integration of AI and IoT fosters human-centered, smart technologies that enhance sustainability and resilience in the agri-food system. Real-time integration of these tools will be crucial in achieving intelligent, sustainable, and adaptive food processing solutions.

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Chapter 22
Challenges and Opportunities for AI and IoT Technology in Contemporary Avian Production Systems

Victor Massaki Nakaguchi and Tofael Ahamed

Abstract Artificial intelligence (AI) and the Internet of Things (IoT) can transform poultry farming production systems. Key applications include automated health diagnostics, precise climate control within housing, and advanced tracking of individual animals and quality assessment. As data-based decision-making technology evolves rapidly, challenges and opportunities for applying novel technologies are surging—driven in part by broader trends in digital transformation (DX) across agriculture. This chapter thoroughly analyzes how recent groundbreaking AI-based algorithms and IoT systems innovations can benefit poultry farming practices. In addition, this chapter addresses broader issues related to adopting these technologies, including the ethical implications of implementing AI-based systems and concerns about the socioeconomic impacts on farming communities.

Keywords Precision livestock farming · AI · Deep learning · Smart agriculture · Digital transformation

22.1 Introduction

Poultry farming is the primary source of animal-based protein, supplying vital nutrients to countless individuals globally and serving as a key component of food security (Alnafissa et al., 2021). The global output and demand for poultry-derived foods have surged ahead of other livestock products. Poultry eggs and meat have been consolidated as the most consumed animal protein worldwide, owing to their cost-effectiveness, faster production cycles, and superior feed efficiency compared to

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beef or pork. In contrast, the growth in production and consumption of other livestock products, such as beef and lamb, has been more gradual, hindered by higher production costs and environmental challenges.

In 2020, chicken meat accounted for 35% of the world's total meat production, marking the most significant increase in absolute numbers and percentage since 2000. Over this period, chicken meat production soared by 104 percent, adding 61 million tons, making it the most widely produced type of meat that year (FAO, 2022). Besides, in the coming years, the rise of environmental and health concerns will drive a global shift toward poultry and fish over red and processed meats, especially in Europe and North America. At the same time, in Sub-Saharan Africa, affordability will further boost poultry consumption, leading to significant global growth in poultry demand (OECD/FAO, 2023). In this scenario, poultry farmers face challenges fitting their practices into tighter sanitary regulations, evolving legislation, and the need to adopt advanced systems due to labor shortages. Farmers must adapt their operations as consumers increasingly demand sustainable and humane practices. Additionally, the push for automation to address labor gaps presents financial and operational complexities. Balancing these demands while maintaining productivity and profitability remains a persistent test for the industry.

The poultry farm industry is typically divided into two main categories: broiler and layer farming. Broilers are specially bred for meat purposes; they mature rapidly and produce a high quantity of meat, making them ideal for large-scale meat production. Layers, in contrast, are raised primarily for egg-laying. They are usually housed in facilities focused on egg production, where the avians are managed to maximize both the quantity and quality of eggs they produce. Among domesticated birds, chickens, turkeys, and ducks hold primary roles in meeting various production needs. While most poultry species can be used for both egg and meat production, they are typically bred and managed with a primary focus. Chickens, for example, have specialized breeds explicitly developed for egg-laying (layers) or meat production (broilers). Turkeys are predominantly raised for meat, quails are mainly bred for egg production, and ducks vary by breed, serving either purpose. These distinctions reflect the diverse roles each species plays in meeting the needs of the poultry industry. Recently, some poultry sectors are gaining more attention than others; for instance, quail farming is becoming a prominent strategy to broaden the range of dietary protein sources (Darwish et al., 2018; Vargas-Sánchez et al., 2019). This is especially pertinent in developing areas with fast-expanding populations, where establishing alternative, protein-rich food sources is essential to meet growing needs and counteract the challenges of protein insufficiency and malnutrition.

At present, the industrial poultry production systems are characterized as highly mechanized and intensive, aiming to meet the growing global demand for poultry products (Fig. 22.1). Over the years, improvements in genetics, nutritional science, and machinery have spurred the establishment of extensive, vertically integrated broiler and egg production systems, expanded global poultry markets, and enabled the housing of millions of birds per facility with improved egg collection and processing systems (Ricke, 2021). On the other hand, unbalanced genetic selection for

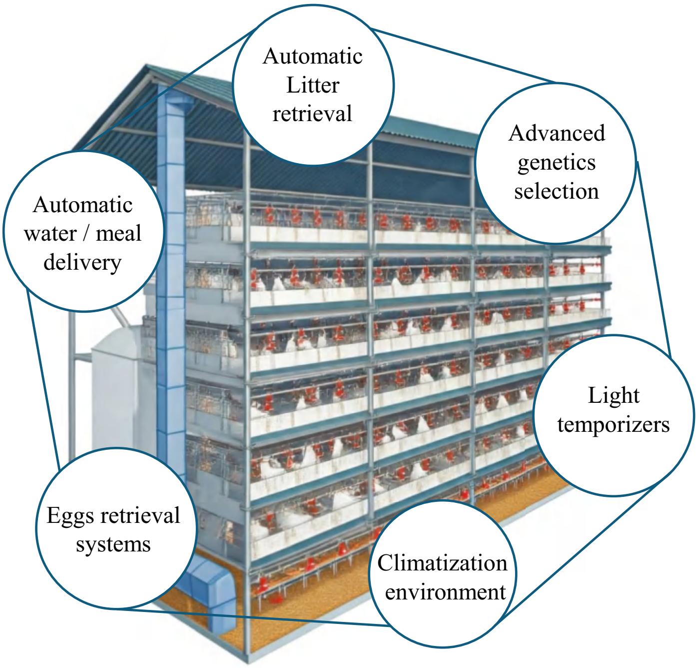

Fig. 22.1 Status of automation in vertically integrated poultry production

productivity traits over metabolic or physiological traits has caused an increased incidence of metabolic diseases (Korver 2023), posed substantial risks, and further burdened the production chain with increased costs. Additionally, the consequent development of problematic abnormal behaviors such as aggression, lameness, cannibalism, and feather pecking has also contributed to financial setbacks (Granquist et al., 2019; Olejnik et al., 2022). In this context, animal welfare concerns are prominent, as birds are often raised in overcrowded conditions with limited mobility and natural behavior (Jones & Comfort, 2020). Moreover, disease outbreaks like avian influenza remain a persistent threat due to high stocking densities and biosecurity challenges (Tilli et al., 2022).

Traditional poultry production systems lack real-time, individual-level monitoring, hindering the tracking of each bird's health, welfare, and quality throughout production. Current technologies struggle to monitor poultry welfare and predict real-time problems accurately, while analyzing the extensive data needed to forecast bird health remains a significant challenge. Additionally, waste management and greenhouse gas emissions pose sustainability issues for industry. Consequently, artificial intelligence (AI) and the Internet of Things (IoT) are emerging as solutions to these challenges across the production chain.

The era of data-driven decision-making has come to supply the technology development aiming to bridge the gap between production tracking efficiency and diminish waste of resources, proposing a more closed-loop way to achieve high demand of consumption balanced with environmental conservation (Hamidon et al., 2023). Therefore, this chapter presents challenges and opportunities for implementing AI-IoT technology, favoring contemporary avian production systems. Section 22.1 gives an introductory of our theme; Sect. 22.2 presents an overview of AI and IoT in the poultry farming industry; Sect. 22.3 discusses the challenges associated with the adoption of groundbreaking technologies in a consolidated production chain; Sect. 22.4 is related to the opportunities that come with development of new technologies associated with AI-IoT driven systems; and finally, Sect. 22.5 concludes this chapter.

22.2 AI and IoT Technologies in the Poultry Farming Industry

By 2025, artificial intelligence had matured into a critical enabler of innovation across sectors. It was driven by breakthroughs in machine learning and deep learning, the explosion of big data, advances in computing power, and its integration with fields such as robotics and the Internet of Things. At its core, AI refers to systems capable of performing tasks that traditionally require human intelligence—such as perception, decision-making, and pattern recognition. A significant branch of AI, known as deep learning, utilizes layered neural networks to learn representations from large datasets. In computer vision, convolutional neural networks (CNNs) have become the dominant architecture, capable of analyzing audio and visual data to detect objects, classify sounds and images, and interpret complex scenes. These capabilities are now beginning to be adopted in poultry farming, where AI-driven computer vision enables more precise, efficient practices. For instance, CNN-based models, such as BirdNet (Kahl et al., 2021), Faster R-CNN (Ren et al., 2016), YOLO (Redmon et al., 2016), EfficientDet (Tan et al., 2020), and CenterNet (Duan et al., 2019), are used to detect embryos at early stages (Nakaguchi & Ahamed, 2023b), track poultry movement (Neethirajan, 2022), or count individuals using camera enclosed to cages (Geffen et al., 2020); (Cao et al., 2021), and detect of diseases (Nasiri et al., 2022). These models are increasingly integrated with edge computing hardware like microcontroller-compatible devices or AI accelerators, allowing on-site analysis without ground-based connectivity. This fusion of AI, computer vision, and embedded systems marks a significant shift in poultry sciences and agriculture, transforming it from manual observation and evaluation to intelligent, data-assisted decision-making (Nakaguchi & Ahamed, 2023a). As the field continues to grow, efforts are being made to ensure these technologies remain accessible, energy-efficient, and robust enough for deployment in dynamic outdoor environments.

The Internet of Things (IoT) refers to a network of physical devices embedded with sensors, processors, and communication modules that enable real-time data collection and interaction with their environment. In agriculture, IoT technologies are essential for monitoring field conditions, automating tasks, and improving farm management decisions. Devices such as soil moisture sensors, weather stations, GPS trackers, and irrigation controllers are deployed across farms to capture detailed data on environmental factors. These devices communicate wirelessly, using protocols that allow them to operate over large areas, even in regions with limited connectivity. Often performed at the edge, local data processing reduces reliance on cloud infrastructure and enhances the system's responsiveness. When integrated with higher-level analytics or AI models, IoT systems can optimize various operations, from adjusting irrigation schedules based on real-time soil moisture levels to detecting unusual patterns in crop health. Although device interoperability, power management, and long-term deployment challenges remain, IoT drives innovation in the automation and data integration sectors.

A couple of artificial intelligence (AI) and Internet of Things (IoT) technologies emerge as a promising pathway to enhance sustainability and productivity in the poultry field (Astill et al., 2020). Recently, several review articles have summarized the current situation of AI-IoT applications in the poultry sector and their respective bottlenecks in their implementation on a large scale. Ojo et al. (2022) conducted a comprehensive systematic review of IoT and machine learning applications in poultry health and welfare management, categorizing current research into behavior and environmental monitoring, disease analytics, and control interventions. They highlighted the growing use of AI-enabled IoT systems for automated and efficient poultry management, with deep learning models showing significant promise over traditional methods. However, despite advancements, the authors identified ongoing challenges such as data quality issues, limited model interpretability, and the need for scalable, reliable systems.

In another article, Okinda et al. (2020) found that AI-based computer vision presents a promising real-time, automated poultry monitoring solution, thanks to its non-invasive and non-intrusive characteristics. The review discussed the use of both machine learning and deep learning approaches in poultry surveillance. However, issues like inconsistent lighting, obstructions, and insufficient labeled data must be overcome. The authors stressed the importance of future studies to refine and enhance computer vision methods for improving poultry welfare monitoring. Franzo et al. (2023) reviewed the application of big data in poultry production, highlighting the potential of sensor technologies, advanced statistical techniques, and pathogen genome sequencing to optimize farming systems. The authors concluded that AI and sensing technologies will play a greater role in solving problems in animal farming, offering production-based and commercial advantages. They also observed that integrating diverse data sources will be crucial for developing predictive models to anticipate disease occurrence and promote sustainable and healthful food production.

Chang and Tu (2023) introduced an intelligent monitoring and control system for indoor poultry farms using IoT sensors to track environmental factors such as temperature, humidity, light, wind speed, and CO_2 levels. Integrated with a programmable logic controller (PLC) and cloud platform, the system enabled real-time monitoring and automated environmental adjustments. Results showed improved efficiency, reduced energy use, and decreased carbon emissions from 147 to 94 kg CO_2 e/kWh. However, limitations included the need for a more intuitive interface and the potential for AI integration to predict equipment failures, highlighting opportunities for further advancements in innovative poultry farm management. Farooq et al. (2022) comprehensively review IoT applications in livestock farming, focusing on the technologies, architecture, and challenges involved. The authors conducted a detailed survey of existing research on IoT-based livestock systems, examining network infrastructures, communication protocols, platforms, and application domains such as animal health monitoring, tracking, feeding, and shelter environment control. The review results show IoT integration has significantly enhanced livestock management through real-time monitoring, automation, and data-driven decision-making. However, while IoT presents significant benefits, challenges such as data security, interoperability, and infrastructure costs persist. They also highlighted future directions, including integrating AI, blockchain, and 5G for more robust and scalable innovative livestock systems.

Notably, the poultry farm industry is transitioning from mechanical circular automation systems to innovative, adaptive digital and remotely controlled autonomous ones. As technology evolves rapidly, the introduction of new devices and sensors creates challenges for adaptation and supply, requiring continuous revisions to systems, equipment, and sourcing plans.

22.3 Challenges

Poultry farming includes various production systems, each presenting challenges in automation and implementing AI and IoT technologies. Conventional cage systems are the easiest to automate due to their controlled environment. However, the limited space reduces the opportunity for advanced tracking solutions and demands more investment in implementing sensing systems to access all cages. Aviary systems require more sophisticated monitoring to assess bird behavior and optimize conditions while maintaining automation efficiency. Barn or cage-free systems introduce egg collection, manure management, and avian tracking difficulties, as unrestricted movement makes centralized automation less effective. Free-range systems further complicate automation with outdoor access, requiring solutions for tracking bird location, detecting predators, and managing environmental variations. Organic systems pose additional challenges due to strict regulations on feed, medication, and outdoor time, necessitating precise data collection to ensure compliance and productivity (Fig. 22.2).

The current landscape of poultry production presents various complex challenges that highlight the urgent need for technological innovation and more innovative practices. One of the most pressing ethical and operational issues is the lack of scalable, cost-effective *in-ovo* sex identification technologies, leading to the routine culling of billions of male chicks in egg-laying operations—a practice increasingly

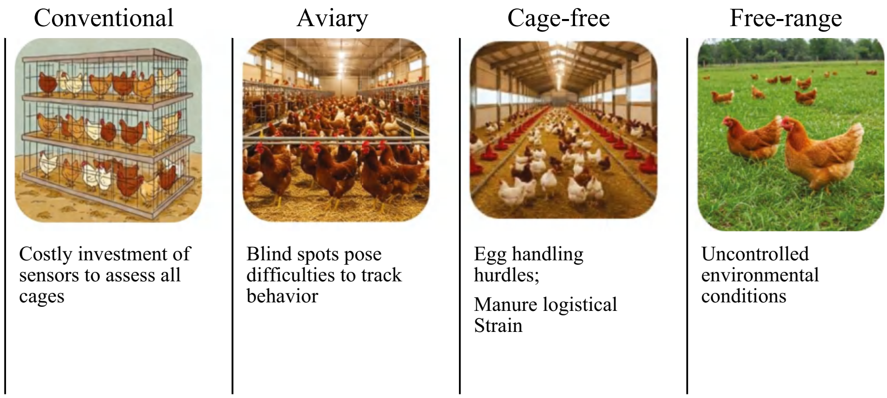

Fig. 22.2 Main AI and IoT implementation challenges among raising systems

criticized by both consumers and regulators. Meanwhile, the development of advanced machinery tailored for precision poultry farming remains slow, with many automated systems still lacking the sensitivity, flexibility, or affordability needed for widespread adoption. High costs and limited durability of sensors further hinder the deployment of real-time monitoring solutions at scale, particularly in low- and middle-income settings. In addition, traditional production systems often suffer from inefficiencies such as excessive water and energy use, suboptimal spatial planning, and high volumes of organic waste, all of which undermine sustainability goals. Overcoming these challenges will require a concerted effort to make next-generation AI, IoT, and robotics more accessible, adaptable, and economically viable for poultry producers worldwide.

Another obstacle is the high initial cost of implementing AI-driven solutions and IoT infrastructure, which can be prohibitive for smaller producers. Additionally, the complexity of integrating these technologies with existing systems and ensuring interoperability demands specialized knowledge and training. The potential for cybersecurity threats poses another significant concern, as interconnected systems are vulnerable to breaches that could compromise data and operational safety. Data management is also a challenge; handling the immense amounts of data generated requires robust storage solutions and analytical tools to extract actionable insights effectively. Lastly, there is a need for regulatory frameworks that can keep up with rapid technological advances while safeguarding animal welfare and environmental standards. Balancing these challenges with the potential benefits of improved efficiency, enhanced animal health monitoring, and optimized production processes will be key for the avian production sector to thrive in this evolving landscape. For AI-based technologies, especially in the computer vision-related field, Li (2025) highlighted that despite the increasing research in precision poultry farming, a significant challenge remains the lack of large-scale, open-access datasets. These datasets are crucial for developing and validating different computer vision approaches. The absence of such datasets with consistent evaluation metrics and baselines makes it difficult to reproduce research findings and compare the effectiveness of various methods.

Regarding the impact of technology shifting, while automation and AI promise significant gains in efficiency and sustainability, they also represent complex socio-economic challenges, particularly in regions where poultry production is a substantial source of employment for rural populations. In many of the world's largest poultry-producing nations, smallholder farms and manual labor form the backbone of the industry, providing income and livelihoods to millions of people in low-income and rural communities. The rapid adoption of automated systems, AI-based decision-making, and innovative machinery could displace these workers, widening economic inequality and threatening social stability if not carefully managed. This shift risks marginalizing those without access to technical training or digital infrastructure, creating a divide between large, tech-enabled operations and traditional, labor-intensive farms. The challenge, therefore, is not only technological but also social: how to implement advanced systems in a way that supports inclusive development, reskilling opportunities, and economic resilience for vulnerable rural workers, ensuring that innovation benefits all levels of the poultry production chain.

22.4 Opportunities

Despite challenges, AI and IoT offer significant opportunities to enhance efficiency and sustainability in every system. For instance, conventional cage systems can benefit from machine vision-driven monitoring for early disease detection and automated feeding adjustments; aviary system opens opportunities for adaptive systems that optimize perches, lighting, and nutrition; barn or cage-free systems can leverage IoT sensors and robotic vision systems for real-time tracking, automated manure handling, and rover-grading egg collection; free-range systems can integrate GPS tracking, environmental sensors, and predator detection monitoring to improve bird safety; and organic systems stand to gain from IoT-enabled precision farming tools that monitor feed quality, outdoor conditions, and compliance metrics.

Poultry farms can overcome automation hurdles by implementing adjusted AI and IoT solutions while improving productivity, animal health, and regulatory compliance. Table 22.1 summarizes the opportunities for AI and IoT to improve the poultry industry.

AI-based technologies combined with IoT have the potential to radically transform poultry production by closing the gap between generalized sampling and truly individualized monitoring. In this area, current practices remain limited or largely experimental. In the near future, advanced computer vision, machine learning, and sensor integration could enable continuous, real-time tracking of each bird's behavior, movement, vocalizations, and physiological status through smart cameras, wearable sensors, and interconnected monitoring systems. These technologies would allow for early detection of stress, disease, or welfare issues at the individual level, moving beyond today's population-based health checks. Similarly, AI-powered

Table 22.1 AI and IoT opportunities for contemporary avian production systems

Parameter	AI opportunities	IoT opportunities	Benefits
Health monitoring	Predictive disease detection using computer vision, audio analysis, or anomaly detection in behavior Detect stress levels via audio/visual processing	Real-time tracking via wearable sensors and environmental sensors Nest boxes, sensors, and ambient monitoring sensors	Early intervention, reduced mortality, and better welfare Improved egg laying Bird welfare
Feeding optimization	Smart feeding schedules based on growth prediction	Automated feeders that respond to real-time data on feed levels and consumption	Reduced waste, better feed conversion ratios
Environmental control	AI-based climate control models that learn optimal temperature/humidity profiles	IoT sensors for temperature, humidity, CO_2, and ammonia monitoring	Improved comfort, reduced stress, better productivity
Egg production and sorting	Machine vision for noncontact quality assessment (e.g., freshness, cracks, dirt)	Innovative conveyors and RFID-enabled trays for real-time egg tracking	Higher grading accuracy, reduced labor, and traceability
Behavior analysis	Computer vision models for monitoring activity levels, pecking, or aggression Monitoring nesting patterns and signs of distress or laying issues	Cameras and movement sensors for continuous data collection	Better understanding of welfare and behavior-driven health issues
Disease outbreak control	AI models to predict spread patterns based on location, symptoms, and past data	IoT for contact tracing between birds, barns, and flocks	Faster containment and more strategic response
Breeding and genetics	AI for genetic trait analysis and selection based on performance and health data	IoT is used to monitor the performance traits of individual birds at scale	Enhanced genetic gains and more productive lines
Supply chain and logistics	Demand forecasting, shelf-life prediction based on freshness models	Smart tags and sensors for real-time tracking of poultry and eggs Cold chain tracking for eggs using temperature and humidity sensors	Lower spoilage, improved traceability, optimized logistics
Waste management	AI models to optimize manure processing and energy recovery	IoT sensors are used to monitor waste output and composting conditions	Reduced environmental impact and resource recovery

egg and meat grading systems could evolve to assess every product for defects, freshness, and quality—automatically, and at scale. With fully integrated AI and IoT ecosystems, production tracking could become so precise that a single defective egg could be traced back instantly to the exact bird or cage of origin, unlocking the ability to investigate root causes—health, nutrition, or environmental stressors. While such systems are still in their infancy, their development signals a future where poultry farming becomes hyper-personalized, data-driven, and capable of achieving unprecedented precision.

22.5 Conclusions

Current AI systems—including computer vision for real-time monitoring, machine learning for predictive analytics, and natural language and sound processing for early disease detection—enable precise control over animal health, welfare, and productivity. Vision-based systems can detect lameness, feather pecking, or distress, while acoustic AI models can be trained to identify respiratory issues or abnormal vocalizations. Machine learning algorithms analyze vast sensor and environmental data streams to optimize feeding regimes, growth predictions, and climate control settings. In egg production, AI-driven sorting systems are expected to assess shell quality, cleanliness, and freshness without touching and destroying samples. These AI-based systems will create an interconnected smart farm that can self-adjust, alert operators to anomalies, and forecast outcomes when combined with IoT devices like health trackers, environmental sensors, and automated feeders. Altogether, both technologies allow higher operational efficiency, reduced labor demands, improved biosecurity, and a more sustainable, scalable approach to meat and egg production. In conclusion, integrating AI and IoT technologies in the poultry farming industry represents a transformative step toward more innovative, sustainable, and efficient livestock management. Despite challenges such as the cost of infrastructure and data security, the synergy of AI and IoT will continue to drive innovations in poultry farming, offering significant potential for improving productivity, animal welfare, and environmental sustainability.

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Chapter 23
AI and IoT to Integrate Automation in Farm Management: A Path to Sustainable Agriculture in Changing Climates

Shahriar Abdullah Al-Ahmed and Tofael Ahamed

Abstract A significant shortage in the agricultural labor force is threatening sustainable development and driving geographic transformations for cross-border food production as urgent global issues to ensure food security in a changing climate. In response, the agricultural sector is moving toward mechanization, creating opportunities to integrate autonomous machinery and strengthen collaboration with research organizations to achieve sustainability. This concluding chapter focuses on how sensors, sensing technologies, Internet of Things (IoT), and Artificial Intelligence (AI) are advancing sustainable agricultural practices and supporting the achievement of the Sustainable Development Goals (SDGs). The key considerations of transformation are discussed, including increasing productivity, mitigating labor shortages, and optimizing land and water use in arid regions for climate-smart agriculture. Furthermore, the application of machine learning and deep learning across the agricultural value chain is highlighted, from intelligent automation in fruit crop production to post-harvest evaluation in various agricultural systems. This includes intelligent automation in fruit crop production and the evaluation of post-harvest efficiency in crops, orchards, livestock, aquaculture, and poultry systems.

Keywords Infield and orchard automation · In-house automation · Agricultural data management · Livestock and poultry management · Precision agriculture

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23.1 Background

The concept of automation in climate-smart agriculture varies significantly across Japan, Europe, and the United States. In Japan, regulatory frameworks require strict adherence to safety standards before fully autonomous machinery can be deployed on farms. Due to a declining agricultural workforce, individual farmers are increasingly responsible for larger workloads, with many being older and experiencing health challenges. The market for autonomous agricultural machinery is expanding rapidly, intensifying competition both domestically and internationally. The simultaneous operation of multiple machines is becoming more prevalent, facilitated by advancements in remote internet-based control systems. AI and IoT technologies are being utilized for smart greenhouse management, thereby reducing the burden on farmers. These tools help reduce the amount of work required and make it easier to control factors such as temperature, humidity, and light at various stages of vegetable and fruit growth. In traditional greenhouses, farmers must continually check and adjust these settings, which is inconvenient. By using a special type of controller called a Fuzzy PID controller, a new method of feedback is introduced, which significantly enhances the accuracy of controlling the greenhouse environment. AI-based data-driven methodologies create opportunities for predictive analysis, strategic planning, and long-term investments in agriculture (Fig. 23.1).

Therefore, precision agronomics concepts, covering cutting-edge research articles and review notes, are structured in the previous chapters to provide insight and enable climate-smart agriculture. Additionally, integrated with a deep learning approach and IoT, utilizing high-resolution satellite remote sensing imageries, drone imageries, and ground reference GIS datasets to handle big data, this enables the generation of faster and more accurate solutions for site-specific management of crop production, from decision-making to demonstration levels.

23.2 Supervised and Remote Autonomy for Infield and Orchard Automation

Agricultural machinery is evolving into intelligent robotic systems that utilize AI to process data, predict outcomes, and support decision-making. Japanese manufacturers are developing fully autonomous machines designed to enhance efficiency and productivity, which can be remotely monitored, reducing the need for constant human supervision. Continuous technological innovation is essential to adapt to the evolving agricultural sector. It is projected that a substantial proportion of agricultural tasks will be automated throughout the entire growing season, employing cameras, satellite navigation, and adaptive AI. As both software and hardware improve, machine interoperability and autonomous operation are becoming increasingly feasible. A diverse range of equipment is now available to enhance operational reliability and efficiency. The software that manages these systems aims to reduce

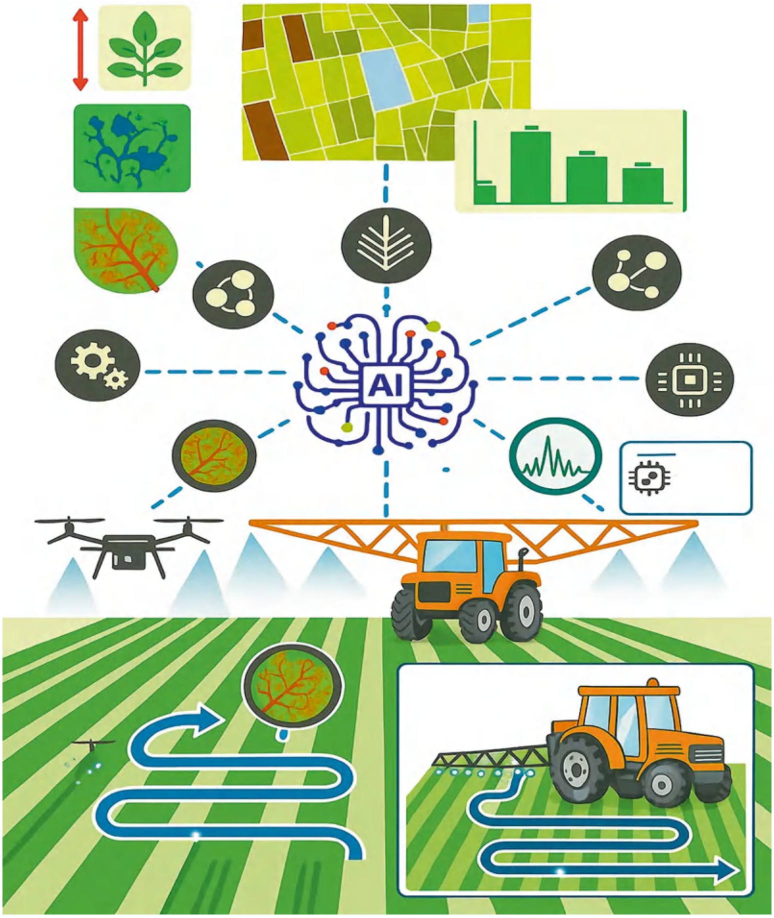

Fig. 23.1 AI and IoT to integrate automation in farm management

operator stress and provide comprehensive situational awareness. Precision in tasks such as seeding, fertilization, irrigation planning, and pesticide application is improving with the combination of robotics and computer vision, thereby optimizing agricultural outcomes. The overarching objective is to replicate traditional farming practices as accurately as possible through the use of automation. Major Japanese corporations are integrating satellite-based guidance and autonomous steering systems into routine operations. However, widespread adoption of smart agricultural machinery requires software solutions that address environmental sustainability, yield optimization, and crop management. Additionally, effective marketing and management support is necessary to facilitate the integration of autonomous systems into mainstream agricultural practice (Fig. 23.2).

This book provides a concise overview of the latest trends in farming, particularly how automation and robotics are being utilized to reduce labor requirements.

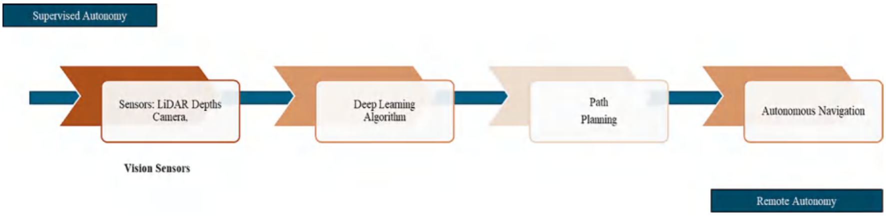

Fig. 23.2 Spectrum of transformation from supervised autonomy to remote autonomy

This book proposes 3D cameras and Light Detection and Ranging (LiDAR) as potential solutions for navigation systems in orchard environments, although some areas lack Global Navigation Satellite System (GNSS) signal quality due to vegetation or obstacles such as trees or canopies (Ailian Jiang & Tofael Ahamed, 2023, 2025). Modern farming focuses on utilizing AI and smart devices to make farm work more precise, a trend expected to become increasingly common in the future. There is a large shortage of workers in the farm-to-transport industry. Detecting targets in orchards is a crucial step in making farm operations more automated. As farm technology continues to improve, farming is becoming smarter and more automated. Managing and running orchards also needs new technology to boost efficiency and quality. Advanced computer models, utilizing AI-based deep learning models such as Mask R-CNN and YOLACT, can identify trees in orchards and mark safe areas for vehicles, thereby helping to accurately locate objects and keep vehicles safe while in operation. The book also explains systems, and different sets of data are used to train models that can spot objects. In orchards, tasks such as navigating field edges, avoiding obstacles, and handling numerous branches are essential for automation and self-driving systems. It is also important to remember that tasks like pesticide spraying and pollination are major parts of farm work. Fruit trees, for example, often require 10–15 spray applications from flowering to harvest. Similarly, ensuring effective pollination during the brief flowering window can be a significant labor-intensive challenge that automation seeks to solve, especially with declining populations of natural pollinators.

23.3 AI-Driven Agriculture for In-House Automation for Vegetables, Management of Poultry

AI can also be used to automatically monitor the growth and condition of plants within indoor farms. Deep learning and computer vision techniques can accurately detect leaf diseases, assess plant stress, and evaluate the quality of seedlings grown indoors (Hamidon & Tofael Ahamed, 2022, 2023). Utilizing IoT systems is expected to help achieve greenhouse gas reduction goals more quickly (Fig. 23.3).

Farm managers can make informed decisions and remotely control indoor systems to ensure green energy is utilized for optimal plant growth. Plant phenotyping

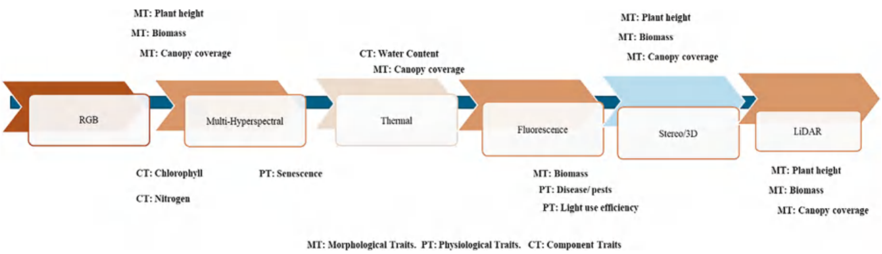

Fig. 23.3 AI-driven plant phenomic analysis for crop abiotic and biotic stress detection using sensors

measures plant features to help plants grow better indoors. It is important for helping farmers make decisions. To help crops better handle climate change, plant phenotyping, such as high-throughput plant phenotyping (HTPP), which rapidly assesses many plants in indoor settings, can be combined with AI to enhance stress detection capabilities (Chutichaimaytar et al., 2025; Hamidon & Tofael Ahamed, 2022, 2023). Greenhouse automation is in high demand because it works well in different environmental conditions and helps produce more fruit. Beyond climate control, a critical challenge in indoor farming for fruiting crops, such as tomatoes, cucumbers, and strawberries, is pollination. In the absence of natural pollinators, such as bees, this task has traditionally been performed manually, which is both time-consuming and expensive. AI-driven automation offers a transformative solution. Robotic pollination systems, equipped with computer vision, can identify flowers at their peak receptivity and then use robotic arms with soft-effectors or targeted air jets to gently pollinate them. Other innovative approaches include the use of small, autonomous drones that mimic the behavior of bees. These technologies not only mitigate labor shortages but also have the potential to increase fruit set and yield by ensuring pollination occurs at the optimal time. Although significant progress has been made in the field with robots, utilizing the latest deep learning technology to enable robots to see and understand what they are picking has not yet been widely adopted in real-world applications. Food diversification is a key intervention strategy for addressing food crises that has been supported by the Food and Agriculture Organization (FAO). Both aquaculture and animal farming can benefit from smart machine vision technologies coupled with artificial intelligence and the Internet of Things to reduce the need for manual observation. In addition to the robotic platform, several reviews have provided insights into the development of pest and disease detection models, recommending effective methods for deploying deep learning applications and Convolutional Neural Network (CNN) models for managing horticultural crops (Apacionado & Tofael Ahamed, 2023). These improvements ultimately contribute to food security. For instance, by deploying cameras, environmental sensors, and IoT devices, real-time data can be analyzed via AI algorithms to monitor poultry behavior, health, and environmental conditions. This enables the automatic detection of anomalies and potential issues, reducing the need for manual observation and enhancing overall operational efficiency. By leveraging AI-driven image recognition and IoT-enabled remote monitoring, poultry farmers can proactively manage their operations, optimize resource utilization, and rapidly respond to emerging challenges, thus contributing to food security through sustainable and technology-driven poultry farming practices (Nakaguchi & Ahamed, 2022; Nakaguchi et al., 2024). AI and IoT can transform poultry farming production systems. Key applications include automated health diagnostics, precise climate control within housing, and recent AI-based algorithms and IoT systems innovations are discussed.

23.4 AIxIoT-Based Large Language Models for Agricultural Data Management

Precision management of agronomical information often referred to as precision agriculture, along with machine learning, comes with local agronomical information management using data-driven, precise geographic information systems (GIS) and satellite remote sensing (RS) imageries to develop policy planning against climate vulnerability.

The integrated data-driven approach has attracted attention in various domains, including sustainable agriculture, land use planning, and crop growth monitoring, due to its spatial coverage. In recent advancements, microclimate characterization and climate risk assessment of agroforestry-based agricultural production are crucial for satisfying the food demand of a growing population with decreasing land resources. Climate risk mitigation, crop insurance, and subsidence factors can play key roles in motivating farmers to adopt intensive production practices in climate risk regions. In this regard, the application of remote sensing methods along with large language models (LLMs) fulfills a significant role in the adaptation of policies to mitigate the adverse effects of climate change through vulnerability analysis, land cover/land use change analysis on large temporal and spatial scales for yield forecasting (Fig. 23.4). With the application of big data schemes in the field of agriculture, researchers can process high volumes of low-density, unstructured, structured, multifactor, and probabilistic datasets with high efficacy. This allows for information abstraction, yield forecasting, crop mapping, crop management prescription, and the use of language models for crop growth enhancement.

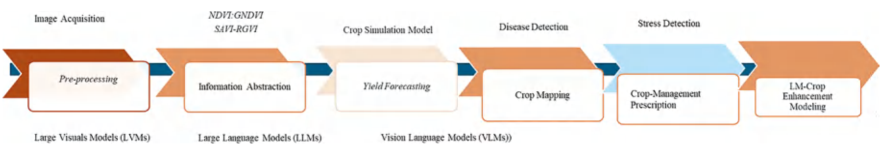

Fig. 23.4 Agricultural data management for a large language model application for crop enhancement management

23.5 Conclusions

The integration of automation systems requires a transformative approach to sustainable agriculture, offering innovative solutions for improving efficiency, animal welfare, and environmental impact. By incorporating advanced technologies such as robotics, AI, the IoT, and data-driven decision-making tools, automation supported by AI and IoT, and big data analytics can streamline daily operations, optimize resource allocations, and enhance real-time monitoring of livestock health. This shift not only boosts productivity but also reduces labor costs and minimizes the ecological footprint of farming practices. Furthermore, AI-powered analytics and IoT-enabled sensors facilitate precision management, enabling farmers to respond proactively to disease outbreaks, improve animal care, and ensure the long-term sustainability of livestock farming. This book outlined advancements in AI- and IoT-driven farm automation and its potential to drive sustainable agricultural practices for the future. Furthermore, all chapters are discussed with the intention of developing AI and IoT applications to solve agricultural problems for sustainability. Despite this, improving pesticide application efficiency and cost-effectiveness remains challenging. Additionally, replacing skilled orchard laborers with harvesting robots requires advanced research and automation. Newly developed orchard architectures with genetic improvements create pathways for harvesting robots to reduce the complexity of their tasks to several degrees of freedom. This reduces complex robots' adaptability in terms of cost and sustainability. In terms of detection and localization, harvesting robots face the challenge of being obstructed by leaves, branches, and fruit clusters.

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