Using of Digital Agriculture, Machine Learning, Remote Sensing and Smart Approaches in Fruit Orchards

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Abstract

In recent years, advances in remote sensing technologies have made considerable progress in the monitoring of orchards. These technologies provide externally, gently and non-destructively, cost-effective and scalable solutions to assess crop quality and health, detect abiotic and biotic stress factors and optimise orchard management practices. The objective of this paper is to provide a comprehensive review of recent advancements in the field of remote sensing techniques, machine learning, deep learning, unmanned aerial vehicles, and intelligent systems in orchard management. This review aims to offer a comprehensive overview of the application of these techniques in orchards and to propose relevant recommendations. Firstly, the paper sets out the principles of remote sensing using various sensors and platforms for the purpose of creating a data pool through the use of broad spectrum, hyperspectral and thermal imaging technologies. The paper then examines in detail the studies on these issues and the resulting detailed information obtained about fruit trees and the environmental environments in which they are located. The subsequent discourse delves into the applications of remote sensing in the context of monitoring fundamental biophysical parameters, including vegetation indices, canopy structure, and water stress. The text does not address the subject of the development of decision-making processes for operational requirements in orchard management, with the objective of ensuring accuracy and timeliness. Furthermore, the text goes on to explore the ways in which diseases can be detected before they reach the damage threshold, the estimated yield, and the practical benefits of remote sensing in precision agriculture applications in orchards, with the aid of illustrative examples. The challenges that may be encountered, such as the processing of data, the integration of data sources, and the scalability of the system, have been thoroughly examined in conjunction with the research and technological advancements. In addition, the study encompassed the following: The utilisation of digital agriculture, machine learning, remote sensing and smart system techniques has been demonstrated to be a highly effective means of increasing fruit production. It is hypothesised that the implementation of such novel approaches in the domain of fruit orchard management by researchers and decision-makers will engender contributions to the enhancement of fruit yield and the sustainability of fruit production.

Keyword: *smart systems, remote sensing, plant health, sustainability, innovative approach*

Introduction

The use of smart systems is increasingly expanding from industry and manufacturing to agriculture and even food production. Their use in agricultural production, in particular, has become a necessity for the agricultural sector to be more efficient, sustainable, and smart in the face of challenges such as increasing global food demand, climate change, and resource scarcity. In this context, machine learning algorithms from smart systems make significant contributions in areas such as soil analysis, crop yield prediction, disease detection, and resource management. Machine learning methods are particularly widely used in agriculture. Various ML algorithms such as decision trees, random forests, support vector machines (SVM), and artificial neural networks have begun to be used extensively in this system. Clustering techniques are used, especially in crop classification and soil type analysis. It has been noted that models such as CNN are effective in tasks such as image processing and object recognition. The main areas where machine learning techniques are applied in agriculture are as follows: Productivity estimation, where the amount of product is estimated using historical data and environmental factors. Disease and pest detection: Leaf diseases and pests can be detected at an early stage using image processing. Soil and water management: Parameters such as soil moisture and pH level are analyzed using sensor data to optimize irrigation and fertilization. Autonomous systems, drones, and robots are guided by ML algorithms to automate planting, harvesting, and spraying operations. However, there are also some obstacles to the widespread adoption of ML applications in agriculture. These include data scarcity and poor data quality, high hardware costs, farmers' adaptation process to technology, and model generalization issues (different results in different regions). It is anticipated that more integrated systems (IoT + ML + cloud computing) will become widespread in the future and that decision support systems will provide farmers with real-time recommendations. Furthermore, it is considered necessary to develop open data platforms and create customized models at the local level (Mohyuddin, et al., 2024). The transformation experienced by the agricultural sector through machine learning (ML) technologies and efforts to integrate Information and Communication Technologies (ICT) into traditional agricultural practices are progressing at a dizzying pace. In the current environment of "data tsunami," a paradigm shift is observed in the fields of smart agriculture and precision farming. Machine learning algorithms can analyze past and real-time environmental data and soil conditions to predict the most suitable crop selection for maximum yield, detect diseases early, and optimize irrigation processes. This facilitates farmers' ability to make informed decisions. Precision agriculture, on the other hand, ensures high accuracy in planting, harvesting, and crop monitoring through autonomous vehicles and drones. The use of these technologies leads to significant increases in resource efficiency. Machine learning optimizes energy consumption, manages fertilizer use, and promotes climate-resilient practices (Mohyuddin et al., 2024). Digital agriculture (or smart agriculture) has entered a transformation process that goes beyond traditional methods and focuses on technology. This transformation comprehensively addresses the role played by agricultural robots and research and development (R&D) activities in this field. The evolution of robots in agriculture initially involved machines that performed only mechanical tasks. However, today these systems have been transformed into systems equipped with sensors, capable of detecting environmental data, making decisions using artificial intelligence and machine learning, and moving autonomously. This evolution has enabled robots to be used not only as physical labor but also as decision support systems. Application areas and robot types include planting and sowing robots that precisely place seeds and can adjust depth and spacing according to soil structure. They operate flawlessly with GPS-guided navigation, while harvesting robots are used specifically for gathering delicate products such as fruits and vegetables. It determines ripeness through image processing. It enables hygienic harvesting without human contact. Spraying and fertilizing robots can perform targeted spraying based on plant health. This allows farmers to reduce chemical use, offering an environmentally friendly approach. Weed control identifies weeds through image processing and artificial intelligence, enabling targeted intervention to target only unwanted plants. Soil and plant analysis sensors collect data such as soil moisture, temperature, and pH, and use this data to optimize irrigation and fertilization decisions. The core technologies used include image processing for plant health, maturity, and weed detection. Machine learning is critical for robots to perceive their environment and make decisions. GPS/GNSS is used for precise positioning of robots in the field, enabling sensors to continuously monitor soil and environmental conditions. Cloud computing enables the analysis of collected data and facilitates remote management. Despite providing all these conveniences, the most common challenge is high cost. The production and maintenance costs of robots are still quite high. Variable field conditions, such as mud, slopes, and rocky terrain, can negatively affect robot performance. Battery life and energy consumption are still factors in energy efficiency. Farmers' adaptation to these technologies is another issue. As is well known, training and support are required for users who are not accustomed to technology. In summary, it is predicted that in the near future, robots will be able to communicate with each other, make real-time decisions, and serve as decision support systems for farmers. Furthermore, in this scenario, the integration of artificial intelligence and robotic systems has the potential to increase agricultural productivity while reducing environmental impacts (Shamshiri, et al., 2018). A study conducted in Thailand evaluated the effects of smart farming technologies in digital agriculture projects implemented in the Chanthaburi region of Thailand. Highlighting the fundamental challenges facing agriculture today, factors such as the growing world population, declining agricultural land, climate change, and the reduction in the agricultural workforce have rendered traditional farming methods inadequate. In this context, smart agriculture technologies have great potential in terms of increasing productivity, optimizing resource use, and ensuring sustainability. This study examines the basic components of smart agriculture in detail. First, thanks to the Internet of Things (IoT) technology, sensors placed in fields collect environmental data such as soil moisture, temperature, and light intensity in real time, and this data is used to automate processes such as irrigation. This ensures both water conservation and plant health. Unmanned aerial vehicles (drones) enable aerial monitoring of large agricultural areas, providing high-resolution images for plant growth, disease, and pest detection, thereby enabling farmers to intervene early. The collected data is processed using artificial intelligence and big data analytics, enabling more accurate decisions to be made regarding product yield estimation, disease diagnosis, and fertilization planning. Machine learning algorithms learn from past data to predict future possibilities and provide recommendations to farmers. All these technologies are managed in an integrated manner through digital platforms called Smart Agricultural Management Systems (SAMs). These systems provide farmers with real-time information about the status of their fields and facilitate decision-making processes. Furthermore, this study examines the example of the Data Center (DCC) established in Thailand's Chanthaburi region, suggesting that regional agricultural data can be collected and analyzed to develop solutions tailored to local conditions. This center is reported to play a significant role in creating digital agriculture strategies specific to the region. The benefits provided by smart agriculture technologies include increased productivity, sustainable production, real-time intervention capabilities, and traceability of production processes. However, this study also points out that there are some obstacles to the widespread adoption of these technologies. High initial costs, farmers' lack of technical knowledge, data security issues, and inadequate infrastructure in rural areas are among these obstacles. In summary, this study paints a promising picture for the future of smart agriculture. It is stated that the widespread adoption of agricultural platforms integrated with full automation, artificial intelligence-supported decision systems, and regional data centers is expected. These developments are anticipated to make the agricultural sector more efficient, sustainable, and resilient (Thongnim, et al., 2024; El-Ansary., 2025). Work is rapidly progressing on new orchard management systems that combine artificial intelligence (AI)-powered robots and Internet of Things (IoT) sensors. These systems use an algorithm called reinforcement learning (RL) to enable robots to adapt to the garden environment and perform tasks more efficiently. The system provides robots with real-time information using IoT data, helping them make more accurate decisions in tasks such as pruning, harvesting, and plant health monitoring. The tests conducted have demonstrated that this AI-focused system operates with fewer resources and higher efficiency compared to traditional methods. Consequently, the adoption and widespread use of these technologies hold significant potential for more sustainable and efficient agricultural practices (Ranganathan et al., 2025).

Use of New Systems Such As Smart, Digital, Remote-Controlled, Unmanned Aerial Vehicles and Machine Learning In Orchard Management

Today, the integration of digital technologies is becoming increasingly important in order to increase agricultural production efficiency, optimize resource use, and ensure environmental sustainability. In this context, advanced technologies such as smart systems (smart, digital, remote-controlled, unmanned aerial vehicles, and machine learning) in orchard management are replacing traditional methods, enabling more precise, faster, and data-driven decision-making processes. In this regard, Bharad and Khanpara (2024) conducted a study in which they integrated robotic technologies into agriculture, initiating a fundamental transformation in this sector and offering innovative solutions to long-standing problems such as labor shortages, rising production costs, and the need for increased productivity. Among these developments, agricultural fruit harvesting robots stand out as a significant innovation with the potential to fundamentally change traditional agricultural practices. This study provides a comprehensive overview of autonomous fruit harvesting robots and examines their impact on agricultural applications. The Agricultural Fruit Harvesting Robot (AFHR) is considered a significant milestone in modern agriculture. These robots are equipped with advanced sensors, actuators, and machine learning algorithms. Thanks to this technology, they can identify ripe fruit, gently grasp it, and efficiently harvest it from trees. The design of the AFHR has been developed to be flexible and versatile, capable of adapting to different fruit types, shapes, sizes, and garden layouts. This allows it to find a wide range of applications in various agricultural environments. Fundamental technological components such as computer vision systems and machine learning algorithms enable the robot to distinguish fruit ripeness levels. This contributes to optimizing harvest timing, thereby increasing yield and reducing waste. Thanks to autonomous navigation systems, robots can move efficiently in orchards, avoid obstacles, and work without damaging plants. Additionally, soft grippers integrated into robotic arms ensure that fruits are handled gently, minimizing the risk of bruising and damage. Autonomous fruit harvesting robots offer a promising solution to address labor shortages, increase operational efficiency, and improve the sustainability of fruit production systems. Continuous advances in technology will further enhance the capabilities of these robots and encourage their widespread adoption in agricultural applications. As a result, AFHR is at the forefront of agricultural innovation and stands out as a technology poised to redefine the future of fruit harvesting. These robots will play a significant role in ensuring higher productivity, sustainability, and profitability in the agricultural sector.

In recent years, for example, work has continued on using an intelligent management system for apple orchards. By transferring each tree, the soil, and the environmental conditions of the apple orchard into a digital environment, a "digital twin" that is a complete copy of the orchard is created. Thanks to this digital twin, the condition of the garden can be monitored in real time using data collected via sensors and cameras (e.g., soil moisture levels, air temperature, tree health). This system analyzes the data it collects to assist farmers in the following areas: It optimizes irrigation by determining how much water each area needs, thereby preventing water waste; it detects potential disease symptoms in trees at an early stage, enabling rapid intervention; it predicts how much yield can be obtained at harvest time; and it reduces costs by ensuring that processes such as fertilization and spraying are carried out at the right time and in the right amount (Schneider Castro, 2025).

As is well known, the agricultural sector must adapt to challenges such as global temperature changes, environmental degradation, declining agricultural labor force, population growth, and changing dietary habits. Various methods such as plant breeding, genetic engineering, and precision agriculture are being applied to increase agricultural productivity. In recent years, with the rapid development of scientific and technological innovations such as unmanned aerial vehicles (drones), smart sensors, robotic systems, and remote sensing technologies; revolutionary methods have emerged in many areas such as real-time product modeling, high-throughput phenotyping, weather forecasting, yield prediction, fertilizer application, disease detection, market tracking, and environmental applications. These methods are critical in terms of product development, yield, and quality. Furthermore, big data analytics, advanced data processing techniques, falling technology costs, faster internet connections, increasing digital connectivity, and advances in processing power are among the key elements supporting the digitalization process in agriculture. This digital transformation contributes to commercial agriculture achieving its goals of smart farming, resilience, productivity, and sustainability. These technologies enable the effective monitoring of plants, soil, and environmental conditions across large agricultural areas, providing farmers with the ability to make precise management decisions that maximize productivity and minimize environmental impacts. However, despite the significant potential offered by smart farming, there are also some challenges, such as high implementation costs, data security concerns, and a lack of digital literacy among farmers. As a result, the agricultural sector is undergoing a rapid transition from traditional methods to digital applications. This transformation offers advantages such as the capacity to produce solutions on a global scale, the efficient use of resources, and the reduction of input costs; it also increases the welfare of farmers and contributes to economic growth. This perspective emphasizes the role of technology in solving critical issues such as environmental degradation and threatened biodiversity, drawing attention to the opportunities offered by digitalization. Future developments are expected to focus on areas such as data encryption, digital literacy, and specific economic policies (Balyan, 2024).

A study examining the integration of digital technologies with precision farming applications in fruit production comprehensively investigates the critical role these technologies play in achieving modern agriculture's goals of productivity, quality, and sustainability. The limitations of traditional methods in agricultural production, particularly issues such as labor shortages, resource waste, and environmental impacts, have increased the importance of digital solutions. The development of precision agriculture applications, especially in fruit production, has been evaluated through the technological tools and methods used in this field. In this context, the integration of digital tools such as remote sensing systems, geographic information systems (GIS), sensor-based monitoring technologies, artificial intelligence-supported decision systems, robotic harvesting machines, and data analytics into production processes has been addressed. The main contributions of these technologies to fruit production can be summarized as follows. Thanks to increased productivity, real-time monitoring of plant growth, soil conditions, and environmental factors, production processes can be managed more precisely and efficiently. Quality control; thanks to image processing and sensor technologies, quality parameters such as fruit ripeness, color, and size can be automatically evaluated, which improves classification and marketing processes. In terms of resource optimization, costs are reduced and environmental impacts are minimized by ensuring that inputs such as water, fertilizer, and pesticides are applied only in the required amounts and at the right time. The data collected on traceability and decision support enables every stage of the production process to be digitally tracked and recorded, offering significant advantages in terms of both food safety and producer decisions. It also addresses some of the challenges to the widespread adoption of these technologies. In particular, high investment costs, lack of digital literacy, inadequate infrastructure, and data security issues are the main factors limiting the adoption of technology in rural areas. Briefly, this study emphasizes that the integration of digital technologies with precision agriculture practices in fruit production is one of the fundamental dynamics that will shape the future of agricultural production. By making these technologies more accessible, user-friendly, and economical, it will be possible to achieve higher yields, quality, and sustainability in fruit production (Murthy and Gutam 2024)

Schneider Castro et al. (2025) conducted a thesis study at the Politecnico University in Italy, researching the design, development, and implementation of a monitoring system for an apple orchard. The system used in this study is reported to provide useful information about apples, such as their health status and location, by creating an integrated digital twin (DT) of the orchard in question. The work carried out within the scope of the thesis is a continuation of a project previously initiated by the Department of Environmental, Land, and Infrastructure Engineering (DIATI) and the Department of Mechanical and Aerospace Engineering (DIMEAS) at the Politecnico di Torino.Data collection was performed using multispectral cameras and a stereo camera mounted on the Agri.Q agricultural unmanned ground vehicle (UGV), developed by DIMEAS and controlled remotely. Multispectral cameras have determined the health status of each tree by measuring the light reflected from the leaves during photosynthesis. Meanwhile, a point cloud was extracted from the SVO file recorded by the stereo camera; apples were detected and located using artificial intelligence (AI) and neural networks with the integrated Inertial Measurement Unit (IMU). Additionally, a LiDAR scanner was used to obtain the geographic reference point cloud of the orchard. Within the scope of the project, the necessary support structure for mounting the sensors on the UGV was designed; camera placement and orientation were considered to ensure that the apple trees could be framed as desired and that the images had an appropriate overlap ratio. Following the data collection process, point clouds obtained from various camera and sensor outputs were combined to form a single integrated point cloud. As a result, the system developed within the scope of this thesis enabled the monitoring of apple orchards through their digital twin, and the health status and location of apples were successfully determined. Multispectral and stereo cameras, LiDAR scanners, and AI-supported analysis methods have enabled a significant step toward digitalization in agricultural production. The results obtained demonstrate the effectiveness of digital twin technology in precision farming applications and lay the foundation for future similar studies.

Melnychenko et al. (2024) conducted a study on the development of an intelligent system that integrates multi-unmanned aerial vehicle (UAV) imaging systems with deep learning techniques to make fruit detection and monitoring processes in agricultural production more efficient and accurate. This system, developed by Melnychenko and colleagues, combines multiple UAV images obtained from different angles and heights to provide a solution that ensures high accuracy in fruit detection and positioning. Deep learning algorithms, particularly convolutional neural networks (CNN), have been effectively used in the automatic recognition and classification of fruits. In this context, the study in question responds to the need for fast, automatic, and accurate data collection over large areas, overcoming the limitations of traditional fruit detection methods. The system makes a significant contribution to solving the problem of time-consuming and costly manual observation and data collection processes, particularly in large-scale agricultural areas. In the associated thesis work conducted in relation to this article, a similar digital twin approach was adopted; however, this time a ground-based agricultural unmanned ground vehicle (UGV) was used to develop a monitoring system specifically for apple orchards. Tree health and fruit locations have been successfully detected using multispectral and stereo cameras, LiDAR scanners, and artificial intelligence-supported analysis methods. Both studies serve as important examples in terms of digitalization in agriculture and the widespread adoption of precision farming practices. Consequently, these studies demonstrate how innovative technologies developed to increase agricultural production efficiency, optimize resource use, and reduce dependence on human intervention can be effectively implemented through both airborne and ground-based platforms.

As is well known, almond cultivation has become an important agricultural activity worldwide in countries with suitable ecological conditions, due to increasing demand and high nutritional value. In this context, this systematic review study conducted by Guimarães et al. (2024) comprehensively informs about current trends, research gaps, and future potential applications regarding the use of remote sensing technologies in almond orchards. This study analyzed 82 scientific articles published between 2010 and 2023 in accordance with the PRISMA protocol and identified the main areas of application of remote sensing in almond farming. According to the findings, water management is the area with the highest concentration of remote sensing applications, addressed in 34 studies. This was followed by applications such as image classification (14 studies), tree segmentation and parameter extraction, plant health monitoring, and disease detection. The countries contributing most to almond production worldwide are the United States, Australia, and Spain, respectively. Given that these countries also hold leading global almond production positions, this study examines and evaluates active research in all areas of application in these countries. This study systematically presents the current status of remote sensing technologies in almond orchards, identifies gaps in knowledge, and offers guidance for future research. It also makes significant contributions to the development of sustainable agricultural practices and the dissemination of precision agriculture technologies. The recommendations presented in this study can be summarized as follows: While research on water management is generally quite intensive, there is a need for more research in areas such as disease detection, tree segmentation, yield estimation, and nutrient status monitoring. Advanced technologies, such as hyperspectral imaging and thermal sensors, have not been sufficiently researched in almond farming. To obtain more accurate and comprehensive results, data from different sensors (e.g., RGB, multispectral, LiDAR) to obtain more accurate and comprehensive results, the more widespread and systematic use of machine learning and deep learning algorithms, and the diversification of remote sensing platforms, for example, developing more sustainable solutions by using satellite images, fixed camera systems, and ground-based sensors together, without relying solely on UAV-based data. In addition, it is recommended that, in order to increase geographical diversity, while a large portion of research is concentrated in leading producer countries such as the USA, Australia, and Spain, similar studies should also be conducted in other producer countries. This is important for more accurately understanding the effects of climatic and geographical differences, and it is suggested that application-oriented studies should be increased. In summary, it is emphasized that academic studies should interact more with agricultural practitioners and produce practical solutions. Lachgar et al. (2023) conducted a review study that comprehensively examined current trends, technological developments, and application areas related to the use of unmanned aerial vehicles (UAVs) in smart agriculture applications. According to this study, with the acceleration of digitalization in the agricultural sector, UAVs have become an important tool in data collection, analysis, and decision support processes. It is emphasized that UAVs are used particularly in areas such as crop health monitoring, disease and pest detection, irrigation management, yield estimation, mapping, and fertilizer optimization. Additionally, it is stated that these systems offer faster, more economical, and more precise solutions compared to traditional methods, thanks to their capabilities such as high-resolution imaging, real-time data transmission, and AI-supported analysis. The article compares the advantages and limitations of different types of UAVs (fixed-wing, rotary-wing, etc.); it also evaluates the role of sensor technologies (multispectral, thermal, RGB) in agricultural applications and states that UAV-based systems have the potential to increase efficiency in agricultural production, but there are still issues to be resolved regarding data processing infrastructure, regulations, user training, and economic accessibility.

Zhang et al. (2021) conducted a comprehensive review study that systematically examined perception and analysis approaches for the use of small unmanned aerial vehicles (UAVs) in orchard management. In recent years, the miniaturization of sensors and the widespread adoption of UAV technologies in agriculture have enabled the development of precision farming applications, particularly in orchards. However, one of the biggest obstacles to the widespread adoption of these technologies is the lack of a standardized application workflow. Orchards are complex systems that require tree-based management throughout the entire growth cycle, from flowering to fruit ripening and harvest. Therefore, technologies capable of collecting data at the local and individual tree level are needed. In this context, UAVs offer significant potential with their high-resolution imaging and rapid data collection capabilities. UAVs offer significant advantages in terms of efficiency, accuracy, and time savings in

orchards. There is diversity in data processing techniques; however, this diversity makes standardization difficult in practice. Although the performance of new technologies (e.g., artificial intelligence-supported analyses) is promising, these systems need to be tested and optimized under field conditions. Conclusions and Recommendations: Standard workflows need to be developed to promote the widespread use of UAV-based systems in orchard management. Integrating sensor data and developing automated decision support systems will increase application success. Future research should focus on issues such as application accuracy, economic feasibility, and user-friendly interfaces.
Sarkar (2025), in the book chapter titled “Automation and the Future of Food,” discusses the integration of machine learning and remote sensing technologies for the early diagnosis of diseases in orchards. He states that diseases in agricultural production pose serious threats to product quality and yield, while traditional diagnostic methods are time-consuming, require expertise, and are costly processes. He defines a machine learning workflow that includes steps such as collecting leaf images, preprocessing, segmentation, feature extraction, and classification, and demonstrates how this process can be supported by remote sensing data. Models trained with different sensor data such as RGB, multispectral, and thermal images have been highlighted for their ability to detect diseases with high accuracy in the early stages. However, challenges such as data quality, labeling process, and model generalization have also been noted. As a result, the integration of these technologies offers a powerful solution for early intervention and precision farming applications in orchards; it also emphasizes the need to make them more accessible in the future through real-time systems, mobile applications, and cloud-based analysis platforms.
Zheng et al. (2021) conducted a review study examining the integration of remote sensing and machine learning in agricultural phenotyping and management processes. They emphasized that the rapid and accurate measurement of plant characteristics, particularly in strawberry farming, is a critical need for both plant breeding and agricultural management. In this context, data obtained using various sensors such as high-resolution RGB, multispectral, hyperspectral, chlorophyll fluorescence, and LiDAR are processed using machine learning and computer vision techniques to evaluate many agricultural characteristics, such as enabling the assessment of numerous agricultural characteristics such as fruit/flower detection, ripeness and quality analysis, leaf and stem characteristics, water stress status, and disease and pest detection.
Sharma and Shivandu (2024), in their review study, examined how the integration of artificial intelligence (AI) and Internet of Things (IoT) technologies has transformed plant monitoring and management in precision agriculture applications. They reported that innovative methods such as high-throughput phenotyping, remote sensing, and agricultural robots (AgroBots) have significantly reduced labor costs and environmental impacts by automating processes such as harvesting, sorting, and weed detection. Data on plant characteristics is collected through remote sensing, spectral imaging, and robotic systems; this data supports decision-making processes such as fertilization, irrigation, and pest management. DGPS and remote sensing systems are reported to provide accurate and real-time information about soil conditions and plant health. Advanced image segmentation techniques are said to ensure high accuracy in plant and fruit detection despite variable light conditions and complex backgrounds. Examples such as the PACMAN SCRI project used in apple production and the PANTHEON SCADA system applied in hazelnut orchards demonstrate the transformative power of AI and IoT in agricultural applications. The integration of upcoming 5G and future 6G mobile networks is noted to potentially support the widespread adoption of smart farming applications by resolving connectivity issues. However, research gaps remain in areas such as the integration of different data sets, scalability for small and medium-sized farms, and the development of real-time decision support systems. It is recommended that robust AI models and IoT devices suitable for different agricultural conditions be developed, user-friendly interfaces be designed, and measures be taken regarding data privacy and security. It is reported that addressing these shortcomings will significantly contribute to the more effective and sustainable use of AI and IoT in agriculture.

Results and Discussion

This study comprehensively examines the opportunities offered by digital agriculture technologies in orchard management, contributing to making production processes more efficient, sustainable, and intelligent. Thanks to innovative approaches such as machine learning, remote sensing, unmanned vehicles, and the Internet of Things, fundamental agricultural activities such as plant health monitoring, early diagnosis of diseases, yield estimation, irrigation, and fertilization can be carried out in a more precise and data-driven manner. These technologies reduce labor costs, minimize environmental impacts, and accelerate decision-making processes. However, there are also some technical and application-based challenges in this transformation process. In particular, issues such as access to these systems for small and medium-sized enterprises, data security, infrastructure deficiencies, and user training are among the areas awaiting solutions. Therefore, future efforts should aim to make digital agriculture systems more accessible, scalable, and user-friendly. Furthermore, transforming data obtained through the integration of different technologies into meaningful and real-time decision support systems will increase efficiency in agricultural production. In this context, it is recommended that training programs, open-source software, and mobile applications be developed to facilitate farmers' adaptation to technology. The spread of digital agriculture will directly and positively impact not only production efficiency but also food safety and environmental sustainability.

Declaration of Competing Interest
The authors report no declarations of interest.

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