Biosystems Engineering and Renewable Energies

Journal homepage: https://bere.gau.ac.ir

GUASNR ISAMEM

Review Paper

Artificial intelligence in precision agriculture: Technologies, applications, challenges, and future prospects

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Biosystems Engineering and Renewable Energies 2025, 1 (2): 165-183

KEYWORDS

Crop yield prediction
Deep learning,
IoT
Remote sensing

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Article history
Received: 2026-5-20
Revised: 2026-6-9
Accepted: 2026-6-12

ABSTRACT

Artificial intelligence (AI) and machine learning have emerged as important technologies for advancing precision agriculture through data-driven decision-making, real-time monitoring, and automation across the crop production cycle. This review provides a comprehensive assessment of AI-driven agricultural technologies and their integration with enabling systems, including unmanned aerial systems, remote sensing, the Internet of Things, big data analytics, and robotics. Unlike previous reviews that primarily focus on specific AI techniques or individual agricultural applications, this review offers an integrated perspective on technological architectures, practical applications, implementation challenges, and sustainability implications within the Agriculture 4.0 framework. AI-based approaches support crop health monitoring, disease and pest detection, resource management, and crop yield prediction through advanced machine learning and deep learning techniques. In particular, convolutional neural networks, vision transformers, and hybrid architectures have demonstrated strong capabilities in processing multispectral, hyperspectral, and multimodal agricultural data. Despite their potential to improve productivity, resource-use efficiency, and environmental sustainability, several challenges continue to limit widespread adoption, including data scarcity, limited model generalizability, interoperability constraints, high implementation costs, and insufficient digital skills among smallholder farmers. Additional concerns related to data privacy, ownership, transparency, and algorithmic bias further complicate implementation. This review discusses recent advances, current limitations, and future research directions, emphasizing the development of scalable, interpretable, and human-centered AI systems, as well as the integration of federated learning and physics-informed approaches to support resilient and sustainable agricultural systems.

1. Introduction

Global agriculture is facing unprecedented challenges, including climate change, population growth, declining natural resources, and increasing food demand. These challenges have intensified the need for sustainable and efficient farming practices, creating opportunities for the adoption of artificial Intelligence (AI) and other digital technologies. The development of precision agriculture started to depend on AI and machine learning (ML), which transformed traditional farming methods into data-based scientific work (Ahmed et al., 2024; Oliveira & Silva, 2023; Qazi et al., 2022; Sachithra & Subhashini, 2023). AI-based systems in agriculture enable farmers to make decisions based on data while they monitor their crops in real time and automate processes from planting to harvesting, improving productivity and operational efficiency (Kalbhor, 2025; Min et al., 2025; Qazi et al., 2022). The implementation of ML and Internet of Things (IoT) technologies in precision agriculture and Agriculture 4.0 results in better resource management, which leads to higher crop production outcomes (Kalbhor, 2025; Manono et al., 2026; Qazi et al., 2022; Sharma et al., 2021). The modern data-driven farming approach of Agriculture 4.0 implements solutions to combat agricultural production challenges, which include expensive production methods, insufficient workforce, water limitations, and ecological impact. By integrating AI, unmanned aerial systems (UAS), IoT, big data analytics, and agricultural robotics, the system automates farming operations and enhances agricultural efficiency. Agriculture 4.0 uses real-time data collection from soil, crop, and weather data to enable farmers to make precise decisions while using resources effectively, which leads to higher crop yields and better-quality produce (Vijayakumar et al., 2025).

AI has significantly transformed agricultural monitoring and management by enabling the integration of remote sensing, ML, and intelligent decision-support systems. High-resolution satellite imagery and UAS provide valuable information for monitoring crop conditions, while multispectral data from platforms such as Sentinel-2 facilitate the assessment of important crop health indicators (Jung et al., 2021; Gara et al., 2022; Alaoui et al., 2024). When combined with in-situ sensor measurements of soil moisture, temperature, and nutrient status, these technologies provide a comprehensive understanding of field conditions and support data-driven agricultural management (H. Singh et al., 2025; Manono et al., 2026).

https://doi.org/10.22069/bere.2026.24740.1043

Recent advances in AI, particularly deep learning (DL) approaches, have further enhanced the capacity to analyze complex agricultural datasets. Convolutional neural networks (CNNs) and related architectures have demonstrated strong performance in image-based crop monitoring applications, including disease and pest detection, thereby improving the accuracy and timeliness of agricultural interventions (Wang et al., 2022; Preanto et al., 2024; Arputharaj & Karunanithy, 2026). Moreover, emerging technologies such as Generative AI (GenAI) offer new opportunities for agricultural image analysis by improving predictive performance and addressing data scarcity challenges through synthetic data generation and augmentation techniques (Hua et al., 2025; Min et al., 2025). Beyond crop monitoring, AI and ML technologies contribute substantially to sustainable crop management by optimizing resource utilization and supporting informed decision-making. Intelligent irrigation systems leverage real-time sensor data to improve water-use efficiency, while AI-assisted fertilization strategies enable precise nutrient application, reducing excessive fertilizer use and mitigating environmental impacts (Shaikh et al., 2022; Debnath et al., 2024; Mamatha & Shalini, 2025). In addition, predictive analytics and yield forecasting models provide farmers with valuable insights for resource allocation, production planning, and risk management, ultimately enhancing farm productivity and sustainability (Y. Zhang, Liao, et al., 2023; Anokhina et al., 2025).

Despite these benefits, several challenges continue to limit the widespread adoption of AI in agriculture. Model performance is often affected by variations in environmental and agroecological conditions, which can reduce the generalizability of AI systems across different regions and cropping systems (Gikunda, 2024; Min et al., 2025; Oliveira & Silva, 2023; Sachithra & Subhashini, 2023). Additional barriers include interoperability issues among digital platforms, high implementation costs, and limited technical expertise among smallholder farmers (Adli et al., 2023; Gikunda, 2024; Mamatha & Shalini, 2025). Furthermore, concerns related to transparency, explainability, data privacy, and cybersecurity highlight the need for responsible and trustworthy AI frameworks within agricultural systems (Tzachor et al., 2022; Cartolano et al., 2024; Grati et al., 2025).

The future of AI in agriculture remains highly promising as emerging technologies continue to expand the capabilities of precision farming. AI-driven advisory systems, IoT-enabled infrastructures, and advanced computer vision (CV) applications are expected to further improve agricultural efficiency and decision-making processes (N. Singh et al., 2024; Johnson et al., 2025; Luo et al., 2025). In parallel, the integration of AI with remote sensing technologies and climate-resilient agricultural practices may contribute to enhanced environmental sustainability and adaptation to climate change (Jung et al., 2021). Future research should also focus on human-centered AI, federated learning, and physics-informed modeling approaches to develop scalable, transparent, and sustainable agricultural systems that balance productivity with environmental stewardship (Kumar et al., 2023; Katharria et al., 2026).

Previous reviews have primarily focused on individual aspects of agricultural AI, including ML, IoT systems, UAS-based monitoring, and CV applications. However, a comprehensive synthesis integrating AI technologies, precision agriculture applications, sustainability considerations, and emerging developments remains limited. Therefore, this review provides a critical overview of AI-driven technologies, their applications, challenges, and future directions in precision agriculture.

The remainder of this paper is organized as follows: Section 2 presents enabling technologies, Section 3 focuses on crop yield prediction and resource management, Section 4 reviews AI models and techniques, Section 5 examines key challenges, Section 6 highlights sustainability aspects, and Section 7 concludes the paper with future research directions.

2. Technologies Enabling AI in Agriculture

AI-enabled agricultural systems rely on the integration of several key technologies, including UAS, remote sensing, the IoT, big data analytics, and intelligent decision-support models. These technologies generate and process large volumes of spatial, temporal, and environmental data for monitoring crops, soil conditions, and agricultural operations. The resulting data are transmitted through a multi-layered architecture comprising edge devices, fog computing nodes, and cloud platforms, where AI models support analysis, prediction, and decision-making. This technological framework forms the foundation of modern Agriculture 4.0 and enables the effective deployment of AI-driven agricultural applications.

AI enables the transformation of agricultural data into actionable insights for precision farming. By integrating information from satellite imagery, UAS platforms, IoT sensors, weather stations, and historical records, AI systems support crop monitoring, resource optimization, irrigation management, disease detection, and decision-making processes. These capabilities have contributed significantly to improving agricultural productivity while reducing environmental impacts (Sharma et al., 2023). The main utilization of AI in precision agriculture involves using CV and DL models for crop health monitoring. Researchers found that CNNs successfully analyze high-resolution images, which drones and ground-based cameras capture to identify early signs of disease and pest infestations and nutrient deficiencies (Ghazal et al., 2024; Wang & Kang, 2025). Several studies have reported reductions of up to 30% in pesticide and fertilizer use under specific precision agriculture implementations, although the results vary depending on crop type, management practices, and environmental conditions (Mishra, 2025). The systems detect subtle visual changes indicating plant distress before humans can observe them. AI-based disease detection systems have reported classification accuracies exceeding 90% in controlled experimental datasets for crops such as wheat, rice, and tomato (V. K. Gupta et al., 2025).

AI technology provides significant advantages in the field of resource optimization. ML algorithms can analyze soil composition data, weather forecasts, crop growth stages, and historical yield information to determine optimal irrigation schedules and fertilizer application rates (Yao & Ye, 2025). AI-powered intelligent irrigation systems can decrease water usage by 30% while maintaining or improving crop production (Mishra, 2025). AI-model-based precision fertilization practices help reduce nitrogen runoff and other types of environmental pollution while delivering necessary nutrients to crops according to their developmental needs (Yao & Ye, 2025). The combination of AI and variable rate technology (VRT) enables equipment to modify its input application rates based on spatial field differences, which generates prescription maps that show micro-level soil variation and crop requirement data (Taseer & Han, 2024).

2.1 Unmanned aerial systems and remote sensing

Drones, which people officially call UAS, have developed into an important enabling technology because they permit farmers to gather high-quality, instantaneous, and location-specific information that they can use for precise agricultural farming. UAS technology provides its main benefit to agricultural systems because it enables farmers to collect essential field information, which conventional scouting methods fail to deliver, and satellite and manned aircraft systems cannot provide because of their high operational costs and limited monitoring capability and satellite systems. UAS systems can produce centimeter-level agricultural field images through their ability to fly at low altitudes, which lets them capture detailed field patterns that support various resource management methods, crop growth improvement tactics, and eco-friendly farming methods.

Agriculture drone applications are as follows: UAS technologies support a wide range of agricultural applications, including crop monitoring, soil assessment, precision pesticide application, field mapping, irrigation management, and livestock surveillance (Sharma et al., 2023).

Crop health monitoring has developed into its most advanced form because it functions as an established agricultural practice that farmers use throughout their fields. The UAS system, with its multispectral, hyperspectral, and thermal sensor capabilities, can assess vital biophysical and biochemical characteristics of plants. The UAS system uses aerial imagery to calculate vegetation indices, which include the normalized difference vegetation index (NDVI) to measure crop health and chlorophyll levels and canopy thickness (Gerardo & de Lima, 2023). The system enables detection of biotic stressors such as pest attacks and disease outbreaks, along with abiotic stressors, which include water and nutrient Shortages that occur before they become visible to observers (Manishankar et al., 2021). Thermal cameras can detect small temperature changes in the canopy, which function as water status indicators for plants because they show how much water plants lose through transpiration, enabling precise irrigation control (Johansen et al., 2023). The system functions as both a diagnostic tool and a predictive system because scientists use UAS data to build ML models that predict crop growth through the season and create digital field twins that help farmers make decisions about irrigation, crop harvesting, and yield estimation (Pal et al., 2025).

Recent studies have further enhanced UAS capabilities through the integration of AI-powered CV systems. DL models can automatically analyze drone imagery to detect weeds, estimate biomass, classify crops, and support variable-rate pesticide application with high spatial accuracy (Basso et al., 2025; Rashid et al., 2025). In addition, UAS-derived vegetation indices, such as the NDVI, provide valuable information for crop monitoring and biomass assessment (Freitas et al., 2022). Studies have also reported high classification performance for AI-based UAS image analysis, highlighting the potential of these systems for real-time agricultural decision support (S. K. Gupta & Agarwal, 2025; Taseer & Han, 2024).

UAS systems are now being utilized for precise intervention in environmental protection efforts, which require active environmental intervention. Unmanned aerial spraying systems represent a significant advancement over conventional broadcast spraying methods. The system uses UAS survey data to create detailed maps, which enable Variable Rate Application (VRA) of agrochemicals like pesticides and herbicides, and fertilizers (Taseer & Han, 2024). The VRA technology enables a variable input application that uses real-time crop data to determine when and how much agricultural input should be applied to fields. The method dramatically decreases chemical consumption while it reduces environmental damage that occurs from spray drift and decreases farming expenses, and prevents target organisms from acquiring pesticide resistance (Carreño Ruiz et al., 2022; Ivezić et al., 2023). Researchers advanced this field through their research, which combined DL algorithms with UAS technology to enable precise location spraying without human intervention. The study created a system that successfully detected and georeferenced individual artichoke plants in a field, which enables ultra-precise application that targets particular crops while protecting non-target areas (Sassu et al., 2023). The future of sustainable plant protection relies on this combination of automation and intelligent systems which will evolve into advanced environmental protection technologies.

Remote sensing serves as the basic element of AI-powered agricultural systems because it delivers essential observational information, which enables intelligent systems to conduct their analysis. Through the use of multispectral and hyperspectral imaging satellites, UAS, and ground-based sensors, scientists obtain comprehensive spectral data of crops, soil, and water resources. UAS -based NDVI vegetation indices effectively estimate pasture aboveground biomass in integrated crop-livestock systems (Freitas et al., 2022). The combination of Sentinel-2 satellite imagery with leaf area index and foliage biomass site variables allows researchers to predict foliar traits in conifer species, which shows how remote sensing can be used for ecological monitoring in large areas (Gara et al., 2022). The combined application of airborne and ground-based sensing methods enables researchers to conduct multi-scale evaluations while simultaneously improving their ability to gather data at more precise spatial points and through more frequent time intervals (Alexopoulos et al., 2023). The analysis of UAS data through ML techniques enables the creation of both predictive and prescriptive models. The combination of crop simulation models with remotely sensed phenotypic data creates an effective method that helps digital agriculture make better crop productivity estimates and decision-making processes (Jung et al., 2021).

Despite their superior spatial resolution and flexibility, UAS platforms are associated with higher operational costs, limited flight duration, and weather-related constraints. In contrast, satellite remote sensing provides broader spatial coverage and lower monitoring costs but often lacks the spatial resolution required for field-level decision-making. Consequently, the integration of UAS and satellite data is increasingly re-commended to balance accuracy and cost-effectiveness.

2.2 Internet of Things (IoT) and Sensors

Modern agriculture has adopted the IoT as a crucial technology because it enables farmers to implement automated digital farming methods. The main purpose of IoT smart farming solutions is to aid crop field monitoring and the automation of irrigation systems with the help of sensors (Zamir & Sonar, 2023). Through the use of IoT devices together with sensor technology, farmers now have the ability to transition from conventional farming methods, which depend on personal experience, to modern farming techniques that use precise agricultural information. The system demonstrates its operation through three components, which include real-time sensing, wireless communication, and intelligent data analytics to create a system that permanently monitors, evaluates, and responds to conditions found in agriculture.

The combination of AI and IoT technologies enables the creation of sophisticated monitoring systems that provide continuous data streams to assist agricultural decision-making (Dong & Ren, 2025; S. Singh et al., 2025). Field-based smart sensors gather data about soil moisture levels, temperature conditions, humidity measurements, light intensity readings, and other environmental variables, which they send to cloud AI systems for processing (Mansoor et al., 2025). The integrated systems use predictive analytics to create agricultural yield forecasts and pest outbreak predictions and assess various management strategies across different climate change scenarios (Neetu, 2024). Long short-term memory (LSTM) networks have demonstrated their value for forecasting time-based data, which helps farmers predict both yield outcomes and soil health conditions to make better planting choices and market strategies (Nautiyal et al., 2025).

The Applications of IoT-based smart agriculture include irrigation management, soil management, weather management, nutrient management, waste management, and crop management (Naseer et al., 2024). The system operates through multiple agricultural sensors, which scientists establish at different points throughout the fields to record essential field conditions. Soil moisture sensors represent the most commonly used sensors because they deliver precise measurements about water distribution within the root zone, which farmers need to schedule their irrigation activities while preserving water resources (Song et al., 2026). These devices usually work together with soil nutrient sensors, which assess the concentration of essential macronutrients that include nitrogen, phosphorus, and potassium (NPK) to help farmers apply fertilizers in ways that cut their expenses and stop environmental pollution (Mane et al., 2025). A complete microclimate profile for the crop area gets constructed through environmental sensors that track air temperature and humidity, light intensity, and gas concentrations (Mohankumar & Gowtham, 2024). The multi-parameter sensing system enables farmers to transition from using fixed calendar-based methods towards adopting management techniques that they can adjust according to specific environmental conditions.

The distributed sensors that collect data send their information to centralized cloud platforms and local gateways through wireless sensor networks (WSNs) according to Saha et al. (2023). The IoT enables agricultural operations to connect all their farming equipment through this technology, which creates one stream of usable data from multiple remote sensors. The system architecture employs a four-layer structure, which includes the perception layer for sensors and the network layer, which uses Wi-Fi, LoRaWAN, cellular communication protocols, the middleware layer that handles data storage and processing, and the application layer, which provides user interfaces and decision support systems (Morchid et al. 2024). The system allows farmers to monitor their operations from smartphones and computers, which enables them to see all farm activities without needing to be present in the field (Patil & Jadhav, 2023).

Advanced analytics, together with AI and ML technologies, will reveal the complete value of this data. AI algorithms utilize extensive sensor data streams to identify hidden data patterns that show initial signs of plant stress and pest infestations and disease outbreaks that humans cannot yet detect (Nikam et al., 2025). Researchers can use CNNs to develop a leaf disease classification model that achieves high accuracy by analyzing images from drone-mounted or ground-based cameras (Bai et al., 2023). Predictive models use historical data and real-time sensor information about soil, weather, and crop health to predict crop yields, which helps farmers plan their markets and manage resources more efficiently. The researchers developed an optimization-driven deep belief network to improve yield prediction accuracy within an IoT framework (Patel et al., 2024).

The integrated IoT-sensor-AI system shows multiple practical uses that create substantial results. The automated systems in precision irrigation use current soil moisture measurements together with weather predictions to determine optimal irrigation times and locations, which results in water conservation of up to 30 percent according to some implementations (Shrivastav et al., 2024). The wearable accelerometers in livestock management enable remote monitoring of ram mounting behavior, which helps researchers study reproductive health and activity patterns in extensive grazing environments (Goldsmith et al., 2022). The combination of ground-based sensor data with UAS aerial imagery creates an advanced multi-scale monitoring system that enables evaluation of individual plant health and overall field conditions (Boursianis et al., 2022). The comprehensive assessment enables sustainable production increase through effective resource use while reducing harmful environmental impact (Alahmad et al., 2023).

The combination of distributed sensors with edge computing and communication networks enables IoT systems to monitor soil conditions, crop growth, and environmental factors in real time. Recent research shows that energy-efficient IoT architectures that use event-driven sensing and edge-level data fusion systems can decrease unnecessary communication while improving network efficiency. The system improvements result in decreased energy usage while they also improve system performance and capacity to handle increased demand. The IoT system in agriculture enables precise irrigation, crop assessment, and resource control, which leads to higher agricultural output, lower costs, and environmentally friendly farming methods. The ecosystem-oriented approach demonstrates that network-level intelligence serves as a critical component for smart agriculture systems to achieve both effective operations and durable performance (Pham Van Anh et al., 2025). The IoT uses networks of in-situ sensors that monitor micro-environmental conditions through their remote sensing capabilities. The farm operates its continuous data streams through soil moisture probes, temperature, humidity sensors, weather stations, and IoT-enabled pheromone traps, which together create detailed data that shows the current biological and environmental conditions of the farm (Wongchai et al., 2022). The sensor networks operate as the main information system of smart agriculture, which provides real-time data to AI models that support ongoing decision-making. The IoT-based polyhouse automation system uses its real-time temperature and humidity and CO_2 monitoring system to create optimal growing conditions without requiring human input (Ayan et al., 2024). The combination of IoT sensor data with satellite and drone imagery produces a complete digital model of the agroecosystem, which serves as the foundation for advanced predictive analytics (Alahmad et al., 2023).

2.3 Advanced analytics, edge computing, and AI-driven robotics

However, the computational demands of processing high-dimensional agricultural data—particularly from CV and DL models—have driven the evolution from centralized cloud computing toward edge and fog computing architectures. Edge AI, which performs inference and sometimes training directly on field-deployed devices, addresses critical challenges of latency, bandwidth, and connectivity in rural settings (El Jarroudi et al., 2024). This paradigm is especially vital for time-sensitive applications such as robotic weeding or pest detection, where immediate action is required. Research demonstrates that moving computation from the cloud to the edge/fog layer significantly improves response times and data privacy while reducing communication overhead (Lin et al., 2023). Novel edge platforms have been developed to synchronize data across hundreds of remote farm locations, ensuring consistency and integrity in distributed agricultural operations (Carvalho et al., 2024). The integration of Cloud-Fog-Edge infrastructure also supports advanced frameworks like digital twins, which simulate farm dynamics for optimization and scenario testing (Kalyani et al., 2023).

The analytical foundation of agricultural AI depends on CV and ML technologies. The DL system, together with various DL models, demonstrate superior ability to process visual information, which enables them to perform different functions such as evaluating crop health and detecting diseases and pests, and distinguishing between weeds and estimating crop yield (Esau et al., 2023; Kalbhor, 2025). The all-terrain vehicle (ATV) AI vision system enables automated scouting and targeted agrochemical application, which leads to a significant reduction of input materials while maintaining effective results (Padhiary et al., 2024). The ML models that researchers developed from multimodal dataset training use spectral, textural, and environmental feature datasets to achieve accurate crop yield predictions by analyzing satellite images, soil health data, and weather information (Sunny, 2024). The ensemble DL architectures develop stronger model performance through their ability to combine soft sensor information with remote sensing data, which enables effective agricultural sustainability monitoring (Wongchai et al., 2022).

Robotics systems, together with autonomous systems, create the necessary physical components that enable AI systems to execute their decisions in real-world environments. The autonomous rovers, together with robotic harvesters and drone-based applicators, perform their operations through the application of current data analysis. The systems require energy-efficient operation together with their ability to move because research findings about skid-steer rovers demonstrate that their turning performance on loose soil conditions causes power usage to increase because of soil excavation and movement restrictions, which create a need for navigation algorithms that use terrain information (Fiset et al., 2023). Agricultural robotics systems provide solutions to labor shortages while they enable farmers to monitor every aspect of their crops, which represents the main principle of precision agriculture (Zhang & Qiao, 2024).

The integrated cyber-physical system, which implements precision agriculture, uses remote sensing technology together with IoT systems, edge/cloud computing, CV, and ML and robotics. The system operates through an ongoing process that detects environmental changes and biological conditions while multiple intelligent algorithms analyze data to achieve precise spatial and temporal resource optimization, productivity improvement, and sustainability advancement. The future of AI in agriculture depends on technologies that operate together within systems that can be scaled and maintain ethical standards and support farmers according to high-impact reviews (Dara et al., 2022; El Jarroudi et al., 2024). Figure 1 illustrates the major technologies enabling AI applications in agriculture. These technologies include remote sensing, IoT, cloud computing, robotics, big data analytics, and precision farming systems, which support data collection, analysis, and intelligent decision-making in modern agriculture. Table 1 summarizes the comparison of major AI in agriculture.

Collectively, UAS, remote sensing, IoT sensing networks, and edge–cloud computing infrastructures provide the technological foundation for AI-enabled agriculture. Each technology offers distinct advantages in terms of data acquisition, scalability, and decision support, while also presenting challenges related to cost, interoperability, and deployment. Building upon this technological foundation, the following section examines how AI applications are transforming crop monitoring, disease detection, resource management, and agricultural decision-making.

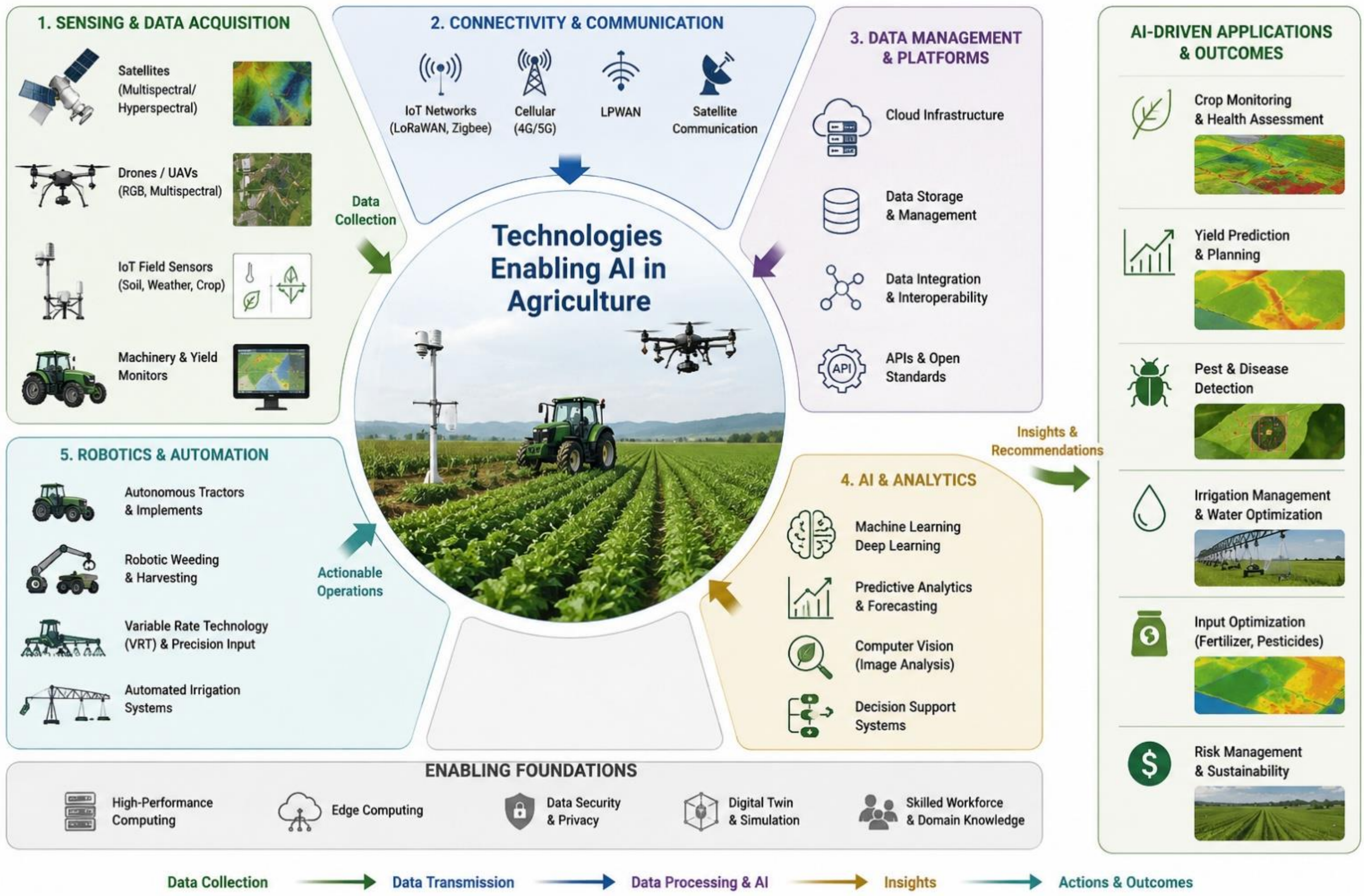

Figure 1. Technologies enabling AI in agriculture include remote sensing, IoT, cloud computing, data analytics, robotics, and precision farming systems

Table 1. Comparison of major technologies enabling AI in agriculture

Technology	Data Resolution	Scalability	Cost	Strengths	Limitations
UAS	Very High	Moderate	High	High spatial resolution, flexible deployment, real-time monitoring	Limited flight time, weather sensitivity, and high operational cost
Remote Sensing	Moderate	Very High	Low–Moderate	Large-area coverage, long-term monitoring, frequent observations	Cloud interference, lower spatial resolution
IoT Sensors	Point-based, real-time	Moderate	Moderate	Continuous monitoring, real-time environmental data	Maintenance requirements, communication dependency
Edge Computing	Real-time processing	Moderate	Moderate–High	Low latency, reduced bandwidth usage, improved privacy	Limited computational resources
Cloud Computing & Big Data Analytics	High analytical capacity	Very High	Variable	Large-scale data storage and advanced analytics	Internet dependency, security and privacy concerns
Agricultural Robotics	Task-specific precision	Moderate	High	Labor reduction, automation, precision operations	High investment cost and technical complexity

3. AI for Crop Yield Prediction and Resource Management

The integration of AI into crop yield prediction and agricultural resource management represents a major shift toward sustainable farming, which relies on data-based methods. Modern AI systems use ML and DL techniques to combine different data sources, which include satellite remote sensing, in-situ IoT sensors, weather forecasts, soil properties, and historical yield records to produce usable information for farmers and policymakers. The method goes beyond standard statistical forecasting because it detects intricate environmental patterns that affect crop yield outcomes. Multispectral satellite images from Sentinel-2 satellites provide essential vegetation indices that serve as the fundamental foundation for AI systems that predict agricultural yield. The NDVI and enhanced vegetation index (EVI) function as effective indicators of canopy health and biomass development because they measure how healthy plants reflect light in both the red and near-infrared spectral bands (Aslan et al., 2024). The recent systematic reviews established that models reach better accuracy results through the combination of time-series vegetation metrics together with climatic data (temperature, rainfall) and soil parameters (nitrogen, phosphorus, potassium) (Karthikeyan & Murugan, 2024; Screpnik et al., 2025).

AI is transforming resource management through its ability to forecast agricultural yields while operating in precision agricultural systems. The AI-based systems use real-time data from IoT soil moisture probes and aerial thermal imaging of drones and meteorological stations to deliver targeted water, fertilizer, and pesticide solutions. The systems use canopy temperature as a water stress indicator to determine when to activate irrigation systems, which results in better water conservation (Pramesti, 2025). CV algorithms identify pest outbreaks and plant deficiency symptoms, which help determine precise interventions that reduce pesticide usage and environmental harm (Reddy et al., 2024). The Cyber-Physical System (CPS) framework of contemporary precision agriculture operates through its closed-loop system that performs three functions: sensing, thinking, and acting.

The agricultural sector encounters numerous obstacles that hinder the implementation of AI technology. The main problem arises from advanced ML models, which function as "black boxes" because their internal workings remain hidden, preventing users from understanding their operation (T. Hu et al., 2023). Explainable AI (XAI) techniques exist to provide model decision-making processes because they serve as essential climate change research tools that help the development of agricultural practices (Choi et al., 2025; Malashin et al., 2024). Smallholder farming systems in developing regions experience model generalization problems because of two main problems, which include data scarcity and low-quality data. The models experience performance decline because of "domain shift" when they encounter new geographic locations, seasonal changes, and different crop varieties, which introduce variations in climate, soil, and management practices (Skobalski et al., 2024). The new solutions include physics-informed neural networks, which incorporate essential crop growth biophysical principles into their design, along with digital twin systems that develop virtual farm models for testing various scenarios and optimizing outcomes.

The ultimate goal of these AI-driven innovations is to enhance global food security while promoting environmental sustainability. AI establishes a comprehensive toolbox that enables organizations to tackle climate variability challenges, population growth issues, and their limitations in natural resource availability (Sachithra & Subhashini, 2023; Screpnik et al., 2025). The development of the industry will progress to create trustworthy AI systems that provide transparent results and serve all agricultural producers in developing sustainable farming practices. Figure 2 presents the integration of AI technologies for crop yield prediction and efficient agricultural resource management. It illustrates the use of diverse data sources, including satellite imagery, weather information, soil characteristics, historical yield records, and IoT-based sensor data, which are processed using ML and DL models.

To provide a clearer comparison of the major AI approaches used in crop yield prediction and resource management, Table 2 summarizes the characteristics of ML and DL methods, including their commonly used models, input data requirements, strengths, and limitations. Such a comparison helps identify the suitability of each approach under different agricultural conditions and data availability scenarios. Table 2 compares ML and DL approaches for crop yield prediction and resource management, highlighting their common models, data requirements, strengths, and limitations.

Recent advances in foundation models have expanded the capabilities of agricultural AI. Large vision models (LVMs) and vision transformers (ViTs) can learn generalized visual representations from large-scale agricultural image datasets, improving crop classification, disease detection, and yield prediction. Similarly, Agricultural Large Language Models (Agri-LLMs) are emerging as intelligent decision-support systems capable of integrating agronomic knowledge, weather information, and farm management recommendations through natural language interactions. These models offer improved scalability and adaptability; however, challenges related to computational requirements, domain adaptation, and explainability remain important research topics.

Despite the promising performance of AI-based prediction systems, several challenges remain. Models developed using specific datasets or agroecological conditions may not generalize effectively to other regions, creating transferability concerns. In addition, uncertainty quantification is often overlooked, as many models provide predictions without reporting confidence levels or uncertainty estimates. Reproducibility also remains a challenge because many studies rely on proprietary datasets, region-specific observations, or insufficiently documented training procedures. Addressing these limitations is essential for improving the reliability, transparency, and practical adoption of AI-driven agricultural decision-support systems.

4. AI Models and Techniques in Agriculture

4.1 Machine learning

ML has emerged as an important technology in agriculture because it significantly improves how farmers handle resources, predict outcomes, and address environmental problems that arise unexpectedly. The system transforms comprehensive data collections, which encompass satellite images, drone sensor data, soil measurement data, and weather station information, into practical agricultural insights that enhance each phase of farming operations. Precision agriculture uses this technology because it enables farmers to treat their fields as distinct sections that have different farming requirements.

Crop yield prediction is one of the most important applications of ML in agriculture, providing essential information for food security planning, market forecasting, and farm management decisions. The combination of historical yield data with current weather information, soil conditions, and remote sensing crop health data enables advanced ML systems to predict crop yields with exceptional precision. Researchers evaluated different ML models using historical U.S. sweet corn datasets to establish which factors had the greatest impact on yield predictions, and they proved the effectiveness of these methods in actual field situations (Dhaliwal & Williams, 2024).

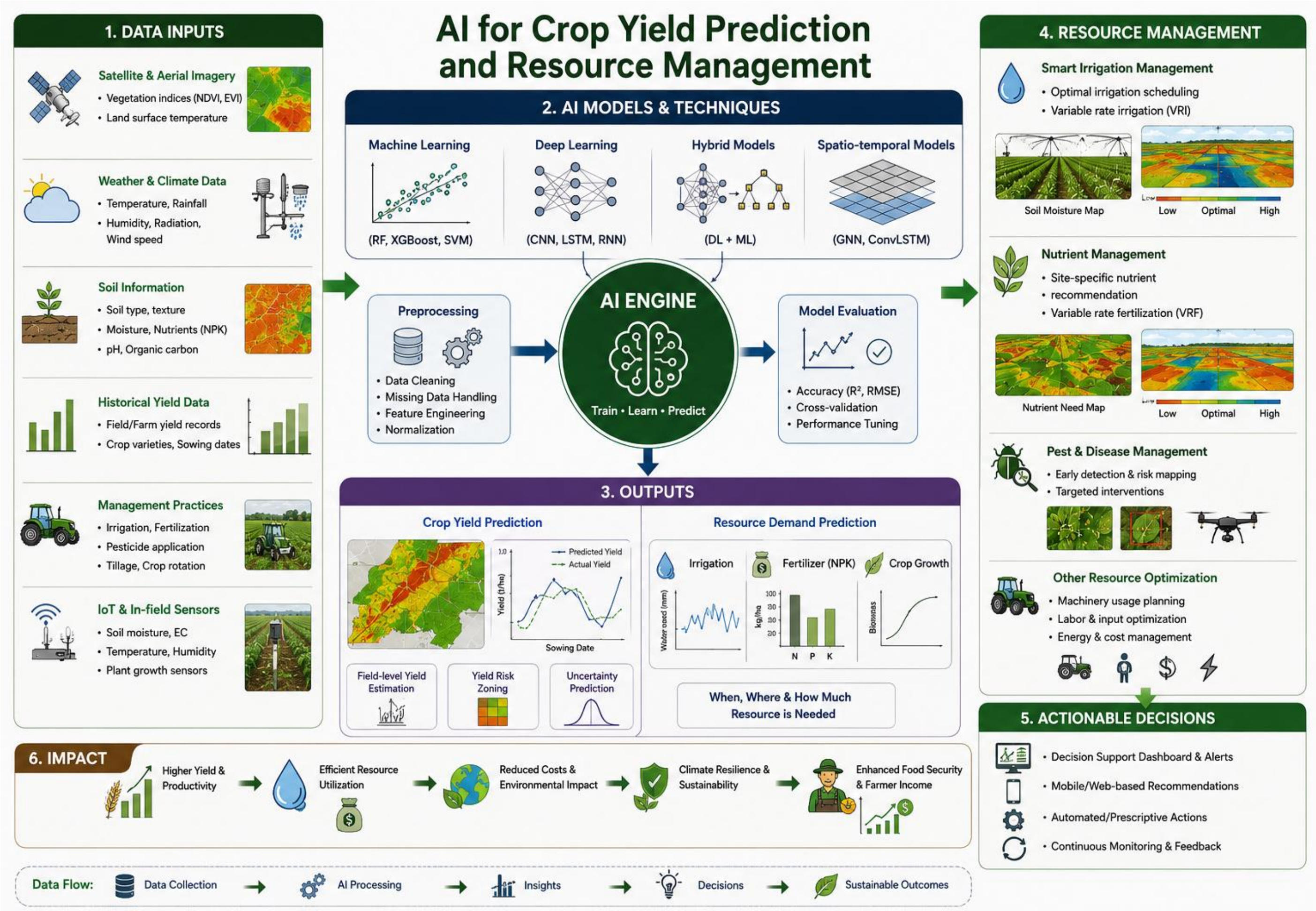

Figure 2. AI for crop yield prediction and resource management

Table 2. Comparative analysis of ML and DL approaches for crop yield prediction and resource management.

Approach	Common Models	Input Data	Strengths	Limitations
ML	RF, SVM, XGBoost	Soil properties, weather data, historical yield records, sensor measurements	Requires relatively smaller datasets, is computationally efficient, and easier to interpret	Limited ability to automatically extract complex features from high-dimensional data
DL	CNNs, LSTM, ViTs, Hybrid Models	Satellite imagery, UAV images, time-series weather data, multimodal datasets	High predictive accuracy, automatic feature extraction, effective for complex and large datasets	Requires large labeled datasets, high computational cost, lower interpretability

Researchers created ML-based decision-making systems to assist East African countries in managing climate change effects on agriculture, which helps to accomplish the United Nations target of eradicating hunger by 2030 (Aworka et al., 2022). The Digital-Twin framework uses UAS data and ML to forecast cotton growth during the entire growing season, which enables farmers to monitor crop development and make decisions about irrigation and pest management (Pal et al., 2025).

The system operates to monitor plant health because it needs to identify diseases and pests at their initial stages. ML uses DL models such as CNNs to achieve optimal performance when it comes to processing visual information. The models use high-resolution leaf images that people take with smartphones or ground-based cameras, or UASs, to detect early signs of disease and pest infestation, which remain hidden until later stages. The system detects diseases at an early stage, enabling farmers to apply timely treatments through precise methods that need less pesticide use, thus protecting the environment (García-Vera et al. 2024). The combination of UAS technology with ML creates a strong system that enables researchers to conduct high-throughput phenotyping that delivers essential data for managing agricultural fields, which include multiple locations and various crop types (Kakarla et al. 2022). The combination of hyperspectral imaging, which collects wavelength data across multiple spectral bands, with ML methods enables researchers to achieve advanced capabilities for detecting and diagnosing distinct agricultural diseases (García-Vera et al. 2024).

ML models are widely used for soil nutrient and fertility prediction using sensor-derived data. The health and fertility of soil are fundamental determinants of crop success, yet traditional soil testing methods require extended time and high costs, while their testing areas remain restricted. The ML models can eliminate these testing restrictions because they use spectral sensor data and chemical probe data to deliver real-time assessments of nutrient status, organic matter content, and potential degradation at large-scale testing. Research has shown that Random Forest algorithms can achieve 84% accuracy in predicting soil fertility, while CNN-based models for soil classification have reached an impressive 95.21% accuracy, providing farmers with immediate, precise information to guide their fertilization strategies. Some places' environmental problems, which stem from excessive phosphorus fertilization, make this analysis essential because ML-driven research enables evaluation of phosphorus use efficiency and development of sustainable application methods (Yan et al 2021).

These advancements depend on remote sensing technologies, which work together with ML to create their technological foundation. The basic observational data comes from satellite and UAS imagery, but scientists need advanced computational techniques to align and interpret this information. DL systems make it possible to match Synthetic Aperture Radar (SAR) and optical imagery, which functions as an essential requirement for complete scene analysis because they can properly synchronize these two datasets that have different geometric properties (Hughes et al., 2020). This data fusion method enables effective monitoring that operates without interruption during cloudy weather while it collects crop health data through optical/NDVI and structural integrity data through SAR, as demonstrated in research that observes maize lodging (X. Hu et al., 2023).

Although ML models such as Random Forest, SVM, and XGBoost have demonstrated strong performance in crop yield prediction and soil nutrient assessment, their effectiveness depends heavily on the quality and completeness of input data. These models generally require structured datasets and extensive feature engineering, which may limit their scalability in heterogeneous agricultural environments. Nevertheless, they remain attractive because of their lower computational requirements and greater interpretability compared with DL approaches.

4.2 Deep learning

DL has emerged as one of the most powerful AI approaches in modern agriculture because of its ability to automatically extract complex features from large-scale and high-dimensional datasets. Unlike traditional ML methods that rely heavily on manual feature engineering, DL models can learn hierarchical representations directly from images, sensor measurements, and multimodal agricultural data (Koul, 2021). The use of DL technology in agriculture establishes an important junction where AI meets food production systems to solve major problems that affect productivity, sustainability, and resource management. Systematic reviews and empirical studies from recent times show that DL methods successfully operate in different agricultural domains, with CNNs becoming the main image processing framework for agricultural applications (Attri et al 2023; Chettri et al 2026). The applications enable farmers to monitor crops, detect diseases, predict yields, and manage their operations with precision, which transforms traditional methods of making agricultural decisions.

DL models use visual data from smartphone cameras, ground-based sensors, and UASs to monitor crop health and identify diseases. The CNN-based systems achieve outstanding accuracy in plant disease classification through their capability to process leaf images, which uncover patterns that remain hidden from human observers (Pacal et al., 2024; Subramanian et al., 2025). Advanced ViT models demonstrate their ability to process large maize leaf image datasets, which allows them to detect multiple disease types at once (Pacal, 2024). DL systems gain improved diagnostic capabilities through hyperspectral imaging because these systems record hundreds of spectral bands, which detect plant biochemical and physiological changes before humans notice visible symptoms (García-Vera et al., 2024; Wang et al., 2021).

The system detects chemical leaks at an early stage, which allows operators to take specific actions, resulting in less chemical waste and stopping big crop damage from happening. Researchers have made substantial progress in yield forecasting by combining satellite observation data with advanced DL solutions. The research uses time-series transformers and recurrent neural networks (RNNs) to analyze satellite images, which help create crop growth models that show the entire season (Ibañez & Monterola, 2023). The models use vegetation indices that include NDVI, which comes from multispectral data, and combine with weather information and soil attributes to achieve exceptional yield prediction accuracy according to (Kavipriya & Vadivu, 2024; Sharma et al., 2025). The capability to predict crop output several months prior to harvest enables essential decision-making processes for supply chain operations as well as market valuation and food security strategies at both regional and nationwide levels (Ibañez & Monterola, 2023).

DL technology works best for managing weed control, thereby producing substantial economic benefits and environmental advantages in this field. Semantic segmentation models like U-Net and DeepLabV3+ enable pixel-level identification of weeds within crop fields through their ability to analyze high-resolution images (Rai et al. 2023; Y. Zhang et al. 2023). The system develops accurate spatial mapping, which enables targeted herbicide treatment at specific locations, resulting in 90% less chemical applications compared to traditional spraying methods (Rai et al. 2023). The detection systems combine with robotic platforms to create weeding systems which operate in real time by identifying crops and weeds in challenging environments (López-Martínez et al. 2023).

DL techniques have significantly improved soil classification and digital soil mapping through image-based analysis. The research study conducted by Abhishek et al. (2025) showed that models reached more than 95% accuracy when they performed soil classification through image-based analysis. The DL systems develop optimal soil sampling methods by selecting test sites that represent the complete range of field conditions. Pham et al. (2023) created soil sampling methods that require fewer samples while maintaining their analytical standards for soil testing. This system combines multiple data sources, such as topographic information and vegetation index measurements, and historical yield data to develop complete soil health evaluations, which assist in making fertilizer and irrigation decisions.

The architectural evolution in agricultural DL reflects increasing sophistication in handling multimodal data. The hybrid method, which combines CNNs with transformers, enables users to extract spatial features while performing temporal modeling tasks (Tian, 2025). The multivariate fusion method combines optical imaging data with synthetic aperture radar (SAR) data, which provides crop structure details that remain accessible regardless of cloud conditions or daylight. The combination of different types of data through complementary data fusion methods creates monitoring systems that can function effectively in multiple types of weather situations. The research team developed domain adaptation methods that enable models to operate successfully across various geographic sites, agricultural environments, and different sensor technologies (Alibabaei et al., 2022; Liu et al., 2021).

The field of agriculture continues to face major obstacles that hinder its ability to implement DL technologies despite recent progress. Data scarcity especially affects rare disease conditions and extreme weather events because it hampers model development (Ghanbari et al. 2024). Research on transfer learning and few-shot learning methods needs to continue because the "domain shift" problem causes trained models from one region to function poorly in different locations that have distinct climate conditions, soil types, and crop varieties. Transfer learning has emerged as an effective solution to agricultural data scarcity. Instead of training DL models from scratch, pretrained models can be fine-tuned using relatively small agricultural datasets. This approach reduces annotation requirements, shortens training time, and improves model performance in data-limited environments (Hossen et al., 2025; Wu et al., 2025). More recently, foundation models and large vision models have demonstrated strong potential for agricultural applications by learning generalized representations from massive datasets. These models support crop classification, disease detection, yield estimation, and field monitoring tasks even when labeled agricultural data are limited (Cao et al., 2025; Haghighat et al., 2026).

Despite these advantages, challenges related to domain adaptation, computational cost, and model explainability remain active areas of research (Ignesti et al., 2024; Wu et al., 2025). Small-scale farmers encounter difficulties because they need advanced model training, which requires excessive computational resources, but MobileNet's edge-deployable lightweight designs provide effective solutions for on-device processing. The combination of DL systems with IoT technology creates complete precision agriculture systems according to (Maghdid et al., 2024; Saranya et al., 2023). Sensor networks gather real-time information about soil moisture levels, temperature, humidity, and crop conditions, which DL models use to produce practical insights. The closed-loop system supports irrigation scheduling, nutrient management, and pest control through automatic decision-making, which distributes resources effectively to achieve maximum crop production according to (Logeshwaran et al., 2024). Farmers can test various management methods through digital twin technology, which creates virtual models of their actual farms that enable them to predict outcomes before conducting field experiments. Table 3 provides an overview of how DL technologies have expanded their presence in various agricultural fields.

DL models offer superior performance in processing high-dimensional and unstructured agricultural data, particularly imagery collected from satellites, UAS platforms, and ground-based sensors. However, these models often require large annotated datasets, computational resources, and specialized hardware for training and deployment. Their black-box nature also presents challenges related to interpretability and user trust, particularly in operational agricultural decision-support systems.

4.3 Computer vision

Unlike ML and DL, which primarily describe modeling approaches, CV refers to the set of techniques used to acquire, process, and interpret visual information from images and videos for agricultural decision-making. CV has emerged as an important enabling technology for precision agriculture, that brings essential changes to agricultural practices because it changes how farmers handle crop assessment, resource administration, and essential decision-making processes. The system uses image acquisition, processing, and analytical capabilities to perform tasks that required human workers to complete work that needed their precision for output assessment before. CV systems, which operate in precision agriculture applications, create fundamental changes to agricultural field management practices by converting fields from single-entity systems into dual systems that treat agricultural areas as separate, complex operational components.

Agricultural CV technology uses DL models, which include CNNs as its primary technology for processing visual data from drones, ground robots, and smartphones (Wang & Kang, 2025). The system operates across multiple domains, but its primary function focuses on assessing agricultural crop health. CV algorithms use multispectral and hyperspectral imagery analysis to reveal hidden signs of diseases, nutrient deficiencies, and water stress, which remain invisible to human observers until later stages. Near-infrared (NIR) hyperspectral imaging has been successfully applied to discriminate between maize haploid and diploid seeds, which serves as a vital breeding program development tool for doubled haploid technology (He et al., 2022). Advanced segmentation methods, which use DL technologies, enable accurate detection of diseased leaf areas, which helps reduce chemical applications through specific treatment methods (Anu Kiruthika et al., 2024).

Weed and pest management represent another primary field in which people can use their expertise. Traditional herbicide application is increasingly being replaced by precision spraying, which uses real-time CV technology for treatment. The RoWeeder system establishes an innovative method for unsupervised weed mapping because it detects crop rows, which the system uses to create a model that differentiates between crops and weeds without needing extensive labeled data (Marinis et al., 2024). This technology provides a solution for agricultural AI, which requires data to operate, which serves as a major obstacle that prevents widespread technology use (Ignesti et al., 2024). Machine vision algorithms now undergoing development to create agricultural pest recognition systems that use advanced DL models for pest detection in various field environments (Han et al., 2024).

The revolution of agricultural yield prediction and automated harvest systems is currently underway. Automatic detection of fruit blossoms is a key predictor of future yield, and recent frameworks have been developed to achieve multi-class blossom detection with high efficiency and minimal labeled training data (Zhou et al., 2024). In cranberry farming, vision foundation models are being used to analyze time-series aerial and ground imagery to characterize the ripening process, enabling high-throughput phenotyping and early disease detection (Johnson et al., 2025). For strawberries, the combination of ViT and attention-based CNNs has shown promise in simultaneously detecting diseases and assessing fruit quality, building upon previous work with limited success (Aghamohammadesmaeilketabforoosh et al., 2024). The new technologies work together to determine optimal harvest times while they also work to diminish losses that occur after crops have been collected.

The technologies have multiple different deployment platforms that support their operation. UAS deliver aerial surveillance, which enables complete field observation to collect information that ground-based methods cannot obtain. The study found that aerial platforms achieved 92.3% accuracy in agricultural tasks through their UAS imagery, which required 28% less processing time than ground-level photos (S. K. Gupta & Agarwal, 2025). Ground-based systems that operate through all-terrain vehicles (ATVs) and robotic platforms deliver high-resolution analysis capabilities to handle tasks such as selective harvesting and in-row weeding (Padhiary et al. 2024). The selection process for aerial versus ground-based data requires users to choose between two competing factors, which show spatial coverage and resolution differences, while spatiotemporal fusion techniques enable access to both data types. The scientific field has made impressive progress, yet important obstacles still exist. The natural environment displays continuous variability because of multiple factors, which include lighting changes, weather developments, leaf occlusion, and the wide variety of crop species and their different growth stages (Ghazal et al., 2024). The majority of contemporary models require specific datasets for their training, yet they face difficulties when applied to unfamiliar locations, new crops, or different seasons, which results in a domain shift problem (Ignesti et al. 2024). The need for large datasets that contain precise labels acts as the primary constraint because building such datasets requires substantial financial resources and extensive time efforts. The intricate model architecture requires extensive computational resources, which prevent its real-time operation on edge devices located in resource-limited environments (Padhiary et al. 2024).

Table 3. The DL technology application in agricultural domains.

Domain	Key Technical Approach	Core Contribution
Weed management	Real-time DNNs (YOLO variants)	Targeted herbicide application, reducing chemical usage (Rakhmatulin et al., 2021)
Smart irrigation	IoT + ML prediction pipelines	Optimized water scheduling in resource-scarce contexts (Tace et al., 2022)
Pest scouting	CNN-based robotic detection	Autonomous greenhouse monitoring, outperforming classical methods (Gutierrez et al., 2019)
Diseases Detection	DL-based models	Diseases controlling within the early stage of crop (Barman et al., 2024; Ferentinos, 2018; Liu & Zhang, 2025; Sopialena et al., 2022)
Crop monitoring	DL-based CV across the life cycle	From planting through harvest quality assessment (Cao et al., 2025; Dhanya et al., 2022)

Future directions in the field point toward more robust, adaptable, and data-efficient AI models. The integration of generative artificial intelligence (GenAI) serves as an effective solution to combat data shortages by producing synthetic training data that accurately simulates the complex characteristics of actual agricultural environments (Min et al., 2025). The current trend emphasizes model development, which enables users to easily transfer their skills to new contexts without needing extensive retraining, as researchers work toward creating agricultural AI systems that function like traditional plug-and-play devices (Ignesti et al., 2024). The field has reached a mature stage, which now requires professionals to evaluate algorithms based on their ability to maintain performance and provide understandable results while functioning seamlessly with existing farm operations, thus enabling worldwide access to CV advantages for farmers. Figure 3 illustrates the major AI models and techniques applied in modern agriculture, including ML, DL, transfer learning, reinforcement learning, and natural language processing. It also highlights important agricultural applications such as crop monitoring, disease detection, weed management, irrigation optimization, and precision farming. Table 4 presents recent key review papers on AI and DL applications in agriculture and summarizes their main contributions.

Overall, ML methods remain effective for structured agricultural datasets and scenarios with limited computational resources. In contrast, DL and CV approaches generally achieve higher predictive performance for image-based and multimodal applications, although they require larger datasets and greater computational capacity. Recent advances in transfer learning and foundation models are helping bridge this gap by improving model performance in data-scarce environments while reducing annotation requirements.

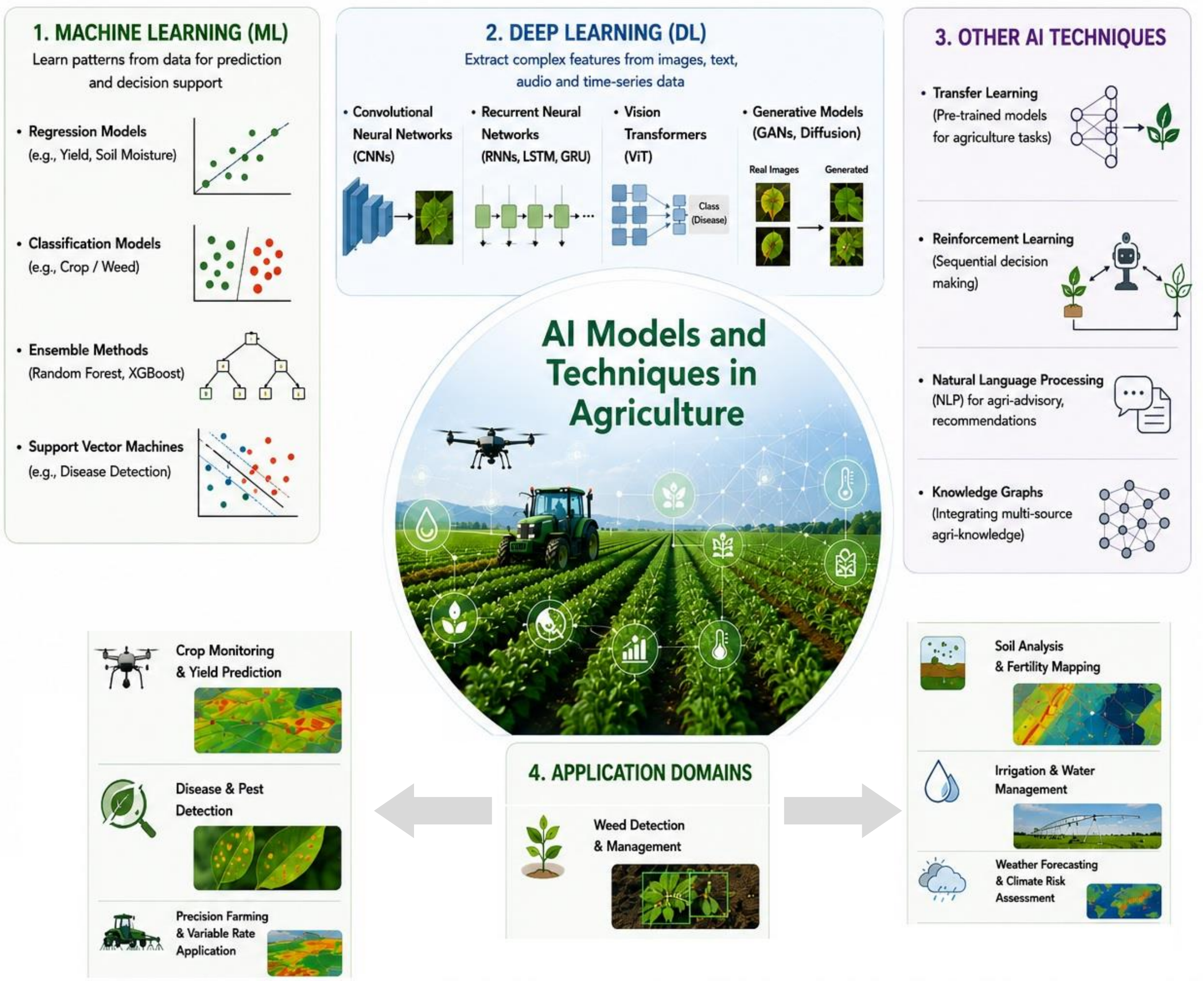

Figure 3. AI Models, techniques, and applications domain in agriculture

Table 4. Recent key review papers on AI and DL applications in agriculture

Review Focus	Key Diagnostic Signal	Reference
AI for sustainability in agriculture	Optimization objectives broadening beyond yield	Sachithra & Subhashini (2023)
DL's impact on agriculture	DL consistently outperforms classical ML across tasks	Albahar (2023)
AI across the agriculture value chain	Coverage spans planting through distribution	Assimakopoulos et al. (2024)
DL-based CV for smart agriculture	CV becomes agriculture's dominant AI sub-field	Dhanya et al. (2022)
Transfer learning in agriculture	TL recognized as foundational, not optional	Hossen et al. (2025)
Multimodal LLMs in agriculture	Foundation models entering agricultural AI	Haghighat et al. (2026)
AI methods in agri-food engineering	Data scarcity and infrastructure remain primary barriers	Wu et al. (2025)
CV and DL in crop growth	Applications now cover full crop lifecycle	Cao et al. (2025)

5. Challenges in Implementing AI in Agriculture

The application of AI to agricultural practices can create fundamental changes that improve farm output and environmental sustainability and increase global food production. The project faces multiple interconnected challenges that affect its technological, socioeconomic, infrastructural, and ethical aspects. The latest comprehensive studies show that organizations face technical challenges because their actual operations in farming use multiple systems around the world. Data scarcity and data quality issues represent the main barrier that organizations must overcome. AI models succeed when they receive extensive amounts of dependable agricultural data. The required agricultural data needs to contain soil properties, weather patterns, spectral imagery data, and yield records, which must exist as complete and reliable datasets. The required data exists as scattered pieces that contain restricted access information, and which different farms and regions have collected using inconsistent methods (Aranguri et al., 2025; Hasteer et al., 2024). Satellite images create a "mixed pixel problem," which reduces accuracy because smallholder farms use fields that are smaller than the sensor's resolution. The Earth-observing satellite system needs to establish standard spectral band definitions that will enable the development of consistent long-term datasets that scientists require for effective model training and validation.

The agricultural field contains multiple difficulties that prevent ML from reaching its full potential according to its current state of development. The requirements for model training need substantial datasets that possess high quality and proper labeling, while the system must have sufficient computational resources to handle real-time processing, and the advanced models operate as "black-box" systems, which farmers find difficult to trust because they lack a clear understanding (Deepa et al., 2023; Mayur Rajaram Salokhe, 2023). The protection of sensitive geospatial and operational data that farmers provide requires precise frameworks that need to establish data privacy and ownership rights as the primary issue. The agricultural sector needs to solve these problems because they will enable the technological revolution to provide benefits that reach all farmers in every part of the world.

The implementation of DL technologies in agriculture produces significant effects on both economic development and environmental protection. The technologies permit farmers to apply their resources with exact precision, which results in decreased waste, reduced environmental harm, and increased farm revenue. The worldwide agricultural system benefits from advanced yield prediction methods and crop monitoring technologies, which strengthen food security evaluation systems and emergency detection mechanisms for potential crop shortages (Ibañez & Monterola, 2023). The successful execution of the project needs to resolve ethical issues regarding data security, which mandates the use of differential privacy methods to safeguard confidential agricultural data. The project aims to create agricultural AI systems that provide advantages to all farmers while supporting environmentally friendly food production solutions that sustain the increasing global population, who deal with climate change challenges.

The infrastructure limitations create a problem that affects rural and emerging development areas. The agricultural sector needs reliable high-speed internet, constant power supply, and sufficient computing capacity to operate and manage advanced AI technologies according to (Begho et al., 2025; Choruma et al., 2024). The digital divide creates greater social disparities because farmers who work in low-resource environments lack access to advanced technology, which developed nations provide to their large agricultural enterprises. The absence of essential digital infrastructure restricts advanced precision agriculture methods, which depend on real-time data gathering, cloud processing, and edge AI technology (El Jarroudi et al. 2024).

The adoption process faces major challenges because of socioeconomic factors and human capital limitations. There is a significant shortage of professionals who possess both agricultural knowledge and digital skills, which are necessary for successful AI system operation and management (Manning, 2024). Many farmers who belong to older age groups or traditional agricultural communities face difficulties in using advanced AI systems, which require them to operate complicated platforms and understand system results (Aranguri et al. 2025). The economic obstacles for AI systems arise from their expensive initial costs, which compete against their unpredictable ROI and restricted financing options. The adoption decision process depends on perceived usefulness and innovation willingness, risk tolerance, and social influence, according to research, which shows that economic conditions and age affect both facilitating factors and hindrances to technology adoption (Dibbern et al., 2024; Hampel & Fabulya, 2024).

The main challenges that farmers face when they need to understand model outputs and trust the results of the model function are basic obstacles that block their approval of this system. The agricultural decision-making process needs to have complete visibility because it involves both substantial financial risks and environmental impacts. Farmers and agronomists need XAI systems that show them the complete reasoning behind their recommendations instead of using unexplainable "black box" systems. Stakeholders will not accept AI system recommendations until they comprehend the reasons that lead to those particular recommendations (Alexander et al., 2024). The trust deficit gets more serious because people worry about algorithmic bias, which affects models that use regional farm data, because these models fail to work properly in unfamiliar agricultural settings, which harms specific farmer groups.

The discussion about data ownership and privacy rights, together with liability issues in data management, remains unresolved among regulatory offices and ethical organizations. Farm-level data, which contains specific field boundaries and yield maps together with input application records, holds extreme value as highly confidential information. Farmers find themselves facing major difficulties because they need to deal with three data ownership questions, which include identifying the data owners, understanding permission rights for data usage, and determining if agribusinesses or insurers will exploit the data according to their interests (Alexander et al., 2024). Farmers need protection from identity exposure, which occurs through re-identification of anonymized spatial data. This protection should be established through strict privacy regulations, such as differential privacy, which allow model development but hide farmer identities. The current situation creates various legal problems that block organizations from using AI solutions that cause crop damage or environmental harm because of their undefined responsibility laws.

The process of implementing systems faces obstacles because of technical integration difficulties. The existing farm management systems and their associated legacy hardware and software platforms face integration problems because they cannot work together with new AI technologies. The agricultural technology ecosystem contains multiple proprietary systems that lack standardization and create isolated data environments that prevent complete system monitoring needed for successful AI implementation (Hasteer et al., 2024). The farmers face increased operational difficulties because they must spend more money to adopt different technologies that do not work together. The core difficulty of agricultural system modeling arises from the system's natural environmental and biological complexity. Crop-environment-management interactions show complex behavior that depends on specific situations and exhibits different patterns across different regions, seasonal changes, and various soil types. AI models that get trained on one geographical area cannot deliver accurate results in other regions because of variations in climate, soil composition, pest control methods, and agricultural traditions.

The domain shift problem needs either local model adaptation to new conditions or the creation of new AI systems that can operate in different agricultural environments. Agricultural systems require ongoing model updates because climate change and pest resistance patterns increase their operational challenges. The solution to these complex problems needs cooperative participation from researchers, policymakers, technology developers, and farming communities. The development of solutions requires context-specific approaches that provide economical solutions while prioritizing the needs and limitations of end users to achieve fair and sustainable AI implementation in agriculture. Table 5 summarizes the major challenges limiting the adoption of AI in agriculture and outlines potential solutions proposed in recent research.

6. Sustainability and Environmental Impact

The integration of AI into agriculture presents a complex duality: while AI-driven technologies offer significant pathways to enhance environmental sustainability, the deployment of these very technologies carries its own non-trivial ecological footprint. A comprehensive assessment requires examining both the benefits AI confers on farming practices and the hidden costs associated with its development and operation.

On the benefit side, AI functions as the fundamental technology that enables precision agriculture to achieve its highest resource management efficiency. The AI algorithms use satellite imagery data, IoT sensor data, and drone data to create detailed water and fertilizer, and pesticide application plans which operate at the field level.

Table 5. Challenges and potential solutions for AI adoption in agriculture

Challenge	Description	Impact on Agriculture	Potential Solution
Data Availability and Quality	Limited, fragmented, and inconsistent datasets	Reduced model accuracy and generalizability	Standardized data collection, data sharing, and augmentation
Computational Constraints	High processing and storage requirements	Increased implementation costs	Cloud computing, edge computing, and lightweight models
Domain Shift	Poor model transferability across regions	Reduced reliability in new environments	Domain adaptation and continuous model retraining
Black-Box Models	Limited transparency and explainability	Reduced user trust and adoption	XAI frameworks
Infrastructure Limitations	Limited internet access and electricity supply	Restricted deployment in rural areas	Investment in rural digital infrastructure
Human Capacity Gaps	Lack of technical skills and AI expertise	Slow technology adoption	Training programs and agricultural extension services
Privacy and Security Risks	Concerns about ownership and misuse of farm data	Resistance to data sharing	Privacy-preserving technologies and clear regulations
Interoperability Issues	Incompatibility among agricultural systems	Operational inefficiencies	Standardized communication protocols and platforms

The targeted method of pollution control successfully decreases the primary pollution sources, which come from farming operations. Intelligent irrigation systems can achieve water savings of 20 to 30 percent because they provide moisture only at needed times and needed locations based on current soil moisture conditions and evapotranspiration information (Khadka & Kumar, 2024; Neetu, 2024). AI systems that detect pests and diseases rely on CNNs to process hyperspectral and visual images, which enables targeted treatment that reduces pesticide requirements by 15 to 25 percent (Fazari et al., 2021; Nautiyal et al., 2025). The chemical input reduction results in two advantages for farmers because it decreases their expenses while it protects against groundwater and surface runoff pollution, which creates eutrophication and dead zones in aquatic ecosystems (Kusumavathi et al., 2025). Predictive analytics for yield predicting and optimal harvest timing can reduce post-harvest losses, which create a major carbon footprint across food systems (Anurag Chandra Mishra et al., 2024; Sunny, 2024).

The environmental cost of AI infrastructure negates the positive benefits this technology provides. The operation of advanced AI systems, particularly large DL models, requires substantial energy resources for their training processes. Data centers, which store the equipment needed for model development, require high electricity usage, which results in major carbon dioxide emissions when fossil fuels serve as their power source (Rilling et al., 2024). Studies have shown that training a single large AI model can emit hundreds to thousands of kilograms of CO2-equivalent, which needs to be assessed against the total environmental benefits generated from its implementation (Falk et al., 2024). The "attribution problem" becomes critical because cloud computing exists as an abstract entity that hides its actual energy consumption and physical effects (Falk et al., 2024). Edge AI enables data processing on agricultural machinery, drones, and local servers, which reduces transmission and latency expenses but creates more problems through its need for waste management of dedicated hardware and environmental damage from rare earth metal extraction used in processors and batteries.

The complete assessment of AI environmental effects requires the use of systems analysis techniques, which include the life cycle assessment (LCA). LCA establishes a comprehensive method that enables organizations to measure their environmental impact throughout the entire product lifecycle, starting from raw material acquisition through production, usage, and final disposal. The LCA assessment of AI systems in agriculture compares the environmental benefits achieved through improved farming methods with the resource consumption and emissions generated by the AI system development process. Research indicates that a net positive environmental benefit is most likely achieved when AI systems are deployed at scale, powered by renewable energy, and designed with efficiency as a core principle—not merely as an add-on feature (El Jarroudi et al., 2024). The organization can achieve greater net advantages through three key methods, which include using quantized or pruned neural networks that need less computational power, implementing federated learning to reduce data transfer requirements, and developing AI tools together with agroecological design principles that emphasize biodiversity and soil health more than just crop production (Kusumavathi et al., 2025). AI does not bring about environmental sustainability in agriculture because its effects depend on its operational design and its implementation and its operational design and its deployment methods, and its energy sources. The path forward lies in a conscious effort to minimize the "hidden ecological costs" of AI while maximizing its potential to foster resilient, resource-efficient, and ecologically harmonious farming systems (Zhuk, 2023). The digital transformation of agriculture needs technologists and agronomists, policymakers, and farmers to work together for the successful implementation of green practices.

7. Future Prospects and Conclusion

7.1 The future of AI in agriculture

The upcoming developments in agricultural AI technology will change farming from its current practice of responding to problems into a system that uses advanced predictive abilities to manage agricultural operations for maximum efficiency and environmental protection. Current research demonstrates that AI is not merely an incremental improvement but a foundational transformation of agricultural practices, which extends to multiple fields, including precision farming, autonomous machinery, and sustainable resource management (Agarwal et al., 2024; Ogunjimi et al., 2025; Rajesh, 2024). The system combines multimodal sensing technologies through satellite imagery, drone remote sensing, and ground-based IoT sensors to create complete data streams that enable crop health, soil condition, and microclimatic variable monitoring in real time (Kamatchi, 2024; Shruthi & Anil Kumar, 2025). The new decision-support system uses data fusion technology to identify plant physiologic changes that occur before visible symptoms appear so that pest and disease and nutrient deficiency issues can be treated at their earliest stage.

The combination of DL frameworks, which include CNNs and Random Forest ensemble methods, achieves outstanding results for crop disease detection and yield prediction according to results from ML algorithms (Kamatchi Sundravadivelu, 2024). The models utilize spectral signatures from multispectral and hyperspectral imaging to detect stress indicators through vegetation indices, which include the NDVI that measures plant health by comparing red and near-infrared reflectance. The latest CV developments enable machines to detect specific pathogens with better than 90% accuracy in laboratory conditions, which decreases the need for hand-based inspections and visual judgment (Vardhan et al., 2025). The necessary change requires organizations to advance their capabilities from detecting problems toward predicting future events through their capability to use historical weather information and soil moisture measurements, and pest life cycle data for assessing outbreak risks and recommending preventive actions (Pal et al., 2024).

AI brings revolutionary changes to traditional agricultural methods through its application in autonomous agricultural robotics. The self-driving tractors, which use CV and reinforcement learning methods, can achieve centimeter-level precision during their work with precision planting, targeted herbicide application, and selective harvesting tasks (Agarwal et al., 2024; Pal et al., 2024). The system reduces environmental damage through its chemical treatment system, which applies only necessary treatments while helping farmers decrease their operational expenses (Khadka & Kumar, 2024). In greenhouse environments, AI-driven climate control systems have demonstrated the ability to optimize growing conditions dynamically, resulting in yield improvements of 15-20% compared to conventional management approaches (Hoseinzadeh & Garcia, 2024). The 136 peer-reviewed studies that examined digital agricultural technologies established that these technologies provide economic benefits through increased agricultural output and decreased labor requirements, while the resources are used more efficiently and chemical runoff is minimized (Papadopoulos et al., 2024).

The current technical advancements face serious obstacles that need to be solved before technologies can achieve widespread use. The Global South faces a critical data shortage, which prevents research on underrepresented crops and regions because training datasets lack sufficient coverage. AI systems develop and validate their models through testing, which uses only three main temperate climate crops that include corn, wheat, and soybean (Johnson, 2024). The digital divide in rural areas worsens because local infrastructure lacks dependable internet access and sufficient computing facilities (Dibbern et al., 2024). The issue of model interpretability continues to exist because DL models, which perform exceptionally well, require farmers to trust their AI recommendations through understanding their decision processes (Alexander et al., 2024; Joosse, 2024).

The ethical and governance dimensions of agricultural AI cannot be overlooked. Data ownership and privacy rights, together with algorithmic bias issues, need thorough examination because digital technologies are increasingly transforming farming operations (Tzachor et al., 2022). Farmers usually share their sensitive operational information, which includes exact field boundaries and farming methods. This information poses a risk because it can be used to identify them when matched with public land records. Farmers need differential privacy frameworks together with strong data governance policies because these measures will safeguard their interests while supporting data sharing that helps improve models. The growing concentration of AI development within major agribusiness companies creates two major problems. These problems involve market power distribution and the risk that small producers will be excluded because they cannot afford expensive proprietary systems (Hampel & Fabulya, 2024).

The most effective future path involves cross-disciplinary research, which combines agricultural science with computer science, climate science, and social policy studies. Smallholder farmers can receive personalized advisory services through GenAI models, which use agricultural knowledge bases to create accessible mobile phone interfaces that deliver actionable insights. The combination of AI and biotechnology through gene editing and synthetic biology creates new opportunities to produce climate-resilient crop varieties, which scientists will develop with predictive modeling of future environmental conditions (Pasupuleti, 2025). The success of AI in agricultural applications requires both advanced technology and fair distribution, sustainable environmental practices, and compliance with United Nations Sustainable Development Goals (Kisliuk et al., 2023). The increasing global food demand, which will rise between 50 and 100 percent by 2050, together with diminishing resources and rising climate dangers, makes AI essential for developing resilient, productive, and sustainable food systems (Angle & Moran, 2025).

7.2 Conclusion

The introduction of AI into agricultural practices establishes a complete modern development that changes traditional farming methods into intelligent systems that use data to create precise results. The agricultural industry has achieved higher efficiency rates, productivity growth, and better resource management by uniting AI with UAS, remote sensing, IoT sensor networks, big data analytics, CV, and autonomous robotics. Real-time crop health monitoring together with early disease and pest detection, precise irrigation, fertilization, yield prediction, and automated field operations create solutions that solve urgent global problems that include labor shortages, climate variability, water scarcity, and environmental degradation.

The agricultural industry has not yet achieved its full potential for AI because important challenges still exist despite the progress made in recent developments. The agricultural sector faces substantial challenges because farmers who operate small farms lack the technical skills to handle digital systems, and digital infrastructure remains deficient in rural regions. Data collection standards, data collection methods, model development requirements, and high operational expenses create difficulties. A comprehensive LCA should evaluate AI model environmental impact because training and running these models produce environmental damage, which must be balanced against the sustainability benefits created in practice. The development of human-centered agricultural solutions requires stronger and more general solutions, which must be developed through research efforts. The organization has specific goals, which include developing XAI frameworks that create transparent systems to build trust among farmers, using GenAI and federated learning to solve data access challenges, and establishing technology platforms that work together while using physics-informed neural networks to create realistic biophysical simulations. The design process must include equitable access and inclusive design methods because these elements need to deliver Agriculture 4.0 advantages to small-scale farmers from developing countries. The complete success of AI-powered agricultural technologies depends on researchers, technology developers, policy makers, and farming communities working together to solve both technical problems and socio-economic barriers. The development of responsible, ethical, and sustainable innovations will enable AI to create food systems that remain productive and sustainable while delivering food security for an expanding global population amid rising climate risks.

Funding declaration

The authors declare that they did not receive funds, grants, or other support for the preparation of this paper.

Competing interests

No competing financial interests or personal relationships are known to the authors that could have influenced this study.

Data availability statement

No original data were used in this review study.

References

Abhishek, K. V., Akhil, T., Chandan, K., Likhith, H. V., Sindhu, K. S. (2025). Agrovision: Enhancing agricultural precision through machine learning. *International Journal of Scientific Research in Engineering and Management*, *09*(04), 1–9. https://doi.org/10.55041/IJSREM44895

Adli, H. K., Remli, M. A., Wan Salihin Wong, K. N. S., Ismail, N. A., González-Briones, A., Corchado, J. M., & Mohamad, M. S. (2023). Recent advancements and challenges of AIoT application in smart agriculture: A review. *Sensors*, *23*(7), 3752. https://doi.org/10.3390/s23073752

Agarwal, R., Bhardwaj, I., Sharma, A. K., Sanghi, A., & Agarwal, G. (2024). Innovations in Agri-Tech: A review of artificial intelligence applications and challenges in modern agriculture. *2024 Second International Conference on Advanced Computing & Communication Technologies (ICACCTech)*, 599–604. https://doi.org/10.1109/ICACCTech65084.2024.00101

Aghamohammadesmaeilketabforoosh, K., Nikan, S., Antonini, G., & Pearce, J. M. (2024). Optimizing strawberry disease and quality detection with vision transformers and attention-based convolutional neural networks. *Foods*, *13*(12), 1869. https://doi.org/10.3390/foods13121869

Ahmed, B., Shabbir, H., Naqvi, S. R., & Peng, L. (2024). Smart agriculture: Current state, opportunities, and challenges. *IEEE Access*, *12*, 144456–144478. https://doi.org/10.1109/ACCESS.2024.3471647

Alahmad, T., Neményi, M., & Nyéki, A. (2023). Applying IoT sensors and big data to improve precision crop production: A review. *Agronomy*, *13*(10), 2603. https://doi.org/10.3390/agronomy13102603

Alaoui, M. El, Amraoui, K. EL, Masmoudi, L., Ettouhami, A., & Rouchdi, M. (2024). Unleashing the potential of IoT, Artificial Intelligence, and UAVs in contemporary agriculture: A comprehensive review. *Journal of Terramechanics*, *115*, 100986. https://doi.org/10.1016/j.jterra.2024.100986

Albahar, M. (2023). A survey on deep learning and its impact on agriculture: Challenges and opportunities. *Agriculture*, *13*(3), 540. https://doi.org/10.3390/agriculture13030540

Alexander, C. S., Yarborough, M., & Smith, A. (2024). Who is responsible for 'responsible AI'?: Navigating challenges to build trust in AI agriculture and food system technology. *Precision Agriculture*, *25*(1), 146–185. https://doi.org/10.1007/s11119-023-10063-3

Alexopoulos, A., Koutras, K., Ali, S. Ben, Puccio, S., Carella, A., Ottaviano, R., Kalogeras, A., Alexopoulos, A., Koutras, K., Ali, S. Ben, Puccio, S., Carella, A., Ottaviano, R., & Kalogeras, A. (2023). Complementary use of ground-based proximal sensing and airborne/spaceborne remote sensing techniques in precision agriculture: A systematic review. *Agronomy*, *13*(7). https://doi.org/10.3390/AGRONOMY13071942

Alibabaei, K., Gaspar, P. D., Lima, T. M., Campos, R. M., Girão, I., Monteiro, J., & Lopes, C. M. (2022). A review of the challenges of using deep learning algorithms to support decision-making in agricultural activities. *Remote Sensing*, *14*(3), 638. https://doi.org/10.3390/rs14030638

Angle, J. S., & Moran, C. (2025). AI can improve agriculture more than any other existing industry. *Artificial Intelligence, Machine Learning, & Robotics in Business*, *1*(2), 1–5. https://doi.org/10.32473/aimlrb.1.2.139236

Anokhina, O., Musaeva, M., & Grace, A. (2025). Engineering and technological aspects of the application of artificial intelligence models in modern agriculture. *ITM Web of Conferences*, *72*, 03004. https://doi.org/10.1051/itmconf/20257203004

Anu Kiruthika. M., Gladston, A., Shiny, R. M., & Garcia Nissi S. (2024). Agricultural leaf disease segmentation approaches using deep learning. *2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)*, 585–592. https://doi.org/10.1109/ICDICI62993.2024.10810867

Aranguri, M., Mera, H., Noblecilla, W., & Lucini, C. (2025). Digital literacy and technology adoption in agriculture: A systematic review of factors and strategies. *AgriEngineering*, *7*(9), 296. https://doi.org/10.3390/agriengineering7090296

Arputharaj, P., & Karunanithy, K. (2026). A review on machine learning and deep learning techniques for plant leaf disease detection and classification with IoT in agriculture industry. *Journal of Industrial Information Integration*, *50*, 101078. https://doi.org/10.1016/j.jii.2026.101078

Aslan, M. F., Sabanci, K., & Aslan, B. (2024). Artificial intelligence techniques in crop yield estimation based on Sentinel-2 data: A comprehensive survey. *Sustainability*, *16*(18), 8277. https://doi.org/10.3390/su16188277

Assimakopoulos, F., Vassilakis, C., Margaris, D., Kotis, K., & Spiliotopoulos, D. (2024). Artificial intelligence tools for the agriculture value chain: Status and prospects. *Electronics*, *13*(22), 4362. https://doi.org/10.3390/electronics13224362

Attri, I., Awasthi, L. K., Sharma, T. P., & Rathee, P. (2023). A review of deep learning techniques used in agriculture. *Ecological Informatics*, *77*, 102217. https://doi.org/10.1016/j.ecoinf.2023.102217

Aworka, R., Cedric, L. S., Adoni, W. Y. H., Zoueu, J. T., Mutombo, F. K., Kimpolo, C. L. M., Nahhal, T., & Krichen, M. (2022). Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries. *Smart Agricultural Technology*, *2*, 100048. https://doi.org/10.1016/j.atech.2022.100048

Ayan, A., Shesh, R., Sonu, K., Soumalya, S., Amol, P., Kamlesh, L., Ayan, A., Shesh, R., Sonu, K., Soumalya, S., Amol, P., & Kamlesh, L. (2024). Design, fabrication and monitoring of automated polyhouse. *International Journal of Environment and Climate Change*, *14*(5), 418–423. https://doi.org/10.9734/IJECC/2024/V14I54201

Bai, P. T. K., Lissy, D., & Nesamani, S. L. (2023). Role of IoT in precision agriculture and detecting and classifying rice leaf diseases using cnn method of deep learning. *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)*, 1–5. https://doi.org/10.1109/RMKMATE59243.2023.10369919

Barman, U., Sarma, P., Rahman, M., Deka, V., Lahkar, S., Sharma, V., & Saikia, M. J. (2024). ViT-SmartAgri: Vision transformer and smartphone-based plant disease detection for smart agriculture. *Agronomy*, *14*(2), 327. https://doi.org/10.3390/agronomy14020327

Basso, M., Soares Guimaraes, C. S., Martini Da Rosa, A., Morgan Pereira, P. H., & Pignaton de Freitas, E. (2025). Current and future perspectives on drone-based computer vision for precision agriculture. *2025 IEEE Latin Conference on IoT (LCIoT)*, 270–273. https://doi.org/10.1109/LCIoT64881.2025.11118613

Begho, T., Daubry, T. P., & Irabor, A. E. (2025). A scoping review of artificial intelligence and the future of African agriculture: Opportunities, challenges and the path forward. *Advances in Agriculture*, *2025*(1). https://doi.org/10.1155/aia/2862074

Boursianis, A. D., Papadopoulou, M. S., Diamantoulakis, P., Liopa-Tsakalidi, A., Barouchas, P., Salahas, G., Karagiannidis, G., Wan, S., & Goudos, S. K. (2022). Internet of Things (IoT) and Agricultural

Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things*, *18*, 100187. https://doi.org/10.1016/j.iot.2020.100187

Cao, Z., Sun, S., & Bao, X. (2025). A review of computer vision and deep learning applications in crop growth management. *Applied Sciences*, *15*(15), 8438. https://doi.org/10.3390/app15158438

Carreño Ruiz, M., Bloise, N., Guglieri, G., & D'Ambrosio, D. (2022). Numerical analysis and wind tunnel validation of droplet distribution in the wake of an unmanned aerial spraying system in forward flight. *Drones*, *6*(11), 329. https://doi.org/10.3390/drones6110329

Cartolano, A., Cuzzocrea, A., & Pilato, G. (2024). Analyzing and assessing explainable AI models for smart agriculture environments. *Multimedia Tools and Applications*, *83*(12), 37225–37246. https://doi.org/10.1007/s11042-023-17978-z

Carvalho, A., Riordan, D., Walsh, J., Carvalho, A., Riordan, D., & Walsh, J. (2024). A novel edge platform streamlining connectivity between modern edge devices and the cloud. *Future Internet*, *16*(4). https://doi.org/10.3390/FI16040111

Chettri, K., Sen, B., Ghosal, P., Chettri, K., Sen, B., & Ghosal, P. (2026). Deep learning for precision agriculture: a systematic review of methods, challenges, and future directions. *Knowledge and Information Systems*, *68*(1). https://doi.org/10.1007/S10115-025-02625-W

Choi, J. W., Hidayat, M. S., Cho, S. B., Hwang, W.-H., Lee, H., Cho, B.-K., Kim, M. S., Baek, I., & Kim, G. (2025). Recent trends in machine learning, deep learning, ensemble learning, and explainable artificial intelligence techniques for evaluating crop yields under abnormal climate conditions. *Plants*, *14*(18), 2841. https://doi.org/10.3390/plants14182841

Choruma, D. J., Dirwai, T. L., Mutenje, M. J., Mustafa, M., Chimonyo, V. G. P., Jacobs-Mata, I., & Mabhaudhi, T. (2024). Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-saharan africa. *Journal of Agriculture and Food Research*, *18*, 101286. https://doi.org/10.1016/j.jafr.2024.101286

Dara, R., Hazrati Fard, S. M., & Kaur, J. (2022). Recommendations for ethical and responsible use of artificial intelligence in digital agriculture. *Frontiers in Artificial Intelligence*, *5*. https://doi.org/10.3389/frai.2022.884192

Debnath, J., Kumar, K., Roy, K., & Choudhury, R. (2024). Precision Agriculture: A Review of AI Vision and Machine Learning in Soil, Water, and Conservation Practice. *International Journal for Research in Applied Science and Engineering Technology*, *12*(12), 2130–2141. https://doi.org/10.22214/ijraset.2024.66166

Deepa, R., Sivasamy, A., & Selvam, S. (2023). Optimising agricultural practices with machine learning: a comprehensive review. *International Journal of Agriculture Innovation, Technology and Globalisation*, *3*(4), 354–369. https://doi.org/10.1504/IJAITG.2023.138116

Dhaliwal, D. S., & Williams, M. M. (2024). Sweet corn yield prediction using machine learning models and field-level data. *Precision Agriculture*, *25*(1), 51–64. https://doi.org/10.1007/s11119-023-10057-1

Dhanya, V. G., Subeesh, A., Kushwaha, N. L., Vishwakarma, D. K., Nagesh Kumar, T., Ritika, G., & Singh, A. N. (2022). Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*, *6*, 211–229. https://doi.org/10.1016/j.aiia.2022.09.007

Dibbern, T., Romani, L. A. S., & Massruhá, S. M. F. S. (2024). Main drivers and barriers to the adoption of Digital Agriculture technologies. *Smart Agricultural Technology*, *8*, 100459. https://doi.org/10.1016/j.atech.2024.100459

Dong, C., & Ren, S. (2025). Research on precision agriculture monitoring system based on Internet of Things and artificial intelligence. *Applied and Computational Engineering*, *178*(1), 66–71. https://doi.org/10.54254/2755-2721/2025.PO25380

El Jarroudi, M., Kouadio, L., Delfosse, P., Bock, C. H., Mahlein, A.-K., Fettweis, X., Mercatoris, B., Adams, F., Lenné, J. M., & Hamdioui, S. (2024). Leveraging edge artificial intelligence for sustainable agriculture. *Nature Sustainability*, *7*(7), 846–854. https://doi.org/10.1038/s41893-024-01352-4

Esau, T. J., Hennessy, P. J., MacEachern, C. B., Farooque, A. A., Zaman, Q. U., Schumann, A. W., Esau, T. J., Hennessy, P. J., MacEachern, C. B., Farooque, A. A., Zaman, Q. U., & Schumann, A. W. (2023). Artificial intelligence and deep learning applications for agriculture. *Precision Agriculture*, 141–167. https://doi.org/10.1016/B978-0-443-18953-1.00003-9

Falk, S., van Wynsberghe, A., & Biber-Freudenberger, L. (2024). The attribution problem of a seemingly intangible industry. *Environmental Challenges*, *16*, 101003. https://doi.org/10.1016/j.envc.2024.101003

Fazari, A., Pellicer-Valero, O. J., Gómez-Sanchıs, J., Bernardi, B., Cubero, S., Benalia, S., Zimbalatti, G., & Blasco, J. (2021). Application of deep convolutional neural networks for the detection of anthracnose in olives using VIS/NIR hyperspectral images. *Computers and Electronics in Agriculture*, *187*, 106252. https://doi.org/10.1016/j.compag.2021.106252

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

Fiset, J., Effati, M., & Skonieczny, K. (2023). Power and energy consumption of skid-steer rovers turning on loose soil. *Journal of Field Robotics*, *40*(2), 193–214. https://doi.org/10.1002/rob.22123

Freitas, R. G., Pereira, F. R. S., Dos Reis, A. A., Magalhães, P. S. G., Figueiredo, G. K. D. A., & do Amaral, L. R. (2022). Estimating pasture aboveground biomass under an integrated crop-livestock system based on spectral and texture measures derived from UAV images. *Computers and Electronics in Agriculture*, *198*. https://doi.org/10.1016/j.compag.2022.107122

Gara, T. W., Rahimzadeh-Bajgiran, P., & Weiskittel, A. (2022). Determination of foliar traits in an ecologically distinct conifer species in Maine using Sentinel-2 imagery and site variables: Assessing the effect of leaf trait expression and upscaling approach on prediction accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, *193*, 150–163. https://doi.org/10.1016/j.isprsjprs.2022.09.012

García-Vera, Y. E., Polochè-Arango, A., Mendivelso-Fajardo, C. A., & Gutiérrez-Bernal, F. J. (2024). Hyperspectral image analysis and machine learning techniques for crop disease detection and identification: A review. *Sustainability*, *16*(14), 6064. https://doi.org/10.3390/su16146064

Gerardo, R., & de Lima, I. P. (2023). Applying RGB-based vegetation indices obtained from uas imagery for monitoring the rice crop at the field scale: A case study in Portugal. *Agriculture*, *13*(10), 1916. https://doi.org/10.3390/agriculture13101916

Ghanbari, A., Shirdel, G. H., & Maleki, F. (2024). Semi-self-supervised domain adaptation: developing deep learning models with limited annotated data for wheat head segmentation. *Algorithms*, *17*(6), 267. https://doi.org/10.3390/a17060267

Ghazal, S., Munir, A., & Qureshi, W. S. (2024). Computer vision in smart agriculture and precision farming: Techniques and applications. *Artificial Intelligence in Agriculture*, *13*, 64–83. https://doi.org/10.1016/j.aiia.2024.06.004

Gikunda, K. (2024). Harnessing Artificial Intelligence for Sustainable Agricultural Development in Africa: Opportunities, Challenges, and Impact. *ArXiv-Computers and Society*. https://doi.org/10.48550/ARXIV.2401.06171

Goldsmith, E. L., Rickard, J. P., Mercorelli, L. R., Gonzàlez, L. A., & de Graaf, S. P. (2022). The use of accelerometers for the remote detection of mounting in rams and testosterone-treated wethers. *Computers and Electronics in Agriculture*, *199*, 107129. https://doi.org/10.1016/j.compag.2022.107129

Grati, R., Fattouch, N., & Boukadi, K. (2025). Ontologies for smart agriculture: A path toward explainable AI—A systematic literature review. *IEEE Access*, *13*, 72883–72905. https://doi.org/10.1109/ACCESS.2025.3563202

Gupta, S. K., & Agarwal, R. (2025). Comparative analysis of unmanned aerial vehicle and ground-level data using computer vision in agriculture. *Cureus Journal of Computer Science*, *2*. https://doi.org/10.7759/s44389-025-10304-8

Gupta, V. K., Gupta, A., Jyoti, Jain, P., Singh, H., & Joshi, K. (2025). Role of artificial intelligence in disease detection of various crops in agriculture. *2025 5th International Conference on Intelligent Technologies (CONIT)*, 1–6. https://doi.org/10.1109/CONIT65521.2025.11167165

Gutierrez, A., Ansuategi, A., Susperregi, L., Tubío, C., Rankić, I., & Lenža, L. (2019). A benchmarking of learning strategies for pest detection and identification on tomato plants for autonomous scouting robots using internal databases. *Journal of Sensors*, *2019*, 1–15. https://doi.org/10.1155/2019/5219471

Haghighat, M., Saleh, A., & Rahimi Azghadi, M. (2026). Multimodal language models in agriculture: A tutorial and survey. *Information Fusion*, *129*, 104042. https://doi.org/10.1016/j.inffus.2025.104042

Hampel, G., & Fabulya, Z. (2024). The Risks of AI in Agriculture. *Analecta Technica Szegedinensia*, *18*(4), 32–44. https://doi.org/10.14232/analecta.2024.4.32-44
Han, F., Guan, X., & Xu, M. (2024). Method of intelligent agricultural pest image recognition based on machine vision algorithm. *Discover Applied Sciences*, *6*(10), 536. https://doi.org/10.1007/s42452-024-06224-2
Hasteer, N., Mallik, A., Nigam, D., Sindhwani, R., & Van Belle, J.-P. (2024). Analysis of challenges to implement artificial intelligence technologies in agriculture sector. *International Journal of System Assurance Engineering and Management*, *15*(5), 1841–1860. https://doi.org/10.1007/s13198-023-02164-z
He, X., Liu, L., Liu, C., Li, W., Sun, J., Li, H., He, Y., Yang, L., Zhang, D., Cui, T., Chen, C., & Li, J. (2022). Discriminant analysis of maize haploid seeds using near-infrared hyperspectral imaging integrated with multivariate methods. *Biosystems Engineering*, *222*, 142–155. https://doi.org/10.1016/j.biosystemseng.2022.08.003
Hoseinzadeh, S., & Garcia, D. A. (2024). Can AI predict the impact of its implementation in greenhouse farming? *Renewable and Sustainable Energy Reviews*, *197*, 114423. https://doi.org/10.1016/j.rser.2024.114423
Hossen, M. I., Awrangjeb, M., Pan, S., & Mamun, A. Al. (2025). Transfer learning in agriculture: a review. *Artificial Intelligence Review*, *58*(4), 97. https://doi.org/10.1007/s10462-024-11081-x
Hu, T., Zhang, X., Bohrer, G., Liu, Y., Zhou, Y., Martin, J., Li, Y., & Zhao, K. (2023). Crop yield prediction via explainable AI and interpretable machine learning: Dangers of black box models for evaluating climate change impacts on crop yield. *Agricultural and Forest Meteorology*, *336*, 109458. https://doi.org/10.1016/j.agrformet.2023.109458
Hu, X., Gu, X., Sun, Q., Yang, Y., Qu, X., Yang, X., & Guo, R. (2023). Comparison of the performance of Multi-source Three-dimensional structural data in the application of monitoring maize lodging. *Computers and Electronics in Agriculture*, *208*, 107782. https://doi.org/10.1016/j.compag.2023.107782
Hua, X., Chen, H., Duan, Q., Hong, D., Li, R., Shang, H., Jiang, L., Yang, H., Zhang, D., Hua, X., Chen, H., Duan, Q., Hong, D., Li, R., Shang, H., Jiang, L., Yang, H., & Zhang, D. (2025). A comprehensive review of diffusion models in smart agriculture: Progress, applications, and challenges. *ArXiv-Machine Learning*. https://doi.org/10.48550/ARXIV.2507.18376
Hughes, L. H., Marcos, D., Lobry, S., Tuia, D., & Schmitt, M. (2020). A deep learning framework for matching of SAR and optical imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *169*, 166–179. https://doi.org/10.1016/j.isprsjprs.2020.09.012
Ibañez, S. C., & Monterola, C. P. (2023). A global forecasting approach to large-scale crop production prediction with time series transformers. *Agriculture*, *13*(9), 1855. https://doi.org/10.3390/agriculture13091855
Ignesti, G., Moroni, D., & Martinelli, M. (2024). *Towards the actual deployment of robust, adaptable, and maintainable AI models for sustainable agriculture*. 33–39. https://doi.org/10.15439/2024F2991
Ivezić, A., Trudić, B., Stamenković, Z., Kuzmanović, B., Perić, S., Ivošević, B., Buđen, M., & Petrović, K. (2023). Drone-related agrotechnologies for precise plant protection in Western Balkans: Applications, possibilities, and legal framework limitations. *Agronomy*, *13*(10), 2615. https://doi.org/10.3390/agronomy13102615
Johansen, K., Maltese, A., & McCabe, M. F. (2023). Monitoring agricultural ecosystems. In *Unmanned Aerial Systems for Monitoring Soil, Vegetation, and Riverine Environments* (pp. 125–151). Elsevier. https://doi.org/10.1016/B978-0-323-85283-8.00013-8
Johnson, D. (2024). Food security, the agriculture value chain, and digital transformation: The case of Jamaica's agricultural business information system (ABIS). *Technology in Society*, *77*, 102523. https://doi.org/10.1016/j.techsoc.2024.102523
Johnson, F., Meegan, R., Lowry, J., Oudemans, P., & Dana, K. (2025). Agtech framework for cranberry-ripening analysis using vision foundation models. *2025 IEEE Winter Conference on Applications of Computer Vision, WACV 2025*, 1207–1216. https://doi.org/10.1109/WACV61041.2025.00125
Joosse, T. (2024). Building trust in AI farming tools. *CSA News*, *69*(2), 10–16. https://doi.org/10.1002/csan.21217
Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Current Opinion in Biotechnology*, *70*, 15–22. https://doi.org/10.1016/j.copbio.2020.09.003
Kakarla, S. C., Costa, L., Ampatzidis, Y., & Zhang, Z. (2022). *Applications of UAVs and Machine Learning in Agriculture* (pp. 1–19). https://doi.org/10.1007/978-981-19-2027-1_1
Kalbhor, A. (2025). AI and machine learning in precision agriculture: The future of agricultural precision agriculture. *International Journal for Research in Applied Science and Engineering Technology*, *13*(2), 648–654. https://doi.org/10.22214/ijraset.2025.66920
Kalyani, Y., Bermeo, N. V., & Collier, R. (2023). Digital twin deployment for smart agriculture in Cloud-Fog-Edge infrastructure. *International Journal of Parallel, Emergent and Distributed Systems*, *38*(6), 461–476. https://doi.org/10.1080/17445760.2023.2235653
Kamatchi S. (2024). AI in agriculture: Precision farming and crop monitoring. *Communications on Applied Nonlinear Analysis*, *32*(3s), 469–478. https://doi.org/10.52783/cana.v32.2684
Karthikeyan, J., & Murugan, Dr. A. (2024). A study on enhancing crop yield prediction with accuracy through machine and deep learning models. *South Eastern European Journal of Public Health*, 1217–1227. https://doi.org/10.70135/seejph.vi.2270
Katharria, A., Pant, M., Velásquez, J. D., Snášel, V., Rajwar, K., & Deep, K. (2026). Information fusion in smart agriculture: machine learning applications and future research directions. *Information Fusion*, *129*, 104040. https://doi.org/10.1016/j.inffus.2025.104040
Kavipriya, J., & Vadivu, G. (2024). Exploring Crop Yield Prediction with Remote Sensing Imagery and AI. *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 1–5. https://doi.org/10.1109/ACCAI61061.2024.10601854
Khadka, R., & Kumar, Prof. V. (2024). Enhancing sustainability in agriculture through artificial intelligence. *International Scientific Journal of Engineering and Management*, *03*(12), 1–7. https://doi.org/10.55041/ISJEM02192
Kisliuk, B., Krause, J. C., Meemken, H., Saborío Morales, J. C., Müller, H., & Hertzberg, J. (2023). AI in current and future agriculture: An introductory overview. *KI - Künstliche Intelligenz*, *37*(2–4), 117–132. https://doi.org/10.1007/s13218-023-00826-5
Koul, S. (2021). Machine learning and deep learning in agriculture. In *Smart Agriculture* (pp. 1–19). CRC Press. https://doi.org/10.1201/b22627-1
Kumar, P., Nelson, A., Kapetanovic, Z., Chandra, R., Kumar, P., Nelson, A., Kapetanovic, Z., & Chandra, R. (2023). Affordable Artificial Intelligence -- Augmenting Farmer Knowledge with AI. *ArXiv-Signal Processing*. https://doi.org/10.48550/ARXIV.2303.06049
Kusumavathi, K., Konatala, R., Lal, P., Sarkar, S., Banerjee, H., Bandopadhyay, P., Sethi, D., & Upendar, K. (2025). Artificial intelligence for fostering sustainable agriculture. *Current Plant Biology*, *42*, 100476. https://doi.org/10.1016/j.cpb.2025.100476
Lin, Y.-B., Chen, W.-E., Chang, T. C.-Y., Lin, Y.-B., Chen, W.-E., & Chang, T. C.-Y. (2023). Moving from cloud to fog/edge: The smart agriculture experience. *IEEE Communications Magazine*, *61*(12), 86–92. https://doi.org/10.1109/MCOM.001.2200633
Liu, W., Luo, Z., Cai, Y., Yu, Y., Ke, Y., Junior, J. M., Gonçalves, W. N., & Li, J. (2021). Adversarial unsupervised domain adaptation for 3D semantic segmentation with multi-modal learning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *176*, 211–221. https://doi.org/10.1016/j.isprsjprs.2021.04.012
Liu, W., & Zhang, A. (2025). Plant disease detection algorithm based on efficient swin transformer. *Computers, Materials and Continua*, *82*(2), 3045–3068. https://doi.org/10.32604/cmc.2024.058640
Logeshwaran, J., Srivastava, D., Kumar, K. S., Rex, M. J., Al-Rasheed, A., Getahun, M., & Soufiene, B. O. (2024). Improving crop production using an agro-deep learning framework in precision agriculture. *BMC Bioinformatics*, *25*(1), 341. https://doi.org/10.1186/s12859-024-05970-9
López-Martínez, M., Díaz-Flórez, G., Villagrana-Barraza, S., Solís-Sánchez, L. O., Guerrero-Osuna, H. A., Soto-Zarazúa, G. M., & Olvera-Olvera, C. A. (2023). A high-performance computing cluster for distributed deep learning: a practical case of weed classification using convolutional neural network models. *Applied Sciences*, *13*(10), 6007. https://doi.org/10.3390/app13106007

Luo, X., Xiong, S., Jia, X., Zeng, Y., & Chen, X. (2025). AIoT-enabled data management for smart agriculture: a comprehensive review on emerging technologies. *IEEE Access*, 13, 102964–102993. https://doi.org/10.1109/ACCESS.2025.3578751

Maghdid, S., Askar, S., Xoshibi, F., & Hamad, S. (2024). Deep Learning Algorithms for IoT Based Crop Yield Optimization. *Indonesian Journal of Computer Science*, *13*(2). https://doi.org/10.33022/ijcs.v13i2.3846

Malashin, I., Tynchenko, V., Gantimurov, A., Nelyub, V., Borodulin, A., & Tynchenko, Y. (2024). Predicting sustainable crop yields: Deep learning and explainable AI tools. *Sustainability*, *16*(21), 9437. https://doi.org/10.3390/su16219437

Mamatha, A., & Shalini, S. (2025). Artificial intelligence-based green technologies for efficient agriculture. *ITM Web of Conferences*, *79*, 01027. https://doi.org/10.1051/itmconf/20257901027

Mane R. L., Pawar G. T., Ghadage V. V., Dhope S. G., & Lande P. T. (2025). Smart agriculture management system. *International Journal of Advanced Research in Science, Communication and Technology*, 558–564. https://doi.org/10.48175/IJARSCT-23273

Manishankar, V., Harish, S., Lakshmanan, S., Selvan, L. N., & Vinodhan, R. (2021). Inspection of plant pathogens by using drones. *International Journal of Vehicle Structures and Systems*, *13*(3). https://doi.org/10.4273/ijvss.13.3.20

Manning, L. (2024). Innovating in an uncertain world: Understanding the social, technical and systemic barriers to farmers adopting new technologies. *Challenges*, *15*(2), 32. https://doi.org/10.3390/challe15020032

Manono, B. O., Mwami, B., Mutavi, S., & Nzilu, F. (2026). Precision farming with smart sensors: current state, challenges and future outlook. *Sensors*, *26*(3), 882. https://doi.org/10.3390/s26030882

Mansoor, S., Iqbal, S., Popescu, S. M., Kim, S. L., Chung, Y. S., & Baek, J.-H. (2025). Integration of smart sensors and IOT in precision agriculture: trends, challenges and future prospectives. *Frontiers in Plant Science*, *16*. https://doi.org/10.3389/fpls.2025.1587869

Marinis, P. De, Vessio, R., & Castellano, G. (2024). RoWeeder: Unsupervised weed mapping through crop-row detection. *ArXiv-Computer Vision and Pattern Recognition*. https://doi.org/10.48550/ARXIV.2410.04983

Mayur Rajaram Salokhe. (2023). Machine learning: Applications in agriculture (crop yield prediction, disease and pest detection). *International Journal of Advanced Research in Science, Communication and Technology*, 592–597. https://doi.org/10.48175/IJARSCT-12088

Min, X., Ye, Y., Xiong, S., & Chen, X. (2025). Computer vision meets generative models in agriculture: Technological advances, challenges and opportunities. *Applied Sciences*, *15*(14), 7663. https://doi.org/10.3390/app15147663

Mishra, H. (2025). A review on artificial intelligence, machine learning and IoT integration in precision agriculture. *Journal of Scientific Agriculture*, 101–109. https://doi.org/10.25081/jsa.2025.v9.9497

Mohankumar A., & Gowtham R. (2024). Revolutionizing automated agriculture: A brief overview of an advanced smart agriculture system using Arduino UNO. *Irish Interdisciplinary Journal of Science & Research*, *08*(01), 13–23. https://doi.org/10.46759/IIJSR.2024.8103

Morchid, A., El Alami, R., Raezah, A. A., & Sabbar, Y. (2024). Applications of internet of things (IoT) and sensors technology to increase food security and agricultural Sustainability: Benefits and challenges. *Ain Shams Engineering Journal*, *15*(3), 102509. https://doi.org/10.1016/j.asej.2023.102509

Naseer, A., Shmoon, M., Shakeel, T., Ur Rehman, S., Ahmad, A., & Gruhn, V. (2024). A systematic literature review of the IoT in agriculture—Global adoption, innovations, security, and privacy challenges. *IEEE Access*, *12*, 60986–61021. https://doi.org/10.1109/ACCESS.2024.3394617

Nautiyal, M., Joshi, S., Hussain, I., Rawat, H., Joshi, A., Saini, A., Kapoor, R., Verma, H., Nautiyal, A., Chikara, A., Ahmad, W., & Kumar, S. (2025). Revolutionizing agriculture: A comprehensive review on artificial intelligence applications in enhancing properties of agricultural produce. *Food Chemistry: X*, *29*, 102748. https://doi.org/10.1016/j.fochx.2025.102748

Neetu, G. (2024). AI-Driven Precision Agriculture: Optimizing Crop Yield and Resource Efficiency. *International Journal for Multidisciplinary Research*, *6*(6). https://doi.org/10.36948/ijfmr.2024.v06i06.29913

Nikam, Y. G., Shinde, P. V., Shinde, D. A., Kolekar, S. M., More, R. P., & Nagpure, S. (2025). AI and IoT Integration in Smart Farming: Real-Time Monitoring and Predictive Analytics for Sustainable Agriculture. *2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS)*, 1–5. https://doi.org/10.1109/WorldSUAS66815.2025.11199045

Ogunjimi, O. L. A., Emmanuel, C. O., Negedu, M. U., Elumelu, A. A., Aremo, E. A., & Abhulimen, M. E. (2025). Artificial intelligence and agriculture- An overview concept. *Advances in Multidisciplinary & Scientific Research Journal Publication*, *11*(2), 68–84. https://doi.org/10.22624/AIMS/V11N2P8

Oliveira, R. C. de, & Silva, R. D. de S. e. (2023). Artificial Intelligence in Agriculture: Benefits, Challenges, and Trends. *Applied Sciences*, *13*(13), 7405. https://doi.org/10.3390/app13137405

Pacal, I. (2024). Enhancing crop productivity and sustainability through disease identification in maize leaves: Exploiting a large dataset with an advanced vision transformer model. *Expert Systems with Applications*, *238*, 122099. https://doi.org/10.1016/j.eswa.2023.122099

Pacal, I., Kunduracioglu, I., Alma, M. H., Deveci, M., Kadry, S., Nedoma, J., Slany, V., & Martinek, R. (2024). A systematic review of deep learning techniques for plant diseases. *Artificial Intelligence Review*, *57*(11), 304. https://doi.org/10.1007/s10462-024-10944-7

Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, *8*, 100483. https://doi.org/10.1016/j.atech.2024.100483

Pal, A., Barman, S., Choudhury, Md. R., Kumar, C. S., Manasa, P., & Adhikary, N. K. (2024). Robotic applications and artificial intelligence for the future food security challenge. *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)*, 1–4. https://doi.org/10.1109/SCOPES64467.2024.10990408

Pal, P., Landivar-Bowles, J., Landivar-Scott, J., Duffield, N., Nowka, K., Jung, J., Chang, A., Lee, K., Zhao, L., & Bhandari, M. (2025). Unmanned aerial system and machine learning driven Digital-Twin framework for in-season cotton growth forecasting. *Computers and Electronics in Agriculture*, *228*, 109589. https://doi.org/10.1016/j.compag.2024.109589

Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., & Fountas, S. (2024). Economic and environmental benefits of digital agricultural technologies in crop production: A review. *Smart Agricultural Technology*, *8*, 100441. https://doi.org/10.1016/j.atech.2024.100441

Pasupuleti, M. K. (2025). Next-Gen food security: AI and biotech innovations for sustainable agriculture. *International Journal of Academic and Industrial Research Innovations (IJAIRI)*, *05*(05), 16–28. https://doi.org/10.62311/nesx/rp05113

Patel, J., Chandel, S. T., & Sonker, A. (2024). An optimization driven deep belief network model for crop yield prediction in IoT based smart agriculture. *Multimedia Tools and Applications*, *84*(26), 31069–31091. https://doi.org/10.1007/s11042-024-20418-1

Patil, S., & Jadhav, M. (2023). Providing smart agriculture solution to farmer by using IoT. *International Journal of Scientific Research in Engineering and Management*, *07*(10), 1–11. https://doi.org/10.55041/IJSREM26022

Pham, T.-H., Acharya, P., Bachina, S., Osterloh, K., Nguyen, K.-D., Pham, T.-H., Acharya, P., Bachina, S., Osterloh, K., & Nguyen, K.-D. (2023). Deep-Learning Framework for Optimal Selection of Soil Sampling Sites. *ArXiv-Computer Vision and Pattern Recognition*. https://doi.org/10.48550/ARXIV.2309.00974

Pham Van Anh, Tuan, T. M., Thang, N. D., Tuan, Q. A., & Fujimura, K. (2025). IoT-Based Monitoring System for Smart Agriculture to Enhance Crop Yield Efficiency. *International Journal of Education, Science, Technology, and Engineering (IJESTE)*, *8*(2), 106–117. https://doi.org/10.36079/lamintang.ijeste-0802.960

Pramesti, G. N. D. P. (2025). Utilization of Artificial Intelligence and Remote Sensing for Yield Prediction and Irrigation Management in Drylands. *Journal of Agricultural Economy and Technology Development*, *2*(1), 21–29. https://doi.org/10.59261/jaetd.v2i1.14

Preanto, S. A., Ahad, Md. T., Emon, Y. R., Mustofa, S. (2024). A semantic segmentation approach on sweet orange leaf diseases detection utilizing YOLO. *ArXiv Preprint*. https://doi.org/10.48550/ARXIV.2409.06671

Qazi, S., Khawaja, B. A., & Farooq, Q. U. (2022). IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends. *IEEE Access*, *10*, 21219–21235. https://doi.org/10.1109/ACCESS.2022.3152544

Rai, N., Zhang, Y., Ram, B. G., Schumacher, L., Yellavajjala, R. K., Bajwa, S., & Sun, X. (2023). Applications of deep learning in precision weed management: A review. *Computers and Electronics in Agriculture*, *206*, 107698. https://doi.org/10.1016/j.compag.2023.107698

Rajesh, B. (2024). AI in agriculture: Revolutionizing precision farming and sustainable crop management. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *10*(5), 535–543. https://doi.org/10.32628/CSEIT241051040

Rakhmatulin, I., Kamilaris, A., & Andreasen, C. (2021). Deep Neural Networks to Detect Weeds from Crops in Agricultural Environments in Real-Time: A Review. *Remote Sensing*, *13*(21), 4486. https://doi.org/10.3390/rs13214486

Rashid, A. Bin, Kausik, A. K., Khandoker, A., & Siddque, S. N. (2025). Integration of artificial intelligence and IoT with UAVs for precision agriculture. *Hybrid Advances*, *10*, 100458. https://doi.org/10.1016/j.hybadv.2025.100458

Reddy, K. P., Roshni Thanka, M., Edwin, E. B., Ebenezer, V., & Joy, P. (2024). Farm_era: Precision Farming with GIS, AI Pest Management, Smart Irrigation, Data Analytics, and Optimized Crop Planning. *2024 International Conference on Inventive Computation Technologies (ICICT)*, 1134–1140. https://doi.org/10.1109/ICICT60155.2024.10544687

Rilling, S., Henningsen, J., Milde, K., Martini, D., Wickert, L., & Kelbert, P. (2024). Overview and assessment approaches of energy consumption and ghg emissions through the development and application of artificial intelligence - An example from the agricultural sector. *2024 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)*, 271–276. https://doi.org/10.1109/MetroAgriFor63043.2024.10948837

Sachithra, V., & Subhashini, L. D. C. S. (2023a). How artificial intelligence uses to achieve the agriculture sustainability: Systematic review. *Artificial Intelligence in Agriculture*, *8*, 46–59. https://doi.org/10.1016/j.aiia.2023.04.002

Saha, P., Kumar, V., Kathuria, S., Gehlot, A., Pachouri, V., & Duggal, A. S. (2023). Precision agriculture using Internet of Things and wireless sensor networks. *2023 International Conference on Disruptive Technologies (ICDT)*, 519–522. https://doi.org/10.1109/ICDT57929.2023.10150678

Saranya, T., Deisy, C., Sridevi, S., & Anbananthen, K. S. M. (2023). A comparative study of deep learning and Internet of Things for precision agriculture. *Engineering Applications of Artificial Intelligence*, *122*, 106034. https://doi.org/10.1016/j.engappai.2023.106034

Sassu, A., Motta, J., Deidda, A., Ghiani, L., Carlevaro, A., Garibotto, G., & Gambella, F. (2023). Artichoke deep learning detection network for site-specific agrochemicals UAS spraying. *Computers and Electronics in Agriculture*, *213*, 108185. https://doi.org/10.1016/j.compag.2023.108185

Screpnik, C. R., Zamudio, E., & Gimenez, L. I. (2025). Artificial intelligence in agriculture: A systematic review of crop yield prediction and optimization. *IEEE Access*, *13*, 70691–70697. https://doi.org/10.1109/ACCESS.2025.3560631

Shaikh, F. K., Memon, M. A., Mahoto, N. A., Zeadally, S., & Nebhen, J. (2022). Artificial intelligence best practices in smart agriculture. *IEEE Micro*, *42*(1), 17–24. https://doi.org/10.1109/MM.2021.3121279

Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021). Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access*, *9*, 4843–4873. https://doi.org/10.1109/ACCESS.2020.3048415

Sharma, R. D., Gawade, S., Sharma, R. D., & Gawade, S. (2025). Advancements in precision agriculture: A literature review of machine learning applications for crop monitoring and yield prediction. *Environmental Claims Journal*. https://doi.org/10.1080/10406026.2025.2545839

Sharma, S., Verma, K., & Hardaha, P. (2023). Implementation of artificial intelligence in agriculture. *Journal of Computational and Cognitive Engineering*, *2*(2), 155–162. https://doi.org/10.47852/bonviewJCCE2202174

Shrivastav, V., Yadav, M., Sharma, A., Kumar, D., Sharma, S., & Chauhan, A. S. (2024). IoT and IoE transformations in precision farming agriculture: Sensor based monitoring, Automated irrigation and Livestock monitoring. *2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, 1–14. https://doi.org/10.1109/SCEECS61402.2024.10481981

Shruthi, M. R. & Anil Kumar K. N. (2025). AI-driven techniques for real-time crop monitoring in smart agriculture. *International Journal of Scientific Research in Engineering and Management*, *09*(08), 1–9. https://doi.org/10.55041/IJSREM51797

Singh, G., & Sharma, S. (2024). A comprehensive review on the Internet of Things in precision agriculture. *Multimedia Tools and Applications*, *84*(17), 18123–18198. https://doi.org/10.1007/s11042-024-19656-0

Singh, H., Yadav, P., Rishiwal, V., Yadav, M., Tanwar, S., & Singh, O. (2025). Localization in WSN-assisted IoT networks using machine learning techniques for smart agriculture. *International Journal of Communication Systems*, *38*(5). https://doi.org/10.1002/dac.6004

Singh, N., Wang'ombe, J., Okanga, N., Zelenska, T., Repishti, J., K, J. G., Mishra, S., Manokaran, R., Singh, V., Rafiq, M. I., Gandhi, R., & Nambi, A. (2024). Farmer.Chat: Scaling AI-powered agricultural services for smallholder farmers. *ArXiv-Emerging Technologies*. https://doi.org/10.48550/ARXIV.2409.08916

Singh, S., Gakhar, D., Kumar, Y., AlHommada, M. R., Bhosle, N., & Al-Farouni, M. (2025). Precision agriculture with AI: Leveraging machine learning and IoT for optimized crop management. *AIP Conference Proceedings*, *3343*(1), 040082. https://doi.org/10.1063/5.0292600

Skobalski, J., Sagan, V., Alifu, H., Al Akkad, O., Lopes, F. A., & Grignola, F. (2024). Bridging the gap between crop breeding and GeoAI: Soybean yield prediction from multispectral UAV images with transfer learning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *210*, 260–281. https://doi.org/10.1016/j.isprsjprs.2024.03.015

Song, W., Li, X., Zhang, J., Huang, J., Wang, J., Feng, W., Guo, Y., & Ren, L. (2026). Soil sensors in smart agriculture: Multi-type monitoring technologies and ecological development pathways. *Agriculture*, *16*(3), 359. https://doi.org/10.3390/agriculture16030359

Sopialena, S., Suyadi, S., & Noor, S. A. (2022). Ecosystem monitoring on leaves of leaf rust disease of maize (*Zea mays* L.). *Caraka Tani: Journal of Sustainable Agriculture*, *37*(1), 89. https://doi.org/10.20961/carakatani.v37i1.34920

Subramanian, J., Rohan, D. S., Palanisamy, S., Karagowder, M., Balasubramaniyam, S., Hammeed, F. S., Velleangiri, V., Subramanian, J., Rohan, D. S., Palanisamy, S., Karagowder, M., Balasubramaniyam, S., Hammeed, F. S., & Velleangiri, V. (2025). Advancing agriculture: Deep learning solutions for plant disease detection. *AIP Conference Proceedings*, *3279*(1). https://doi.org/10.1063/5.0263052

Sunny, G. (2024). Al-driven Precision Agriculture: Advancing Crop Yield Prediction. *International Journal for Multidisciplinary Research*, *6*(5). https://doi.org/10.36948/ijfmr.2024.v06i05.29555

Tace, Y., Tabaa, M., Elfilali, S., Leghris, C., Bensag, H., & Renault, E. (2022). Smart irrigation system based on IoT and machine learning. *Energy Reports*, *8*, 1025–1036. https://doi.org/10.1016/j.egyr.2022.07.088

Taseer, A., & Han, X. (2024). Advancements in variable rate spraying for precise spray requirements in precision agriculture using Unmanned aerial spraying Systems: A review. *Computers and Electronics in Agriculture*, *219*, 108841. https://doi.org/10.1016/j.compag.2024.108841

Tian, Z. (2025). Hybrid CNN-transformer approach for remote sensing change detection with bi-temporal feature interaction. In P. Zhu & G. Lin (Eds.), *Fifth International Conference on Applied Mathematics, Modelling, and Intelligent Computing (CAMMIC 2025)* (p. 34). SPIE. https://doi.org/10.1117/12.3070320

Tzachor, A., Devare, M., King, B., Avin, S., & Ó hÉigeartaigh, S. (2022a). Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nature Machine Intelligence*, *4*(2), 104–109. https://doi.org/10.1038/s42256-022-00440-4

Vardhan, P. N. H., Badavath, A., & Srivalli, P. (2025). Artificial intelligence and its applications in agriculture: A review. *Environment Conservation Journal*, *26*(1), 274–280. https://doi.org/10.36953/ECJ.28802904

Vijayakumar, S., Murugaiyan, V., Ilakkiya, S., Kumar, V., Sundaram, R. M., & Kumar, R. M. (2025). Opportunities, challenges, and interventions for agriculture 4.0 adoption. *Discover Food*, *5*(1), 265. https://doi.org/10.1007/s44187-025-00576-3

Wang, C., Liu, B., Liu, L., Zhu, Y., Hou, J., Liu, P., & Li, X. (2021). A review of deep learning used in the hyperspectral image analysis for agriculture. *Artificial Intelligence Review*, *54*(7), 5205–5253. https://doi.org/10.1007/s10462-021-10018-y

Wang, W., & Kang, Y. (2025). A review of computer vision technologies in precision agriculture. *Theoretical and Natural Science*, *101*(1), 35–40. https://doi.org/10.54254/2753-8818/2025.CH22224

Wang, Y., Chen, Y., & Wang, D. (2022). Convolution network enlightened transformer for regional crop disease classification. *Electronics*, *11*(19), 3174. https://doi.org/10.3390/electronics11193174

Wongchai, A., Shukla, S. K., Ahmed, M. A., Sakthi, U., Jagdish, M., & kumar, R. (2022). Artificial intelligence - enabled soft sensor and internet of things for sustainable agriculture using ensemble deep learning architecture. *Computers and Electrical Engineering*, *102*, 108128. https://doi.org/10.1016/j.compeleceng.2022.108128

Wu, K., Ji, Z., Wang, H., Shao, X., Li, H., Zhang, W., Kong, W., Xia, J., & Bao, X. (2025). A Comprehensive Review of AI Methods in Agri-Food Engineering: Applications, Challenges, and Future Directions. *Electronics 2025, Vol. 14, Page 3994*, *14*(20), 3994. https://doi.org/10.3390/ELECTRONICS14203994

Yan, X., Chen, X., Ma, C., Cai, Y., Cui, Z., Chen, X., Wu, L., & Zhang, F. (2021). What are the key factors affecting maize yield response to and agronomic efficiency of phosphorus fertilizer in China? *Field Crops Research*, *270*, 108221. https://doi.org/10.1016/j.fcr.2021.108221

Yao, Y., & Ye, S. (2025). Application of AI in precision fertilization and irrigation management. *Journal of Computing and Electronic Information Management*, *16*(3), 84–87. https://doi.org/10.54097/j0f2t330

Zamir, M. A., & Sonar, R. M. (2023). Application of Internet of Things (IoT) in agriculture: A review. *2023 8th International Conference on Communication and Electronics Systems (ICCES)*, 425–431. https://doi.org/10.1109/ICCES57224.2023.10192761

Zhang, B., & Qiao, Y. (2024). AI, sensors, and robotics for smart agriculture. *Agronomy*, *14*(6), 1180. https://doi.org/10.3390/agronomy14061180

Zhang, Y., Liao, Y., & Li, Y. (2023). A new method of crop yield prediction based on artificial intelligence. *Journal of Physics: Conference Series*, *2665*(1), 012019. https://doi.org/10.1088/1742-6596/2665/1/012019

Zhang, Y., Wang, M., Zhao, D., Liu, C., & Liu, Z. (2023). Early weed identification based on deep learning: A review. *Smart Agricultural Technology*, *3*, 100123. https://doi.org/10.1016/j.atech.2022.100123

Zhou, W., Cui, Y., Huang, H., Huang, H., & Wang, C. (2024). A fast and data-efficient deep learning framework for multi-class fruit blossom detection. *Computers and Electronics in Agriculture*, *217*, 108592. https://doi.org/10.1016/j.compag.2023.108592

Zhuk, A. (2023). Artificial intelligence impact on the environment: Hidden ecological costs and ethical-legal issues. *Journal of Digital Technologies and Law*, *1*(4), 932–954. https://doi.org/10.21202/jdtl.2023.40