Available online at www.agrifarming.org

DOI: http://dx.doi.org/10.18782/2582-7146.259

ISSN: 2582 – 7146

Curr. Rese. Agri. Far. (2026) *7*(1), 37-46

Current Research in Agriculture and Farming

Review Article

Peer-Reviewed, Refereed, Open Access Journal

Artificial Intelligence and Machine Learning Applications in Smart Agriculture: A Comprehensive Review

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Received: 20.12.2025 | Revised: 29.01.2026 | Accepted: 13.02.2026

ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are transforming agriculture by enhancing productivity, resource efficiency, and sustainability. This review examines recent advances in AI- and ML-driven smart farming applications, including crop disease detection, yield prediction, precision irrigation, weed management, soil analysis, livestock health monitoring, and drone-based crop surveillance. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in plant disease diagnosis, while machine learning algorithms such as Random Forest and Support Vector Machines have improved crop yield prediction and soil classification. The integration of AI with the Internet of Things (IoT) enables real-time monitoring, predictive analytics, and informed decision-making across agricultural systems. Despite these advances, widespread adoption remains constrained by high implementation costs, data quality issues, limited digital infrastructure, and inadequate technical expertise, particularly in developing regions. The review highlights recent developments, discusses key challenges, and identifies future research opportunities for developing resilient, intelligent, and sustainable agricultural systems.

Keywords: *Artificial Intelligence, Machine Learning, Smart Agriculture, Precision Farming, Deep Learning.*

INTRODUCTION

Agriculture remains the backbone of the global economy, providing food, fiber, and livelihood to billions of people worldwide. However, the agricultural sector faces unprecedented challenges, including a rapidly growing global population projected to reach 9.7 billion by 2050, climate change-induced weather variability, declining arable land, water scarcity, and the increasing incidence of crop pests and diseases (FAO, 2022). Traditional farming practices, which rely heavily on manual labor, visual inspection, and experience-based decision-making, are increasingly inadequate to meet the rising demand for food production while maintaining environmental sustainability.

Cite this article: Patel, V.A., Waghmare, P.K., & Meena, N.K. (2026). Artificial Intelligence and Machine Learning Applications in Smart Agriculture: A Comprehensive Review, *Curr. Rese. Agri. Far. 7*(1), 37-46. doi: http://dx.doi.org/10.18782/2582-7146.259

In this context, the convergence of Artificial Intelligence (AI) and Machine Learning (ML) with agricultural practices has ushered in a new era of smart agriculture, also referred to as Agriculture 4.0 (Aashu et al., 2024). Smart agriculture leverages advanced computational techniques, sensor technologies, robotics, and data analytics to transform conventional farming into a data-driven, precision-oriented enterprise. AI and ML algorithms can analyze vast amounts of agricultural data collected from diverse sources, including satellite imagery, drone-captured multispectral images, IoT sensors, weather stations, and soil samples, to generate actionable insights for farmers (Fuentes-Peailillo et al., 2024).

The application domains of AI and ML in agriculture are extensive and multifaceted. These technologies enable early detection of crop diseases through image classification using deep learning models, accurate prediction of crop yields based on environmental and soil parameters, intelligent irrigation management systems that optimize water usage, automated weed detection and site-specific herbicide application, real-time livestock health monitoring through wearable sensors, and precision nutrient management guided by soil analysis algorithms (Mohanty et al., 2016). The potential of these technologies to improve agricultural productivity, reduce resource wastage, minimize environmental impact, and enhance farmer profitability makes them indispensable tools for sustainable food production systems.

This review paper aims to provide a comprehensive and systematic analysis of the current state of AI and ML applications in smart agriculture. It examines key application areas, evaluates the performance of various algorithms and models, discusses the integration of IoT and remote sensing technologies with AI-driven analytics, identifies prevalent challenges and limitations, and proposes future research directions. The paper synthesizes findings from recent peer-reviewed literature published between 2020 and 2026 to offer a holistic perspective on the transformative role of these technologies in modern agriculture.

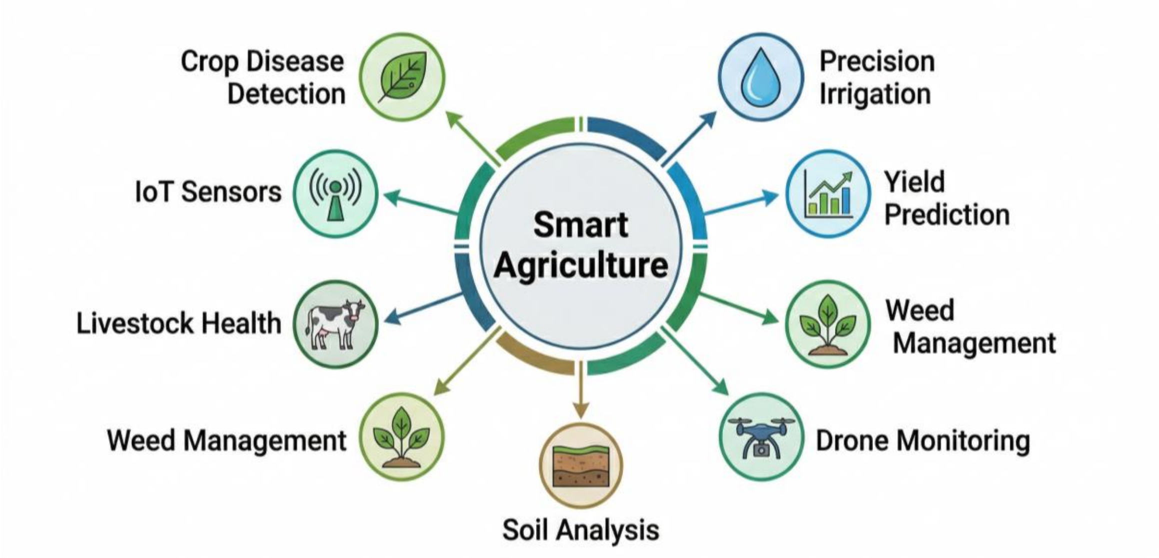

Figure1. Overview of AI and Machine Learning Applications in Smart Agriculture

2. AI and ML in Crop Disease Detection

Crop diseases constitute one of the most significant threats to global food production, causing estimated annual losses of 20–40% of total agricultural output (Savary et al., 2019). Traditional disease detection methods, which rely on manual visual inspection by trained pathologists, are inherently slow, labor-intensive, subjective, and unable to scale effectively across large agricultural landscapes. The advent of AI-powered disease detection systems has fundamentally transformed this paradigm by enabling rapid, accurate, and automated identification of plant diseases from digital images.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as the dominant approach for image-based plant disease detection. Mohanty et al. (2016) pioneered the use of deep CNNs trained on the PlantVillage dataset, achieving an accuracy of 99.35% in identifying 14 crop species and 26 diseases. This seminal work demonstrated the feasibility of smartphone-assisted crop disease diagnosis on a global scale. Subsequent research has built upon this foundation with increasingly sophisticated architectures and larger datasets.

Kumar et al. (2026) proposed the PDD-DL (Plant Disease Detection using Deep Learning) framework, which integrates CNN-based models with IoT-enabled sensors for real-time disease diagnosis. The system achieved an overall accuracy of 98.32%, a precision of 97.85%, a recall of 98.14%, and an F1-score of 97.99%, with a real-time inference speed of 42.6 milliseconds per image. The framework was validated across multiple datasets, including PlantVillage, Rice Disease, and Turkey Disease, demonstrating robust generalizability. Specialized architectures such as WheatLeafNet have been developed for wheat leaf disease detection using Python, TensorFlow, and OpenCV, outperforming established models like ResNet-50 and VGG-16 (Kumar et al., 2026).

Transfer learning approaches using pre-trained models such as ResNet50, AlexNet, GoogLeNet, VGG19, and EfficientNet have further accelerated the development of disease detection systems by leveraging features learned from large-scale image datasets. These models serve as powerful feature extractors, enabling high classification accuracy even with relatively small domain-specific training datasets. The integration of automated decision support systems with CNN classifiers allows the generation of treatment recommendations based on disease severity, facilitating precision pesticide application and targeted crop management interventions (Kumar et al., 2026).

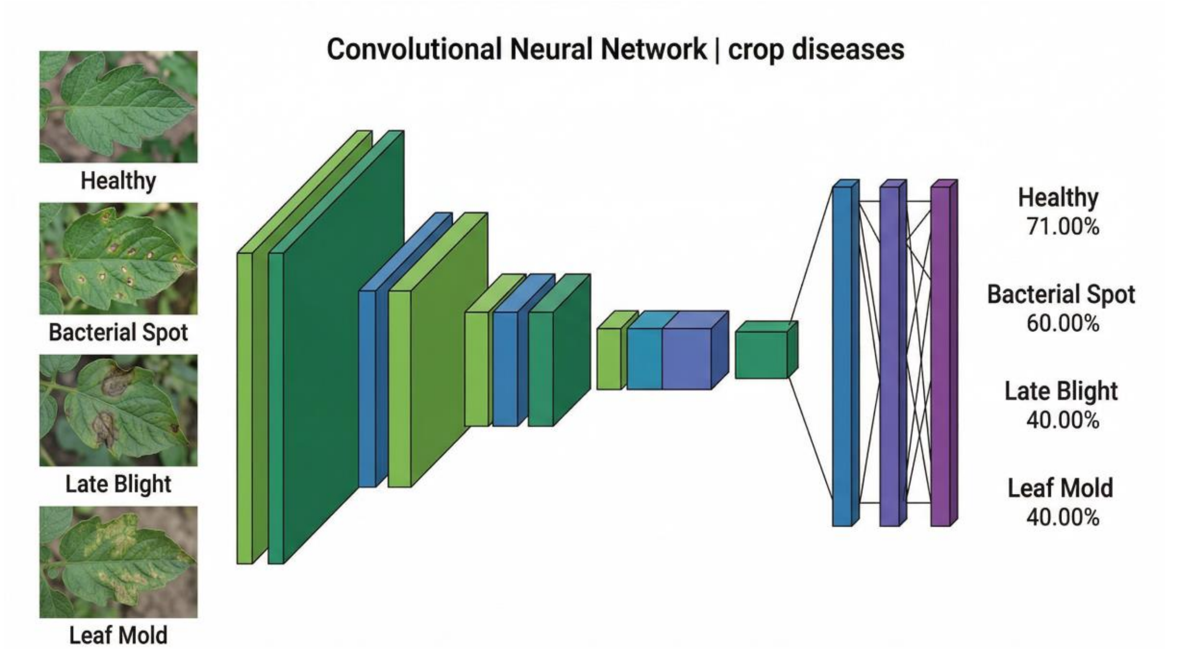

Figure2. CNN-based Architecture for Crop Disease Classification

3. ML for Crop Yield Prediction and Soil Analysis

Accurate crop yield prediction is essential for food security planning, market supply chain management, and informed agricultural decision-making. Machine learning algorithms have demonstrated remarkable capabilities in forecasting crop yields by analyzing complex interactions among soil properties, weather patterns, historical yield data, and management practices (Iniyan et al., 2025).

Iniyan et al. (2025) developed an ensemble learning approach called RFXG, integrating Random Forest (RF) and Extreme Gradient Boosting (XGB) models, for crop recommendation based on soil nutrient parameters, including nitrogen (N), phosphorus (P), potassium (K), pH, rainfall, temperature, and humidity. The proposed RFXG technique achieved a remarkable recommendation accuracy of 98% across twenty-two major crops. Comparative analysis with other ML models, including Extra Trees Classifier, Multilayer Perceptron, Decision Trees, and Logistic Regression, confirmed the superior performance of the ensemble approach.

For soil health assessment and crop yield prediction, back-propagation neural networks (BPNN) combined with multi-source data fusion and geographical information systems (MSDF-GIS) have shown significant improvements in prediction accuracy. Research by Patel et al. (2025) demonstrated that integrated ML models achieved 97% accuracy for crop yield prediction and 92% accuracy for soil health evaluation, substantially outperforming individual models such as CNN (75%), RNN (95%), and RBFN (80%). The system processes data from satellite imagery, soil sensors, and climatic parameters to provide real-time predictions for precision agriculture.

Random Forest models have consistently emerged as top performers in agricultural prediction tasks. RF achieved 95% accuracy in crop yield prediction across Karnataka and Maharashtra regions in India, outperforming SVM, multivariate linear regression, ANN, and KNN models (Pande, 2021). Similarly, RF demonstrated 86.35% accuracy in land classification, while SVM achieved 90.47% accuracy in crop prediction based on soil type, precipitation, and environmental variables (Godara & Toshniwal, 2022). The gradient boosting regressor showed 87.90% prediction accuracy, while the Random Forest regressor achieved approximately 98.9% in yield prediction tasks.

Table1. Comparison of ML Models in Agricultural Applications

ML Algorithm	Application	Accuracy	Reference
CNN (PDD-DL)	Plant Disease Detection	98.32%	Kumar et al. (2026)
RFXG Ensemble	Crop Recommendation	98.00%	Iniyan et al. (2025)
Random Forest	Crop Yield Prediction	98.90%	Pande (2021)
BPNN + MSDF-GIS	Soil Health Assessment	92.00%	Patel et al. (2025)
SVM	Crop Prediction	90.47%	Godara & Toshniwal (2022)
YOLOv5	Weed Detection	98.00%	Dang et al. (2023)
XGBoost	Fertilizer Recommendation	94.70%	Rajan et al. (2026)
Custom CNN	Soil Classification	92.88%	Rajan et al. (2026)

4. Precision Irrigation and Water Management

Water scarcity represents one of the most critical constraints on agricultural productivity worldwide. AI-driven smart irrigation systems offer a paradigm shift from traditional irrigation practices by enabling precise, data-driven water management. These systems integrate IoT sensors, weather data, soil moisture monitoring, and ML algorithms to optimize irrigation scheduling, reduce water wastage, and maximize crop water-use efficiency (Karimi & Madasamy, 2024).

Smart irrigation systems (SIS) enhanced with IoT connectivity utilize sensors deployed in agricultural fields to continuously measure soil moisture levels, temperature, humidity, and other environmental parameters. AI algorithms process this real-time data to determine optimal irrigation timing, duration, and volume for specific field zones. Karimi and Madasamy (2024), in collaboration with La Trobe University and the Australian ag-tech company Aglantis, developed an AI-powered smart irrigation system for sugarcane farming that automates water pump management and monitors environmental conditions without human interaction. The system incorporates intelligent sequencing to determine the optimal order of irrigation across different farm sections and continuous learning from historical data and seasonal crop responses.

The integration of predictive analytics with smart irrigation enables proactive water management based on weather forecasts, crop growth models, and evapotranspiration estimates. These systems can automatically adjust irrigation levels based on real-time soil and atmospheric conditions, preventing both overwatering and underwatering. Research indicates that AI-optimized irrigation systems can reduce water consumption by 20–30% compared to conventional irrigation methods while maintaining or improving crop yields (Fuentes-Peailillo et al., 2024). Future advancements are expected to include AI-driven responses to energy tariffs for cost optimization, integration with renewable energy sources, and advanced soil profile analysis for intelligent crop selection.

5. Drone and UAV-Based Crop Monitoring

Unmanned Aerial Vehicles (UAVs) equipped with AI-powered imaging and analytics systems have revolutionized crop monitoring and precision agriculture. Modern agricultural drones carry high-resolution cameras, multispectral sensors, thermal imaging devices, and LiDAR systems that capture comprehensive spatial and spectral data across agricultural landscapes (Walsh, 2025). When combined with AI algorithms, this aerial data enables unprecedented precision in crop health assessment, yield forecasting, nutrient management, and pest detection.

AI-driven drones can identify aphid infestations in wheat fields with over 90% accuracy and create detailed weed maps that enable precision spraying, reducing herbicide use by up to 50% (Walsh, 2025). For yield prediction, drones analyze crop canopy structure, spectral reflectance, and growth trends throughout the growing season. An AI tool integrating satellite and drone data has demonstrated the ability to predict wheat yields with over 90% accuracy. Drone-derived Normalized Difference Vegetation Index (NDVI) measurements have proven more reliable than handheld chlorophyll meters for detecting nutrient responses and predicting yield in winter wheat.

The agricultural drone market is experiencing rapid growth, with projections indicating the market in India alone will reach USD 631.4 million by 2030 (Keymakr, 2025). AI drones provide millimeter-level accuracy in crop monitoring and can cover vast areas efficiently, making them indispensable for large-scale farming operations. Specialized drones such as the CW-15 VTOL equipped with hyperspectral imagers have demonstrated the ability to reduce chemical usage by up to 35% through targeted precision spraying. The economic impact is substantial, with estimates suggesting drones could save corn, soybean, and wheat farmers USD 1.3 billion annually through optimized resource utilization and reduced crop losses.

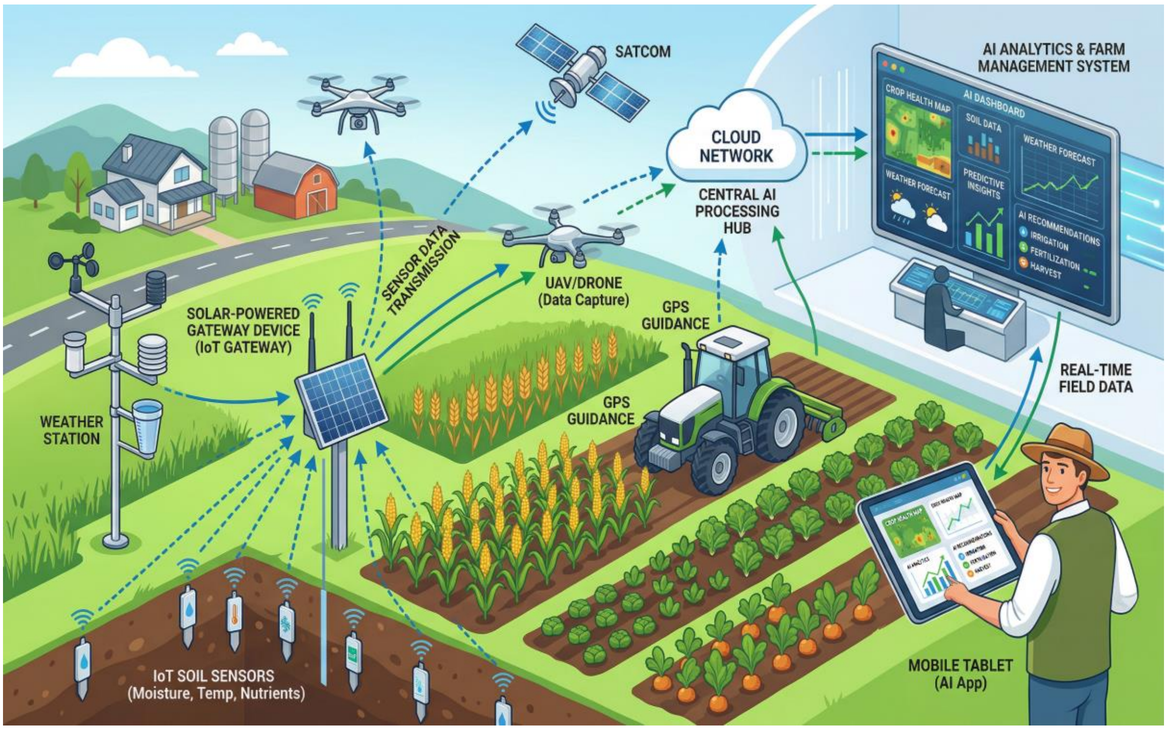

Figure3. IoT and AI Integration in Smart Farming Ecosystem

6. AI-Based Weed Detection and Management

Weed management is a persistent challenge in agriculture, with invasive species competing with crops for nutrients, water, and sunlight, leading to significant yield reductions. Traditional weed control methods involve broadcast herbicide application, which is both economically wasteful and environmentally harmful. AI-powered weed detection systems offer a sustainable alternative by enabling site-specific weed management (SSWM) through automated identification and targeted treatment of individual weeds (Oliveira et al., 2024).

Machine vision and deep learning are the most widely employed ML approaches for weed detection, representing 28% and 19% of all cases, respectively, in a comprehensive systematic literature review (Oliveira et al., 2024). YOLO (You Only Look Once) object detection algorithms, particularly YOLOv5, have shown excellent performance in real-time weed detection across multiple crop species. Dang et al. (2023) established that YOLOv5 achieved the highest accuracy among YOLO variants for detecting invasive species in cotton fields. Research on weed detection in tomato, chili, and cotton crops using YOLOv5 reported F1 scores of 98%, 91%, and 78% respectively, with mean Average Precision (mAP) values of 0.995, 0.947, and 0.811 (Reddy et al., 2025).

Practical applications include smart sprayers that enable site-specific herbicide application, achieving 98% accuracy in targeting weeds while leaving crops unharmed (Raja et al., 2023). Blue River Technology's Smart Sprayer has demonstrated herbicide use reduction of over 90% through precision targeting. Farming robots equipped with AI-powered cameras and CNN models can autonomously navigate fields, identify weeds, and perform mechanical removal or targeted spraying, representing a significant advancement toward fully automated weed management systems.

7. AI in Livestock Health Monitoring

The application of AI in livestock management has transformed animal health monitoring from reactive disease treatment to proactive health management. AI-powered systems utilize wearable sensors, RFID tags, thermal imaging cameras, and IoT devices to continuously monitor physiological parameters, behavioral patterns, and environmental conditions of farm animals (Digi4Live, 2025).

Wearable sensors such as CowManager actively collect real-time data on animal activity, body temperature, heart rate, and daily routines. AI algorithms analyze these data streams to identify subtle deviations from normal behavior patterns that may indicate health issues, including limping, reduced movement, changes in feeding patterns, or early signs of disease. Systems like Connecterra's Ida employ computer vision and ML to monitor animal posture, facial expressions, and activity patterns, identifying subtle signs of discomfort or infection that might be missed by human observation (Digi4Live, 2025).

AI-driven platforms analyze behavioral, visual, and biometric data to detect disease symptoms at both individual and herd levels. By combining daily behavioral data with historical and environmental information, AI systems can predict potential disease outbreaks and recommend preventive actions, enabling early isolation of affected animals and proactive biosecurity management. For precision feeding, AI systems integrated with automated platforms like Lely Vector track feed intake, animal weight, and nutrient conversion efficiency, helping optimize feed schedules while minimizing waste. The Dutch Cattle Expert System by Veepro and the UK-funded BeefTwin project represent notable real-world implementations that demonstrate AI's potential to improve animal welfare, reduce greenhouse gas emissions, and enhance farm profitability.

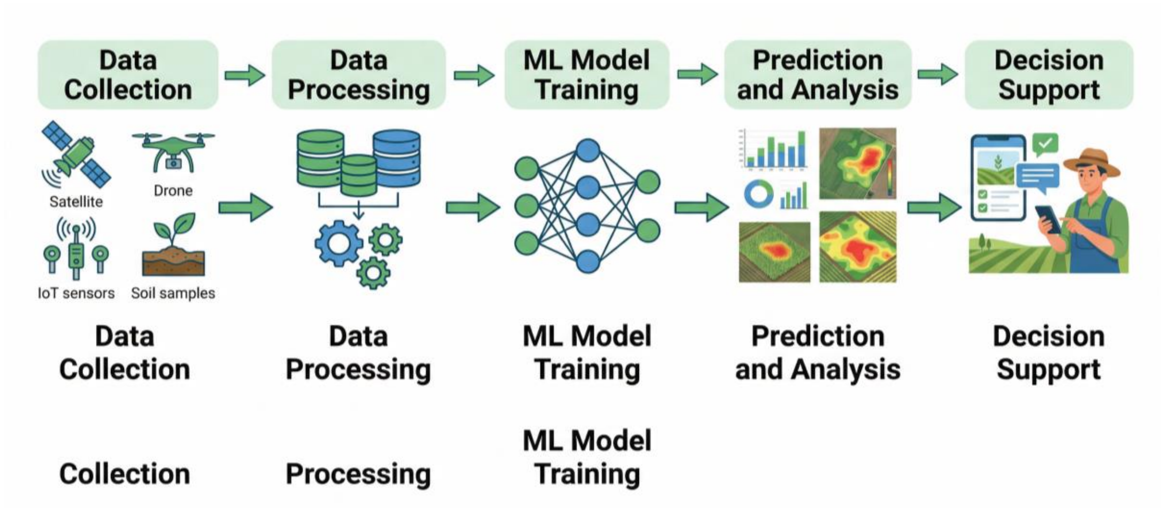

Figure4. Machine Learning Workflow in Precision Agriculture

8. IoT and Remote Sensing Integration with AI

The integration of IoT sensor networks, remote sensing technologies, and AI analytics forms the technological foundation of modern smart agriculture. This convergence enables comprehensive, real-time monitoring of agricultural ecosystems and data-driven decision-making at unprecedented scales (Fuentes-Peailillo et al., 2024).

IoT-based sensor networks deployed across agricultural fields continuously measure critical parameters including soil moisture, temperature, pH, nutrient levels (N, P, K), humidity, and atmospheric conditions. These sensors transmit data through communication protocols such as LoRa, ZigBee, and NB-IoT to cloud-edge computing infrastructure, where ML algorithms process the information to generate predictive insights and management recommendations. The holistic framework proposed by researchers combines IoT sensing with AI-based analytics to achieve precision irrigation, pest and disease forecasting, and optimized resource allocation (Pal et al., 2025).

Remote sensing through satellite platforms such as NASA's Landsat 9 and

ESA's Sentinel-2 provides extensive coverage for large-scale agricultural monitoring. High-resolution satellite imagery enables assessment of soil moisture levels, detection of pest infestations, and monitoring of crop growth patterns. However, limitations including cloud cover, coarse pixel resolution, and delayed data delivery have accelerated the adoption of UAV-based remote sensing, which offers real-time, high-resolution multispectral and near-infrared imaging capabilities. Rajan et al. (2026) proposed an AI-powered Smart Agriculture Prediction System that integrates soil classification using MobileNet-V2 and Custom CNN, crop suggestion using Random Forest (92.4% accuracy), and fertilizer recommendation using XGBoost (94.7% accuracy), with real-time weather data obtained through APIs for dynamic parameter updates.

9. Challenges and Limitations

Despite the remarkable advancements in AI and ML applications for smart agriculture, several significant challenges impede their widespread adoption, particularly in developing countries. The digital divide remains the most fundamental barrier, with many smallholder farmers lacking access to reliable internet connectivity, adequate computing infrastructure, and affordable digital devices necessary for implementing AI-driven agricultural solutions (World Bank, 2025).

The lack of technical expertise and digital literacy among farming communities, particularly in rural areas of developing countries, presents a critical bottleneck. Most smallholder farmers are unfamiliar with AI technologies and require substantial training and support to effectively utilize these systems (Rahman et al., 2025). Financial constraints further compound this challenge, as the high initial investment required for AI hardware, sensors, drones, and software platforms deters adoption by farmers operating on slim profit margins.

Data quality and availability pose significant technical challenges. Effective AI models require large, diverse, and high-quality training datasets that adequately represent the variability in crops, diseases, soil types, and environmental conditions across different regions. Many developing countries lack access to comprehensive, standardized agricultural datasets, and fragmented data collection systems hinder the development of robust, generalizable models. Concerns regarding data ownership, privacy, and security further complicate data sharing and collaborative model development (World Bank, 2025).

Additional challenges include the limited generalizability of models trained on specific crop varieties or geographic regions, the need for continuous model retraining as environmental conditions change, interoperability issues between different technology platforms and sensor systems, and the absence of clear regulatory frameworks governing AI deployment in agriculture. Addressing these challenges requires coordinated efforts from governments, academic institutions, technology developers, and international organizations to build inclusive, accessible, and sustainable AI ecosystems for agriculture.

CONCLUSION

Artificial Intelligence and Machine Learning have demonstrated transformative potential in modernizing agricultural practices and addressing the complex challenges facing global food production systems. This comprehensive review reveals that AI/ML technologies are being successfully applied across virtually every domain of agriculture, from crop disease detection with CNN-based models achieving over 98% accuracy, to crop yield prediction using ensemble methods with 98% recommendation accuracy, to precision irrigation systems that reduce water consumption by 20–30%, and drone-based monitoring systems that cut herbicide usage by up to 90%.

The convergence of IoT sensor networks, remote sensing platforms, and AI-driven analytics has created an integrated smart farming ecosystem capable of real-time monitoring, predictive analysis, and automated decision support. ML algorithms, including Random Forest, Support Vector Machines, XGBoost, and deep learning architectures such as CNNs, RNNs, and YOLO variants, have consistently demonstrated high accuracy across diverse agricultural applications, including disease classification, yield forecasting, weed detection, soil analysis, and livestock health monitoring.

However, realizing the full potential of AI in agriculture requires addressing persistent challenges related to digital infrastructure, technical capacity building, data standardization, financial accessibility, and regulatory governance. The digital divide between developed and developing regions, combined with the lack of digital literacy and technical expertise among smallholder farmers, remains the most critical barrier to equitable technology adoption. Future research should prioritize the development of lightweight, edge-deployable AI models suitable for resource-constrained environments, the creation of open-access agricultural datasets representing diverse agroecological zones, the integration of explainable AI techniques such as SHAP and LIME to enhance farmer trust and model transparency, and the establishment of robust policy frameworks that balance innovation with data privacy and ethical considerations.

As AI and ML technologies continue to evolve and become more accessible, their integration into agricultural systems holds immense promise for achieving sustainable intensification, climate resilience, and food security for a growing global population. The collaborative efforts of researchers, policymakers, technology developers, and farming communities will be instrumental in translating the demonstrated potential of these technologies into widespread, equitable, and impactful agricultural transformation.

Acknowledgements:
The authors acknowledge the support and intellectual contributions of all co-authors in the completion of this manuscript.

Funding:
This research received no specific funding.

Conflict of Interest:
The authors declare no competing interests.

Author Contributions:
Conceptualization, writing, and revision were performed by all authors. All authors approved the final manuscript.

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