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A Review on the Role of IoT and Artificial Intelligence in Smart Agriculture

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ABSTRACT: -

Agriculture today faces big challenges such as growing food demand, changing weather, and limited natural resources. Traditional methods are often not enough to meet these needs. Modern technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) are helping to make farming smarter and more efficient. IoT uses sensors to collect real-time information about soil, water, temperature, and crop health, while AI analyzes this data to give useful predictions and recommendations. Together, these tools support farmers in tasks such as predicting crop yield, detecting plant diseases, improving irrigation, and reducing waste. This paper reviews how IoT and AI are being used in agriculture, the benefits they bring, and the challenges that still exist, such as high costs, poor connectivity, and data security issues. It also discusses future directions like low-cost sensors, edge computing, and blockchain systems that can make these technologies more reliable and accessible. By combining digital tools with farming practices, smart agriculture has the potential to improve productivity, sustainability, and food security for the future.

KEYWORDS: -

Smart Farming

Internet of Things

Artificial Intelligence

Precision Agriculture

Sustainable Farming

INTRODUCTION: -

Agriculture is under pressure due to population growth, unpredictable weather, and shrinking natural resources. Traditional farming methods often fail to meet these challenges in an efficient and sustainable way. Modern technologies are now playing a key role in transforming agriculture into a smarter, data-driven system.

The Internet of Things (IoT) helps farmers by using sensors and devices that monitor soil, water, temperature, and crop conditions in real time. Artificial Intelligence (AI) processes this data to provide meaningful insights such as predicting crop yield, detecting plant diseases, scheduling irrigation, and suggesting the best use of resources. The integration of IoT and AI enables precision farming, reduces waste, and improves overall farm productivity.

These technologies also contribute to sustainable practices by reducing excessive use of fertilizers, saving water, and lowering costs in the long run. Farmers can remotely monitor their fields, make better decisions, and respond quickly to problems. However, challenges remain, such as the high cost of deployment, limited internet connectivity in rural areas, lack of farmer awareness, and concerns about data privacy.

This review paper aims to give a clear overview of how IoT and AI are being applied in agriculture, their strengths and weaknesses, and the future possibilities that can make farming more productive, affordable, and environmentally friendly.

OBJECTIVES: -

The objective of this review paper is to explore the role of modern technologies, particularly the Internet of Things (IoT) and Artificial Intelligence (AI), in transforming agriculture into a smarter and more sustainable system. It aims to provide an overview of how these technologies are applied in key areas such as crop monitoring, disease detection, irrigation management, yield prediction, and farm automation. The paper also seeks to analyze the benefits and limitations of existing approaches, highlighting their impact on productivity, cost-effectiveness, and environmental sustainability. In addition, this review identifies the major challenges and research gaps that limit widespread adoption, including issues related to connectivity, affordability, data security, and farmer awareness. Finally, the paper discusses future directions and emerging solutions such as edge computing, blockchain, and low-cost sensors, with the goal of offering valuable insights for researchers, practitioners, and policymakers working to advance precision agriculture.

METHEDOLOGY: -

The preparation of this review paper followed a structured approach to ensure comprehensive coverage of research on the role of the Internet of Things (IoT) and Artificial Intelligence (AI) in agriculture. A systematic literature review method was adopted, focusing on identifying, selecting, and analyzing relevant studies from reputed scientific sources.

Research articles, review papers, and conference proceedings were collected from digital databases such as IEEE Xplore, Springer, Elsevier (ScienceDirect), MDPI, ACM, and ResearchGate. The selection of papers was limited to publications from 2019 to 2025, as these represent the most recent advancements in smart agriculture technologies. Keywords such as "IoT in agriculture," "AI in farming," "precision agriculture," "smart irrigation," and "crop disease detection using AI" were used to filter relevant works.

After initial collection, duplicate and irrelevant studies were excluded to maintain focus on high-quality research. The remaining papers were further categorized into key themes, including IoT-enabled monitoring systems, AI and machine learning applications, computer vision for crop and disease detection, automation and robotics in agriculture, and integrated IoT–AI frameworks. Each category was analyzed to highlight methodologies, contributions, and limitations.

Comparative analysis tables were prepared to summarize the reviewed works based on parameters such as application area, technology used, algorithms applied, and outcomes achieved. This structured methodology not only ensured an unbiased review but also enabled the identification of research gaps, challenges, and future directions in smart agriculture.

PROBLEM STATEMENT: -

Agriculture is facing significant challenges due to the growing global population, climate change, water scarcity, soil degradation, and unpredictable weather patterns. Traditional farming methods are often inefficient and unable to meet the rising demand for food while ensuring sustainability. Farmers frequently struggle with issues such as low crop yield, pest infestations, improper irrigation, and delayed disease detection, which result in economic losses and reduced productivity.

Although modern technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) have the potential to address these challenges, their adoption is limited due to factors such as high implementation costs, lack of technical expertise among farmers, poor connectivity in rural areas, and limited access to real-time agricultural data. Moreover, existing solutions often lack integration, are not scalable, or are designed for specific crops or regions, which restricts their widespread applicability.

This paper addresses the need to explore and understand how IoT and AI can be effectively applied to agriculture to improve productivity, resource efficiency, and sustainability. It highlights the current technological gaps and challenges, providing a foundation for future research aimed at developing practical, affordable, and scalable smart farming solutions.

LITERATURE SURVEY: -

1. IoT Platforms & Low-cost Agricultural Sensing

Singh et al. (2019) — ESP8266 with soil moisture sensors for smart irrigation; threshold-based relay control; water savings 35–45%; low cost; limitation: simple threshold logic.

Raut & Kale (2018) — Ultrasonic water-level sensing for irrigation; microcontroller-based; reliable detection, small footprint; limitation: local-only logic, no cloud logging.

Zhang et al. (2020) — LoRaWAN-based sensor networks for large fields; low-power, long-range; limitation: lower throughput, complex gateways.

Patil et al. (2021) — Multi-sensor IoT network for temperature, humidity, and pH monitoring; supports precision irrigation; limitation: requires calibration for each soil type.

Chandra et al. (2022) — Wireless sensor network with soil nutrient monitoring; real-time recommendations; limitation: dependency on internet connectivity for cloud processing.

Liang et al. (2020) — Multi-sensor IoT deployment for greenhouse control; automation of light, humidity, and temperature; limitation: high initial setup cost.

2. Machine Learning for Crop Disease Detection & Prediction

Patel et al. (2020) — CNN for tomato leaf disease classification; transfer-learned ResNet50; ~95% accuracy; limitation: field conditions impact accuracy.

Khan et al. (2021) — Multimodal disease prediction combining leaf images and climatic data; ensemble classifier; improved recall; limitation: high computational demand.

Sanchez et al. (2019) — Lightweight CNNs (MobileNet) for edge devices; 80–90% accuracy; low latency; limitation: slightly lower accuracy than large CNNs.

Mishra et al. (2020) — Random Forest + environmental sensor features for early disease detection; robust under noisy data; limitation: model requires site-specific calibration.

Wang et al. (2021) — CNN-based detection of fungal diseases in wheat; high accuracy using UAV images; limitation: drone flight limitations and high-resolution imagery needed.

Sharma et al. (2022) — Deep learning model for pest classification from crop images; accuracy >92%; limitation: requires annotated datasets.

3. Time-series Forecasting & Predictive Irrigation

Lopez & Merino (2020) — LSTM networks for soil moisture prediction 24–72 hours ahead; useful for irrigation planning; limitation: requires historical site-specific data.

Fernandez et al. (2022) — Reinforcement learning for irrigation optimization; RL agent reduces water use while maintaining crop health; limitation: data-hungry, risky in real farm trials.

Ahmed et al. (2021) — ARIMA + sensor data for irrigation scheduling; improves water efficiency; limitation: less adaptive to sudden weather changes.

Gao et al. (2022) — Predictive modeling of crop water stress using ensemble ML models; reduces over-irrigation; limitation: complex model training.

4. Computer Vision for Crop Monitoring

Kumar & Singh (2020) — Drone-based imaging + CNN for early disease detection; 94% accuracy; limitation: lighting and occlusion sensitivity.

Sengupta et al. (2021) — CNN for tomato leaf disease classification; 96% accuracy; limitation: requires high-quality images.

Li et al. (2021) — UAV imagery + deep CNN for weed detection; enables precision herbicide spraying; limitation: high-resolution drone imagery needed.

Ahmed et al. (2022) — Drone + CNN for large-scale field disease detection; rapid monitoring; limitation: high initial investment.

Gao et al. (2023) — Edge AI for real-time pest detection; reduces latency compared to cloud processing; limitation: edge devices have limited memory and compute.

5. Automation & Robotics in Agriculture

Das et al. (2020) — Mobile app-based deep learning for pest identification; user-friendly; limitation: requires good network connectivity.

Wang et al. (2021) — Edge-computing framework for greenhouse automation; real-time decision-making; limitation: high initial deployment cost.

Patel & Shah (2021) — IoT + AI hybrid system for precision irrigation; reduced water consumption 20–30%; limitation: limited scalability.

Singh et al. (2022) — Robotic weed remover with AI vision; reduces labor cost; limitation: high cost for small-scale farms.

Chauhan et al. (2020) — Automated irrigation and fertilization system using IoT and ML; improved efficiency; limitation: needs continuous monitoring.

6. Integrated IoT-AI Frameworks & Advisory Systems

Ahmed & Roy (2021) — Integrated IoT-AI crop monitoring framework; real-time alerts; limitation: requires stable connectivity.

Fernandez et al. (2022) — AI + sensor fusion for predicting irrigation needs; reduces water waste; limitation: requires large historical datasets.

Kumar et al. (2021) — Rule-based and retrieval chatbots for farmers; increased engagement; limitation: generic advice, no sensor integration.

Joshi et al. (2022) — Voice-enabled advisory system in local languages; improves accessibility; limitation: limited intelligence and personalization.

Nguyen et al. (2023) — Retrieval-augmented generation (RAG) for domain-specific advisory; improved accuracy; limitation: requires curated knowledge base and monitoring.

Gupta et al. (2022) — Review on smart farming ecosystems; highlights integration and cost barriers; limitation: high-level survey without deployment details.

Park & Lee (2021) — End-to-end smart farm prototype (sensors → cloud → mobile app); pilot adoption improved with training; limitation: small pilot, no ML advisory included.

7. Key Insights & Challenges

- IoT platforms reduce water usage and improve monitoring but require calibration and stable connectivity.
- Machine learning models (CNN, LSTM, Random Forest, ensemble methods) improve disease detection, yield prediction, and irrigation scheduling.
- Computer vision and UAV/drone-based imaging enable rapid, precise assessment of crop health.
- Automation and robotics reduce labor dependency, but high initial costs remain a barrier.
- Integrated IoT-AI frameworks and advisory systems enhance decision-making but need curated data, cloud/edge support, and multilingual access for farmers.
- Common limitations include high setup costs, model generalization issues, network dependency, and limited accessibility in low-resource settings.

RESEARCH GAP: -

Limited Integration of Multi-Modal Data – Many studies focus either on image-based crop disease detection or sensor-based environmental monitoring. Few frameworks effectively combine UAV imagery, sensor telemetry, and climatic data for holistic crop health assessment.

Scalability Challenges – Several IoT platforms, including low-cost sensor networks, work well in small-scale or controlled environments but face challenges in large-field deployments due to network range, data throughput, and power constraints.

Data Scarcity and Quality – Machine learning models, especially deep learning-based disease classifiers, require large, annotated datasets. Lack of standardized datasets across diverse crops and geographic regions limits model generalization and robustness in real-world conditions.

Real-Time Decision Making and Edge Computing – Most AI-based frameworks rely on cloud processing, which introduces latency and requires continuous internet connectivity. There is a gap in lightweight, real-time edge AI solutions for on-farm decision-making under limited connectivity.

Predictive and Adaptive Irrigation – While LSTM and reinforcement learning models show promise for irrigation scheduling, few systems have been deployed in real farms. Challenges include data-hungry models, seasonal drift, and risk during exploration in reinforcement learning.

Farmer-Friendly Interfaces and Accessibility – Chatbots and advisory systems often lack contextual personalization, sensor integration, or multilingual support, limiting adoption among low-literacy and resource-constrained farmers.

Cost and Resource Constraints – High initial setup costs for IoT sensors, drones, edge AI devices, and automation systems remain a major barrier for small and medium-scale farms. Affordable, modular, and energy-efficient solutions are still lacking.

Integration of Automation and AI – While robotics and automated irrigation systems exist, there is limited research on fully integrated frameworks that combine AI predictions, IoT sensing, and automated interventions in a seamless, adaptive manner.

CHALLENGES AND LIMITATIONS:-

High Implementation Costs – Deploying IoT sensors, UAVs/drones, edge AI devices, and robotic systems can be expensive. Small and medium-scale farmers often cannot afford such solutions, limiting accessibility and scalability.

Connectivity and Network Limitations – Many IoT systems rely on stable internet connectivity for cloud-based processing. In rural or remote areas, poor network coverage reduces system reliability and limits real-time monitoring and decision-making.

Data Scarcity and Quality Issues – Machine learning models, especially deep learning-based disease detection systems, require large, annotated datasets. Availability of high-quality data across different crops, regions, and environmental conditions remains a major challenge.

Sensor and Device Limitations – IoT sensors are prone to calibration drift, environmental interference, and maintenance issues. Low-cost sensors may sacrifice accuracy, while high-precision sensors increase system cost.

Model Generalization and Adaptability – AI models trained on specific datasets often fail to generalize across different farms or environmental conditions. Seasonal variations, soil types, and crop diversity make it difficult to deploy a single predictive model universally.

Real-Time Decision-Making Constraints – Cloud-based AI processing introduces latency. Edge AI solutions exist but are limited by memory, compute capacity, and energy constraints, making real-time adaptive irrigation or disease prediction challenging.

Limited Integration Across Platforms – Most existing systems address specific aspects of farming, such as irrigation, disease detection, or yield prediction, rather than providing a fully integrated framework combining IoT sensing, AI analytics, and automated interventions.

User Accessibility and Adoption – Farmer adoption is hindered by limited technical knowledge, low digital literacy, and language barriers. Advisory systems, chatbots, and mobile interfaces need to be intuitive, multilingual, and context-aware to ensure usability.

Security and Privacy Concerns – IoT-enabled farms generate large amounts of sensitive data, including soil, crop, and environmental information. Data storage, transmission, and cloud processing raise concerns regarding privacy, security, and misuse.

Sustainability and Energy Constraints – Continuous operation of sensors, drones, and automated systems requires power. In resource-constrained environments, energy efficiency and sustainable operation remain key challenges.

CONCLUSION: -

IoT and AI technologies have greatly enhanced crop monitoring, disease detection, and irrigation management in agriculture. Despite their benefits, challenges such as high costs, connectivity issues, data limitations, and adoption barriers persist. Future research should focus on scalable, affordable, and integrated IoT-AI frameworks with real-time decision-making, improved data quality, and farmer-friendly interfaces to achieve sustainable and precision agriculture.

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