



AI AND IOT APPLICATIONS IN SMART AGRICULTURE

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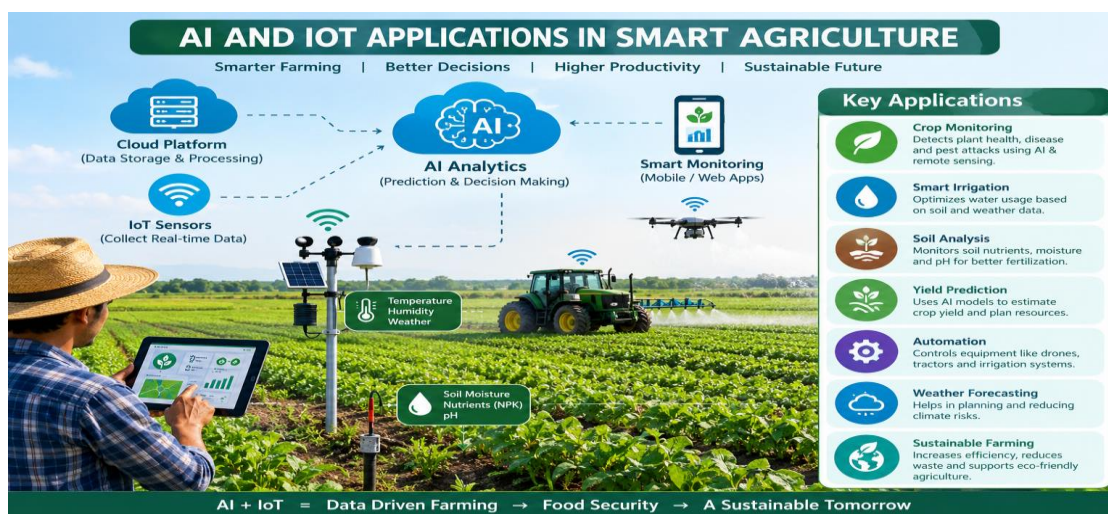
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Abstract: Smart agriculture is evolving from conventional, experience-based farming toward data-driven and automated decision making. The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT), often termed Artificial Intelligence of Things (AIoT), enables continuous sensing, communication, prediction and control across the agricultural lifecycle. IoT devices collect soil moisture, temperature, humidity, nutrient, weather and crop-condition data, while AI models transform these observations into recommendations or automated actions. Recent studies show applications in precision irrigation, crop and yield prediction, soil and nutrient management, pest and disease detection, greenhouse and hydroponic control, weed management, livestock monitoring, post-harvest management and climate-smart farming. This paper reviews research published, Summarizes major AI-IoT approaches, identifies gaps in scalability, interoperability, data quality, connectivity, explainability, cyber security and smallholder adoption, and outlines future directions involving edge AI, federated learning, digital twins, 5G/6G, low-cost virtual sensing and multimodal foundation models. The evidence indicates that AI-IoT can improve resource efficiency and resilience, but practical deployment requires affordable, robust and farmer-centered systems rather than isolated laboratory prototypes.

Keywords: Artificial Intelligence, Internet of Things, AIoT, Smart Agriculture, Precision Agriculture, Machine Learning, Edge Computing, Crop Monitoring, Smart Irrigation

I. INTRODUCTION



Agriculture must increase productivity while coping with water scarcity, climate variability, soil degradation, labor constraints and growing food demand. Conventional farming often depends on periodic field inspection and generalized decisions, which can miss rapid changes in soil, weather and crop health. Smart agriculture addresses this limitation by combining sensing, communication, analytics and automation. IoT provides the physical and communication layer: sensors and connected devices measure field conditions and transmit observations to gateways, edge nodes or cloud



platforms. AI provides the intelligence layer by learning relationships in these observations and supporting prediction, classification, anomaly detection and optimization.

The recent literature describes AIoT as a particularly promising architecture because the value of AI depends on timely and reliable data, while IoT systems need intelligent interpretation to become decision-support systems. Reviews published in report applications ranging from crop monitoring and disease detection to irrigation, nutrient management, supply-chain activities and climate-smart agriculture. AI-IoT integration also supports automated robots, remote sensing, high-throughput phenotyping and digital decision support. However, adoption remains constrained by sensor reliability, connectivity, data heterogeneity, security, cost, technical skills and limited validation across diverse farms.

This paper therefore examines the research trajectory and focuses on how AI and IoT work together rather than treating them as separate technologies. The review emphasizes application areas, common methods, research gaps and future directions relevant to sustainable and scalable smart farming.

II. LITERATURE SURVEY

Research are the established the importance of IoT sensor networks, machine learning, remote sensing and computer vision for precision agriculture. Early systems generally focused on individual tasks such as environmental monitoring, irrigation control, crop classification or disease recognition. The emphasis was on proving that sensor data and predictive models could improve decisions compared with manual practices.

The literature increasingly uses the AIoT concept to describe an integrated architecture. Recent reviews identify AI-based image analysis, predictive analytics, edge / cloud computing and connected sensor networks as complementary components. Kasera et al. Organized applications across pre-harvest, harvest and post-harvest activities and highlighted limitations in devices, datasets, security and methodologies. Another 2024 review reported that AI-IoT integration is being combined with high-throughput phenotyping, remote sensing, agricultural robots and 5G/6G connectivity.

The literature moves toward sustainability and deployment. Reviews discuss AIoT for smart irrigation, nutrient and disease management, soil health and agricultural carbon monitoring. Newer research also investigates virtual sensors that use AI models to estimate environmental variables where deploying physical sensors at every location would be expensive. This direction is important for small and medium-sized farms because field-scale sensing density can otherwise become a major cost.

Overall, the literature demonstrates a shift from monitoring-only systems to closed-loop intelligent systems in which sensing, prediction and actuation are connected. Nevertheless, many studies remain experimental, use limited datasets or evaluate a single crop and location. More longitudinal field trials, standardized datasets, interoperability standards and human-centered evaluations are needed before AIoT systems can be considered broadly deployable.

II.1 EXISTING LITERATURE RESEARCH

Author / Year	Observation	AI / IoT Approach	Key Contribution	Need
2020–2022 studies	Precision monitoring & control	IoT sensors + ML	Established sensor-driven decision support	Often task-specific and small-scale
Kumar et al. (2023)	AIoT in smart agriculture	AI + connected devices	Systematic view of applications and barriers	More real-world validation needed
Kasera et al. (2024)	Pre-, during- and post-harvest	IoT, AI, edge/cloud, 5G	Broad lifecycle survey and 5G framework	Dataset, security and device issues
2024 crop-monitoring review	Crop health & automation	AI, IoT, remote sensing, robots	Real-time crop monitoring and management	Scalability and diverse conditions
2024 hydroponic study	Crop recommendation & nutrients	AIoT sensors + prediction	Integrated nutrient monitoring/recommendation	Controlled-environment emphasis
2025 soil review	Soil health	NPK/pH/moisture	Low-cost, data-driven soil	Sensor accuracy



		sensors + AI	management	and connectivity
Bayar et al. (2025)	Irrigation, nutrients, disease	AIoT + edge/cloud + sensing	Precision management across three domains	Cost, rural connectivity, security
2025 virtual sensors	Environmental sensing	IoT data + ML virtual sensing	Reduces dependence on dense physical sensors	Needs broader field validation
2025 AIoT irrigation	Drought & water stress	LSTM + AIoT + hyperspectral data	High-accuracy water-stress prediction	Complex data and deployment needs
2025 IoT/AI/Big Data review	Climate-smart agriculture	IoT + Big Data + AI	Carbon monitoring and sustainability	Integration and measurement challenges

III. RESEARCH GAP

Despite rapid growth, five major gaps remain. First, interoperability is weak: sensors, gateways, cloud services and AI models frequently use different protocols and data structures. Second, data quality is inconsistent because sensors drift, fail, become contaminated or operate under changing field conditions. Third, many AI models are trained on narrow datasets, so performance can fall when crop varieties, climates, soils or imaging conditions change. Fourth, deployment costs and unreliable rural connectivity limit adoption by smallholder farmers. Fifth, privacy, cybersecurity, model explainability and farmer trust are insufficiently addressed in many prototypes.

There is also a validation gap. Reported accuracy is often obtained from curated datasets rather than multi-season field trials. Future research should report not only model accuracy but also water saved, fertilizer reduction, yield stability, energy consumption, maintenance cost, false-alarm rate and farmer usability. Such metrics would make studies more comparable and better reflect agricultural value.

IV. MOTIVATION

The motivation for AI-IoT smart agriculture is to convert continuous field observations into timely and actionable decisions. Instead of applying the same irrigation or fertilizer rate to an entire field, an intelligent system can identify spatial and temporal differences and recommend site-specific actions. Early disease or stress detection can reduce crop losses and unnecessary pesticide use. Predictive analytics can also help farmers anticipate weather-related risks and schedule operations.

A second motivation is sustainability. Agriculture is a major user of water, fertilizers, energy and land. AI-assisted optimization can support more precise resource allocation, while IoT provides the measurements needed to verify whether interventions are effective. This makes AI-IoT relevant not only to productivity but also to climate resilience, resource conservation and food security.

V. APPLICATIONS OF AI AND IOT IN SMART AGRICULTURE

V.I SMART IRRIGATION AND WATER MANAGEMENT

Soil-moisture, temperature, humidity, rainfall and weather sensors can continuously monitor water conditions. AI models such as regression, random forests and LSTM networks can estimate crop water demand and predict stress. The resulting decision can trigger pumps or valves automatically, enabling variable and demand-based irrigation rather than fixed schedules.

V.II CROP DISEASE AND PEST DETECTION

IoT cameras, mobile devices, drones and environmental sensors generate images and contextual data. Convolutional neural networks and newer vision models can classify symptoms, while sensor data can provide temperature and humidity conditions associated with disease risk. Combining visual and environmental evidence can improve early warning and support targeted treatment.

**V.III SOIL AND NUTRIENT MANAGEMENT**

IoT probes can measure moisture, pH, electrical conductivity and NPK-related parameters. AI models can estimate nutrient status, recommend suitable crops or fertilizer rates, and identify zones requiring intervention. AIoT-based nutrient recommendation is particularly useful when measurements are collected continuously and compared with historical and agronomic datasets.

V.IV YIELD PREDICTION AND CROP MONITORING

Yield models combine weather, soil, satellite/drone imagery, crop growth indicators and historical yield records. Machine learning can detect patterns that are difficult to derive manually. Continuous monitoring supports estimation of crop development and enables farmers to adapt irrigation, nutrients and protection strategies.

V.V GREENHOUSE AND HYDROPONIC AUTOMATION

In protected cultivation, IoT sensors can monitor temperature, humidity, light, pH and nutrient concentration. AI can learn suitable environmental ranges and recommend or automatically control ventilation, lighting, irrigation and nutrient delivery. Hydroponic AIoT systems are especially suited to closed-loop control because the growing environment can be monitored more tightly.

V.VI ROBOTICS, WEED AND HARVEST MANAGEMENT

Connected agricultural robots can use cameras, GPS and proximity sensors to navigate fields. AI-based vision supports weed detection, crop counting, fruit identification, selective spraying and harvesting assistance. IoT connectivity enables remote monitoring of machine status and coordination among devices.

V.VII LIVESTOCK AND POST-HARVEST MANAGEMENT

Wearable sensors and connected cameras can monitor animal activity, location, temperature and feeding behavior, supporting early detection of abnormal conditions. After harvest, IoT sensors can track temperature, humidity and storage conditions, while AI can predict spoilage risks and optimize logistics.

VI. CONCLUSION

AI and IoT together provide a foundation for intelligent, connected and increasingly autonomous agriculture. IoT supplies continuous observations from fields, equipment, crops, animals and storage environments, while AI converts these data into predictions, classifications and recommendations. The literature shows substantial progress in irrigation, disease detection, nutrient management, crop monitoring, greenhouse automation, robotics and sustainability applications.

However, successful smart agriculture cannot be measured by algorithmic accuracy alone. Systems must operate reliably in noisy field conditions, remain affordable, protect data, work with heterogeneous devices and provide understandable recommendations. Future implementations should therefore combine technical performance with agronomic, economic and social evaluation. AIoT is most valuable when it reduces resource waste and risk while helping farmers make better decisions.

VII. FUTURE DIRECTIONS

Future research should prioritize edge AI so that important predictions can be made locally with low latency and limited internet dependence. Federated learning can allow models to learn from distributed farms without centralizing sensitive raw data. Digital twins can connect real-time sensor streams with virtual representations of fields, greenhouses or livestock systems for simulation and optimization. 5G and emerging 6G networks may support high-bandwidth robotics and real-time sensing where infrastructure is available.



Another important direction is multimodal AI, which combines sensor streams, satellite imagery, photographs, weather forecasts and farm records in a single decision model. Low-cost virtual sensors can reduce the number of physical devices required, while self-calibration and fault-detection methods can improve reliability. Explainable AI and farmer-centered interfaces should also become standard so users can understand why an irrigation or disease recommendation was generated. Finally, research should focus on open datasets, reproducible benchmarks, interoperability standards, cybersecurity-by-design and multi-year field trials across different crops and regions.

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