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Artificial Intelligence and Internet of Things in Agriculture: A Comprehensive Review of Challenges, Opportunities and Future Directions

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Abstract

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) is transforming agriculture into a data-driven, automated, and sustainable domain. By integrating intelligent analytics with sensor-rich environments, smart agriculture aims to optimize crop yields, resource utilization, and food supply chains. This review critically examines recent developments in AI-enabled IoT for agriculture, highlighting architectures, algorithms, applications, and implementation challenges. We synthesize insights from more than forty-five scholarly works (2020–2025) and provide a thematic analysis of research trends. Particular attention is given to connectivity constraints, interoperability gaps, cybersecurity risks, and socio-economic barriers that hinder adoption. Comparative evaluations of existing IoT-AI frameworks demonstrate notable improvements in precision farming, yet reveal persistent limitations in scalability, explainability, and energy efficiency. The paper identifies research opportunities in edge/fog computing, federated learning, explainable AI (XAI), and blockchain-enabled trust frameworks. By offering a comprehensive synthesis of progress and open challenges, this review positions AI-driven IoT as a cornerstone for Agriculture 5.0 and provides guidance for researchers, policymakers, and practitioners working toward resilient, inclusive, and sustainable food systems.

Keywords: Smart Agriculture, Artificial Intelligence, Internet of Things, Precision Farming, Machine Learning, Cybersecurity, Agriculture 5.0

1. INTRODUCTION

Agriculture is the backbone of human civilization and remains one of the most resource-intensive sectors worldwide. Growing population pressures, climate variability, and limited arable land continue to challenge global food security. Traditional agricultural practices often rely on human experience, intuition, and seasonal patterns, which can lead to inefficiencies in water consumption, fertilizer application, and pest management. The emergence of the Internet of Things (IoT) and Artificial Intelligence (AI) offers a paradigm shift toward evidence-based, automated, and adaptive farming practices.

The IoT ecosystem in agriculture involves interconnected sensors, actuators, communication protocols, and cloud/edge infrastructures. These devices capture real-time data such as soil moisture, nutrient composition, temperature, humidity, and crop growth indicators. AI algorithms—ranging from classical machine learning to advanced deep neural networks—enable predictive modeling, anomaly detection, and decision support based on these heterogeneous datasets. Together, AI and IoT pave the way for precision agriculture, where resources are applied only where and when needed, significantly improving efficiency and sustainability.

Despite rapid progress, adoption of AI-IoT solutions in agriculture remains uneven. Rural areas often lack reliable connectivity, while farmers face financial and educational barriers to deploying advanced systems. Interoperability challenges between heterogeneous devices, security vulnerabilities in data exchange, and the absence of clear standards further limit scalability. Additionally, AI models often function as “black boxes,” raising questions of transparency and trust in automated recommendations.

Several review articles have attempted to summarize the state of AI and IoT in agriculture. However, most either emphasize technical aspects of IoT architectures or narrowly focus on AI-based crop monitoring without providing a holistic synthesis across infrastructure, algorithms, and socio-economic barriers. This paper addresses that gap by presenting a comprehensive review of the AI-IoT ecosystem in agriculture, organized around five dimensions:

1. IoT frameworks and architectures for agriculture.
2. AI algorithms and applications across crop health, irrigation, and supply chain.
3. Comparative analysis of existing solutions in terms of performance, cost, and scalability.
4. Challenges and limitations across technical, economic, and social domains.
5. Future research directions toward sustainable, explainable, and inclusive Agriculture 5.0.

By systematically analyzing both technical and contextual factors, this paper not only consolidates existing knowledge but also highlights actionable pathways for researchers and practitioners. The contributions of this review are threefold:

To map the current landscape of AI-IoT in agriculture through an integrated taxonomy.
To evaluate strengths and weaknesses of state-of-the-art systems with comparative evidence.
To outline promising future directions including edge intelligence, explainable AI, federated learning, and blockchain-based trust models.

2. BACKGROUND AND FUNDAMENTALS

2.1 Smart Agriculture and Agriculture 5.0

Agriculture has evolved from traditional manual practices to mechanization (Agriculture 2.0), digital automation (Agriculture 3.0), and data-driven precision farming (Agriculture 4.0). The current trajectory often referred to as Agriculture 5.0 envisions fully intelligent and sustainable systems where IoT, AI, robotics, cloud computing, and blockchain integrate seamlessly. The goal is not only to maximize productivity but also to ensure **climate resilience, sustainability, and inclusivity**. Agriculture 5.0 emphasizes reducing environmental footprints, empowering smallholder farmers, and leveraging ethical AI for equitable resource distribution.

2.2 Internet of Things (IoT) in Agriculture

The IoT provides the technological backbone for data collection and connectivity in smart farming. Its components include:

Sensing Devices: Soil sensors, drones, weather stations, and camera modules that monitor moisture, nutrient levels, plant stress, and pest activity.

Connectivity Technologies: Short-range protocols (Zigbee, Bluetooth Low Energy), long-range solutions (LoRaWAN, NB-IoT), and cellular standards (4G, 5G) that ensure data transfer even in remote rural areas.

Data Platforms: Cloud-based and edge/fog infrastructures that store and process raw sensor streams into actionable insights.

Actuators: Devices that automate irrigation pumps, fertilizer dispensers, and climate control in greenhouses based on AI-driven decisions.

IoT-enabled agriculture enables farmers to adopt **precision farming** by applying resources in targeted ways, thereby reducing waste and increasing yields. However, the success of IoT depends on robust communication infrastructure, secure protocols, and energy-efficient devices.

2.3 Artificial Intelligence in Agriculture

AI complements IoT by converting raw sensor data into predictive and prescriptive insights**.** Common AI techniques in agriculture include:

Machine Learning (ML): Algorithms such as Support Vector Machines, Random Forests, and k-Nearest Neighbors are used for disease detection, yield estimation, and classification tasks.

Deep Learning (DL): Convolutional Neural Networks (CNNs) process crop images for disease and pest detection; Recurrent Neural Networks (RNNs) and Transformers analyze time-series data for weather and yield prediction.

Reinforcement Learning (RL): Adaptive irrigation and resource allocation strategies that learn optimal policies over time.

Natural Language Processing (NLP): Tools that process unstructured agricultural data such as farmer queries, advisory services, or even social media reports on crop health.

Hybrid AI Models: Combining DL with evolutionary algorithms or fuzzy logic to handle uncertainty and heterogeneity in agricultural datasets.

2.4 AI-IoT Synergy in Smart Agriculture

The synergy between AI and IoT creates a closed-loop system**:** IoT sensors capture real-time data AI algorithms analyze and predict Actuators implement decisions. This continuous cycle enables autonomous farming ecosystems**.** For instance, CNNs trained on drone images can detect nutrient deficiencies, while IoT-enabled irrigation systems automatically adjust water levels in real time.

However, deploying such intelligent loops faces constraints:
Hardware limitations of low-power IoT devices.
Latency issues in transmitting and processing data at central servers. Security vulnerabilities during data transfer. Explainability gaps**,** where farmers may not trust AI models that provide opaque recommendations.

2.5 Importance of Reviewing AI-IoT for Agriculture

While individual studies showcase promising results, there is fragmentation across methodologies, datasets, and platforms. Some works emphasize computer vision for disease detection, others focus on IoT-enabled irrigation, but few integrate technical, economic, and social perspectives. This review therefore provides a holistic lens by synthesizing across these diverse dimensions, helping researchers, policymakers, and practitioners understand both the state of the art and the gaps that need urgent attention**.**

3. REVIEW OF LITERATURE

Recent studies demonstrate IoT's ability to optimize water management, monitor crop health, and enhance supply chain transparency. Blockchain has been leveraged for secure agri-logistics, while machine learning improves yield prediction. However, heterogeneity in devices, lack of standardization, and vulnerability to cyberattacks remain recurring concerns. Research further emphasizes the need for cost-effective solutions adaptable to diverse agricultural environments.

A. Infrastructure and Connectivity

A major bottleneck for IoT adoption in agriculture is the lack of reliable internet and power infrastructure in rural and remote regions. While urban and peri-urban farms can leverage 4G/5G connectivity, many rural zones still rely on unstable 2G/3G networks or have no connectivity at all. This limits real-time monitoring and decision-making. Furthermore, frequent power outages or the absence of grid electricity complicates the operation of IoT devices that rely on continuous energy supply.

Although long-range low-power communication protocols like LoRaWAN and NB-IoT are well-suited for agriculture (low bandwidth but high coverage, ideal for sensor data), they remain underutilized due to lack of infrastructure investment, standardization, and awareness. Satellite Io services are emerging as alternatives, but cost barriers and latency issues remain concerns.

B. Security and Privacy

IoT systems in agriculture are highly vulnerable to cyberattacks because of their distributed nature and use of low-power, resource-constrained devices. Common risks include:

Weak authentication protocols, making it easier for unauthorized users to access sensors or gateways. Unencrypted data transmission, leading to interception of sensitive farm or supply-chain data. Cloud misconfigurations, where poor access controls leave large datasets exposed.
In addition to technical risks, privacy concerns emerge when GPS-enabled IoT devices monitor machinery, livestock, or even farmworkers. This raises ethical questions about data ownership, surveillance, and misuse by corporations or third parties. Cybersecurity solutions like blockchain-based authentication, federated learning, and end-to-end encryption are being explored, but their implementation in cost-sensitive, resource-constrained farms remains limited.

C. High Costs and ROI

The economic barrier is one of the most pressing challenges for smallholder farmers, especially in low- and middle-income countries. IoT adoption requires upfront investments in:Sensors and actuators (for soil, water, climate monitoring),Cloud services or edge gateways,Maintenance and upgrades Table 1 represents the existing system models along with their techniques, findings, strengths, limitations, and recommendations.

4. CHALLENGES AND LIMITATIONS

Despite significant advancements in AI-IoT applications for agriculture, large-scale deployment remains restricted by a number of barriers. These limitations can be grouped into five broad categories: connectivity and infrastructure, cybersecurity and privacy,

4.1 Connectivity and Infrastructure Gaps

Reliable connectivity forms the foundation of IoT-based agriculture. However, rural and remote agricultural regions often lack stable internet access and consistent power supply, limiting the reach of cloud-enabled smart farming solutions. Traditional cellular networks are frequently unavailable or costly in sparsely populated areas. While long-range communication technologies such as LoRaWAN, NB-IoT, and Sigfox show promise, adoption remains limited due to high deployment costs and lack of awareness among farmers. Moreover, IoT devices in agriculture are generally deployed in harsh environmental conditions (dust, heat, humidity), leading to frequent hardware failures.

Reference	Method Used	Findings	Strengths	Limitations	Recommendations to Overcome Limitations
[1] Majumdar et al. (2024)	Survey and trend analysis of 5G, UAV IoT integration, and AI solutions	Established the pivotal role of 5G and UAV-based IoT for ultra-low latency data flow essential for iterative deep-learning optimization in Agriculture 4.0.	Comprehensive synthesis of connectivity and AI trends; focuses on low-power and scalable communication.	Lacks empirical validation of the proposed multi-layer connectivity models.	Conduct field-level pilot deployments of 5G-UAV integrated iterative learning systems to validate scalability and reliability.
[2] Singh et al. (2025)	IoT field tracking model with fog computing	Demonstrated that fog-based distributed intelligence reduces latency and bandwidth, enabling rapid iterative model updates for irrigation and crop monitoring.	Robust real-time architecture with energy-efficient fog nodes.	Limited consideration of heterogeneous sensor failures in harsh agricultural settings.	Integrate redundancy and self-healing mechanisms with federated learning to handle sensor node failures dynamically.
[3] Li et al. (2025)	UAV space-air-ground integrated IoT network prototype	Provided high-resolution spatio-temporal data capture across challenging terrain, supporting iterative deep-learning models for grazing management.	Novel space-air-ground integration; robust in remote environments.	Limited to grazing applications and lacks cross-crop generalization.	Extend framework to multi-crop contexts and embed adaptive deep-learning layers for diversified agricultural use.
[4] Sallam et al. (2025)	AI-based robust framework for smart cities	Showed that scalable AI service orchestration can be repurposed for agricultural environments requiring high adaptability and real-time decision-making.	Strong emphasis on service orchestration and fault tolerance.	Primarily urban-focused; limited agricultural validation.	Tailor framework to rural agricultural infrastructures and incorporate crop-specific predictive layers.
[5] Singh & Sharma (2024)	Comprehensive review of IoT in precision agriculture	Consolidated best practices for IoT deployment, highlighting sensor-driven iterative data loops critical for real-time agricultural optimization.	Rich synthesis of IoT-enabled precision farming; identifies sensor and connectivity bottlenecks.	Descriptive rather than experimental; lacks deep-learning integration details.	Incorporate iterative deep-learning design patterns and case studies to demonstrate closed-loop optimization.
[6] Mohy-eddine et al. (2024)	Artificial neural network for malicious detection	Showed ANN-based anomaly detection can secure iterative spatio-temporal learning pipelines from cyber intrusions.	High detection accuracy; lightweight enough for edge deployment.	May fail under zero-day attacks or novel adversarial inputs.	Augment with generative adversarial networks and continuous model retraining to detect unseen threats.
[7] Manna et al. (2025)	Feature-extraction-based supervised machine learning for intrusion detection	Strengthened IoT security to maintain the integrity of iterative deep-learning optimization.	High precision in anomaly detection with low false positives.	Computationally intensive on large-scale deployments.	Implement fog-level preprocessing and incremental learning to reduce computational burden.

[8] Ali et al. (2024)	Review of IoT-based smart farming security and privacy	Identified privacy challenges that can disrupt iterative learning cycles if not addressed.	Thorough mapping of privacy-preserving mechanisms.	Limited actionable guidance for integrating privacy with deep-learning pipelines.	Develop standardized privacy-preserving deep-learning frameworks tailored for smart agriculture.
[9] Nawaz & Babar (2025)	Analytical framework for IoT and AI in resource-constrained agriculture	Demonstrated feasibility of iterative optimization even in low-resource environments via lightweight AI models.	Practical focus on resource-constrained settings; strong alignment with real-world farms.	Potential performance degradation under extreme connectivity loss.	Embed opportunistic learning algorithms that operate robustly in intermittent connectivity.
[10] Ghaseminya et al. (2025)	Survey of IoT–Edge–Fog integration with FaaS	Validated that serverless FaaS models enhance scalability of iterative deep-learning workflows for smart farming.	Strong coverage of virtualization and orchestration technologies.	Lacks crop-specific spatio-temporal data validations in process.	Integrate agricultural case studies and benchmark FaaS-based iterative training against standard cloud pipelines.
[11] Roy et al. (2019)	IoT soil sensors	Produced fertility maps for improved nutrient management	High accuracy in soil nutrient detection	Focused on limited soil categories	Broaden sensor validation to multiple soil types and climates
[12] Das et al. (2021)	AI-driven image processing	Enabled automatic pest recognition	Early detection of crop infestations	Accuracy decreases with noisy or unclear images	Train models on diverse datasets and use hybrid vision techniques
[13] Mehta et al. (2020)	Comparative analysis of open-source IoT platforms	Evaluated usability and performance of IoT platforms	Offers practical insight into platform capabilities	Lack of unified standards across platforms	Develop standardized protocols for better interoperability
[14] Reddy et al. (2022)	Robotics for smart harvesting	Demonstrated automated crop collection	Reduced manual labor requirement	High initial cost limits adoption	Build low-cost, modular robotic solutions
[15] Bhatia et al. (2021)	IoT + ML models	Enhanced weather forecasting accuracy	Reliable short-term predictions	Regional dataset limitations	Include multi-region datasets and real-time updates
[16] Ali et al. (2020)	IoT water quality sensors	Enabled aquaculture monitoring	Real-time water quality assessment	Validated in small-scale systems only	Extend trials to large commercial aquaculture setups
[17] Verma et al. (2021)	Solar-powered IoT nodes	Promoted sustainable agriculture practices	Renewable, eco-friendly solution	Limited efficiency during cloudy/rainy days	Combine with hybrid storage and backup systems
[18] Thomas et al. (2022)	IoT + AI integration	Detected crop diseases at early stages	Preventive farming interventions possible	Prone to false positives in some conditions	Improve with multi-modal datasets and continuous training
[19] Nair et al. (2020)	Blockchain-based IoT	Secured data sharing across stakeholders	Enhanced transparency and trust	Computational cost remains high	Use lightweight blockchain frameworks
[20] Chatterjee et al. (2021)	IoT + ML for fertilization	Improved nutrient optimization	Reduced fertilizer wastage	Performance varies across crops	Tailor models for crop-specific nutrient cycles
[21] Banerjee et al. (2020)	GSM-based IoT irrigation	Remote irrigation management	Affordable and user-friendly	Requires GSM coverage	Integrate with LoRa/NB-IoT for rural areas
[22] Joshi et al. (2021)	Fog computing middleware	Real-time agricultural data processing	Reduced latency compared to cloud	Limited scalability in large farms	Hybrid edge–fog–cloud integration
[23] Rao et al. (2022)	Machine learning yield models	Reliable yield prediction	Strong predictive accuracy	Constrained to specific crops	Expand models with diverse crop datasets
[24] Prasad et al. (2020)	Edge computing IoT design	Provided scalable farm IoT architecture	Efficient for large sensor networks	Hardware resource limitations	Apply dynamic load balancing and optimized scheduling
[25] Iyer et al. (2021)	Software-defined networking (SDN)	Improved IoT network flexibility	Enabled dynamic reconfiguration	Security gaps in SDN layer	Embed blockchain or AI-based intrusion detection
[26] Fernandes et al. (2022)	Cost–benefit IoT analysis	Estimated ROI for smart farming projects	Practical focus on economics	Restricted to specific geographic regions	Validate ROI across multiple agro-climatic zones
[27] Mishra et al. (2020)	Ethical & policy analysis	Highlighted IoT data governance issues	Comprehensive mapping of ethical concerns	Limited actionable frameworks	Propose global policies with implementation roadmaps
[28] Jain et al.	RFID-based dairy	Monitored milk	Reliable livestock	Tested only in	Scale up across different

(2021)	monitoring	production and cattle health	productivity tracking	selected farms	dairy systems
[29] Kapoor et al. (2022)	IoT in aquaponics	Balanced water–plant ecosystem monitoring	Sustainable closed-loop system	Limited to pilot projects	Expand to commercial-scale aquaponics systems
[30] Singh et al. (2023)	GPS-enabled IoT monitoring	Tracked tree health in agroforestry	Enhanced forest and crop management	Dependent on GPS availability	Integrate GPS with satellite and drone-based monitoring
[31] Naseer et al. (2024)	Survey on IoT adoption	Mapped global IoT agricultural adoption trends	Broad coverage of adoption practices	Limited empirical case validation	Add regional pilot studies for deeper insights
[32] Friha et al. (2021)	UAVs + SDN taxonomy	Classified IoT technologies in agriculture	Structured overview of tech landscape	No performance evaluation	Validate taxonomy via simulation and field tests
[33] Lad et al. (2022)	Raspberry Pi irrigation model	Automated soil moisture–based irrigation	Low-cost and efficient	Limited field scale	Expand to heterogeneous soil conditions
[34] Kim et al. (2020)	LoRa-based networks	Enabled long-range communication	Energy-efficient solution	Limited bandwidth for heavy data	Use LoRa–Wi-Fi hybrid for high throughput
[35] Zhang et al. (2019)	Drone monitoring system	Real-time crop health detection	Accurate aerial imaging	Weather dependency issues	Integrate multispectral and low-cost ground sensors

Table1: Models Empirical Review Analysis

4.2 Cybersecurity and Privacy Concerns

The widespread adoption of IoT in agriculture opens new cyber-attack surfaces**.** Unsecured communication channels can be exploited for data interception, device hijacking, and Distributed Denial of Service (DDoS) attacks**.** Compromised devices not only threaten farm operations but may also be incorporated into global botnets, as evidenced by the Mirai incident**.**

Data privacy represents another pressing concern. Agricultural IoT systems generate sensitive datasets, including crop yields, land conditions, and farmer profiles. Unauthorized access to such data may lead to market manipulation or breaches of farmer confidentiality. Additionally, AI models trained on centralized cloud data are vulnerable to data poisoning attacks, where malicious inputs degrade model reliability.

Despite increasing awareness, most IoT devices still lack end-to-end encryption, secure firmware update mechanisms, and intrusion detection systems**.** Without addressing these gaps, trust in AI-enabled agriculture will remain low.

4.3 Economic Viability and Return on Investment (ROI)

Although AI-IoT platforms promise long-term cost savings, the initial capital expenditure required for sensors, gateways, communication infrastructure, and AI software remains prohibitive for smallholder farmers, especially in developing nations. Maintenance costs, subscription fees for cloud services, and device replacement add to the financial burden.Additionally, the economic benefits of smart agriculture are unevenly distributed**.** While large-scale agribusinesses can afford advanced AI-IoT deployments, small farmers often struggle to justify the ROI due to lower economies of scale. This digital divide risks widening existing socio-economic inequalities, unless affordable and low-cost IoT solutions are developed.

5. OPPORTUNITIES AND FUTURE RESEARCH DIRECTIONS

While numerous challenges restrict large-scale deployment of AI-IoT in agriculture, the evolving technological ecosystem also offers unprecedented opportunities. By strategically addressing existing barriers, researchers and practitioners can unlock new pathways toward sustainable, secure, and inclusive agricultural systems. This section explores the most promising future directions that are expected to shape the next decade of smart farming.

5.1 Edge and Fog Computing for Low-Latency Intelligence

Cloud computing has long served as the primary platform for agricultural data processing. However, dependence on distant cloud servers introduces latency, bandwidth, and reliability issues, especially in rural environments with unstable connectivity. Edge computing and fog computing represent transformative solutions. By enabling AI algorithms to operate closer to the data source (on gateways, drones, or local servers), they reduce reliance on the cloud, cut latency, and enhance real-time decision making. For example, an edge-enabled IoT system can immediately trigger irrigation adjustments when soil moisture drops, without waiting for cloud analysis. Opportunities: Ultra-low latency for mission-critical actions (e.g., frost protection, pest outbreak response).Reduced network bandwidth requirements. Enhanced privacy since sensitive farm data remains local. Research Gaps are: Lightweight AI model compression techniques (e.g., pruning, quantization). Standardized frameworks for distributing workloads across edge, fog, and cloud layers. Robustness of edge devices under harsh environmental conditions.

5.2 Explainable Artificial Intelligence (XAI) for Trustworthy Farming

Farmers often hesitate to adopt AI-driven recommendations because models behave like black boxes**,** offering little insight into why a particular decision was made. This lack of transparency undermines trust and accountability**.**

Explainable AI (XAI) can bridge this gap by making algorithmic outputs interpretable. Techniques such as feature attribution (e.g., SHAP, LIME), saliency maps for crop images, and natural language explanations can help farmers understand *why* a system recommends more irrigation or flags a pest outbreak.

Opportunities**:** Higher adoption rates due to increased trust. Better debugging and error detection in AI models. Policy compliance where algorithmic transparency is mandated.

Research Gaps are:T ailoring XAI to non-technical users (farmers with limited digital literacy).Balancing interpretability with model accuracy. Developing domain-specific XAI frameworks for agricultural datasets.

5.3 Federated Learning and Privacy-Preserving Analytics

AI in agriculture requires large, diverse datasets to train robust models. However, data centralization raises privacy concerns and creates bottlenecks. Federated learning (FL) addresses this by allowing models to be trained across distributed devices (edge nodes, farms, cooperatives) without transferring raw data to a central server. Only model updates are shared, preserving local data confidentiality.

Opportunities**:** Protects farmer privacy and prevents misuse of sensitive data. Enables collaborative intelligence across farms, regions, and even countries. Reduces central data storage requirements.

Research Gaps are: Defending against poisoning attacks in federated networks. Efficient aggregation techniques for bandwidth-constrained IoT systems. Incentive mechanisms for farmers to participate in federated data sharing.

5.4 Blockchain for Trust and Traceability

Agricultural supply chains often suffer from lack of transparency**,** leading to fraud, food safety issues, and unfair pricing. Blockchain offers immutable, decentralized ledgers for traceability of produce from farm to consumer. When integrated with IoT, blockchain ensures that sensor data on crop quality, storage temperature, and transportation conditions cannot be tampered with.

Opportunities**:** Trustworthy supply chains with end-to-end provenance. Smart contracts for automated transactions between farmers, buyers, and distributors. Increased consumer confidence in food safety and sustainability.

Research Gaps are: High computational and energy costs of blockchain consensus mechanisms. Need for lightweight blockchain tailored to IoT devices.

energy consumption, and carbon footprint**.** Research is moving toward green IoT through: Energy harvesting (solar, wind, bio-energy) for powering devices. Biodegradable or recyclable sensors to minimize environmental impact. Ultra-low-power hardware architectures for prolonged battery life. Future agricultural IoT must align with sustainability goals (SDGs)**,** ensuring technology adoption does not exacerbate environmental problems.

5.7 Integration with 6G and Next-Generation Communication

With 5G rollout underway, researchers are already exploring 6G networks for agriculture. 6G promises terahertz communication, ultra-low latency, AI-native networking, and integrated sensing. For smart agriculture, 6G could support massive device deployments, drone swarms for crop monitoring, and tactile internet for remote machinery control.

Opportunities**:** Seamless connectivity for rural regions through integrated satellite–terrestrial networks.AI-powered network slicing to optimizefarm-specific workloads.

Research Gaps are:High cost of infrastructure rollout. Ensuring backward compatibility with existing 4G/5G devices.

5.5 Policy, Governance, and Ethical Frameworks

Technology alone cannot solve agricultural challenges. Policy frameworks are essential to ensure ethical, equitable, and inclusive deployment of AI-IoT. Governments, NGOs, and international agencies must establish guidelines on:

Data ownership and governance**:** Who controls farmer-generated data?

Ethical AI**:** Preventing bias and ensuring fairness in automated recommendations.
Subsidy and incentive models**:** Helping smallholders access advanced technologies.

Standardization efforts**:** Developing interoperable frameworks for global adoption. Without such governance, AI-IoT adoption may favor large corporations and widen socio-economic divides.

5.6 Sustainable and Green IoT Devices

Sustainability is critical as billions of IoT devices are expected to be deployed in agriculture. Conventional sensors and actuators raise concerns about e-waste,

The reviewed literature demonstrates significant diversity in IoT frameworks, AI models, and deployment contexts for smart agriculture. While individual studies show promising results, a cross-comparative evaluation is necessary to understand what works, where it works, and under which conditions adoption is feasible**.** This section presents a comparative analysis of key contributions and discusses broader insights emerging from the review.

6 COMPARATIVE ANALYSIS OF IOT-AI MODELS

Several studies have proposed IoT-enabled frameworks integrated with AI models for tasks such as crop monitoring, irrigation scheduling, and pest prediction. To provide a holistic overview, Table 1 summarizes representative works from 2020–2025.

Table 2: Comparative Evaluation of IoT-AI Systems for Agriculture (Representative Studies, 2020–2025)

Study / Year	IoT Framework	AI / ML Technique	Application Area	Key Findings	Limitations
Li et al. (2021)	LoRaWAN-based wireless sensor network	CNN for image classification	Crop disease detection	Achieved >93% accuracy for tomato leaf disease	Limited dataset; poor generalizability across regions
Sharma et al. (2022)	NB-IoT & cloud architecture	Random Forest & SVM	Precision irrigation	Reduced water usage by 30% while maintaining yield	High dependency on stable internet
Singh et al. (2023)	UAV + IoT camera sensors	YOLOv5 deep learning	Pest detection in rice fields	Real-time detection with 90% precision	High computational load; requires GPU
Huang et al. (2023)	Hybrid edge-fog architecture	LSTM + GRU	Yield prediction under climate variability	Improved prediction accuracy over ARIMA models	Energy consumption of edge devices remains high
Al-Khatib et al. (2024)	Cloud-based IoT platform	Federated Learning (FL)	Multi-farm disease prediction	Enabled collaborative training without data sharing	Vulnerable to poisoning attacks; model aggregation challenges
Garcia et al. (2025)	Blockchain-integrated IoT	Ensemble ML models	Supply chain traceability	Enhanced transparency & reduced fraud cases	Blockchain overhead increases latency

6.1 Insights from Comparative Analysis

1. **IoT Infrastructure Diversity**

Studies employing LoRaWAN and NB-IoT demonstrate cost-effective long-range connectivity, but they remain underutilized compared to cloud-centric solutions.Hybrid edge–fog–cloud architectures appear increasingly popular to balance latency, cost, and reliability.

2. **AI Algorithmic Trends**

CNNs and YOLO-based architectures dominate image-based disease and pest detection due to their high accuracy.RNNs (LSTM/GRU) are preferred for time-series applications such as yield forecasting and climate prediction.Recent works explore Federated Learning and Ensemble AI models for collaborative, privacy-preserving, and robust decision-making.

3. **Application-Specific Strengths**

IoT + CNN: Strong for crop health monitoring**,** but limited by dataset bias.IoT + ML (RF/SVM): Reliable for irrigation scheduling**,** but require frequent

Scalability remains a major bottleneck: most solutions are validated in pilot projects, not at national or cross-border scales.Data imbalance and quality issues limit generalizability of AI models.Security is rarely a central focus; most systems assume trusted environments,retraining to adapt to seasonal variation.Blockchain + IoT: Strong in traceability, but computationally heavy for constrained devices.

4. **Limitations Across Studies**

Despite the significant progress in integrating Artificial Intelligence (AI) and the Internet of Things (IoT) into agricultural systems, several limitations persist across existing studies. These limitations affect scalability, generalizability, and the long-term sustainability of proposed solutions.

4.1 Data Limitations

Most studies rely on small, region-specific datasets that lack diversity in climatic, soil, and crop conditions. Limited data availability and quality issues—such as missing values, inconsistent labeling, and sensor noise—reduce the robustness of AI models. Moreover, there is a lack of standardized agricultural datasets, making cross-comparison of results challenging.

4.2 Model Generalization and Interpretability

Many AI models, particularly deep learning architectures, demonstrate high accuracy on controlled datasets but struggle with real-world generalization due to environmental variability. The “black-box” nature of these models also poses interpretability issues, hindering farmer trust and practical adoption.

4.3 IoT Infrastructure Constraints

A significant portion of IoT-based studies assumes stable internet connectivity, reliable power supply, and affordable sensor networks—conditions often not met in rural and developing regions. Hardware limitations such as sensor durability, calibration issues, and maintenance costs further restrict scalability.

4.4 Integration and Interoperability Challenges

AI and IoT systems often operate in isolation, lacking interoperability standards for seamless data sharing. Existing research focuses on specific tasks (e.g., crop monitoring or irrigation) rather than developing end-to-end, interoperable solutions that integrate multiple subsystems effectively.

4.5 Economic and Social Barriers

Few studies evaluate the economic feasibility or social acceptance of AIoT technologies in agriculture. The absence of cost-benefit analyses, especially for smallholder farmers, limits understanding of real-world adoption barriers. Furthermore, issues of digital literacy and training are often underrepresented.

4.6 Environmental and Ethical Considerations
Sustainability and ethical dimensions—such as energy consumption of IoT devices, data ownership, and privacy—are inadequately discussed across studies. Without addressing these concerns, large-scale deployment may have unintended environmental or social consequences.

4.7 Lack of Longitudinal and Real-Time Validation

Many research efforts rely on short-term experiments or simulations. Few studies have validated AIoT solutions over multiple growing seasons or under varying environmental conditions. The absence of long-term field validation limits confidence in the practical reliability of these systems.

6.2 Thematic Discussion

6.2.1 Effectiveness of AI Models

While deep learning models consistently outperform traditional ML approaches in accuracy, they demand higher computational power and energy. For agriculture in resource-constrained regions, lightweight CNN variants (e.g., MobileNet, EfficientNet) and compressed models are essential.

6.2.2 Trade-off Between Centralized and Decentralized Architectures

Cloud platforms offer scalability and storage, but rural connectivity limits real-time responsiveness. Edge and federated learning approaches reduce latency and enhance **privacy**, yet they introduce new challenges such as model poisoning and device-level energy constraints.

6.2.3 Security and Trust Considerations

Comparative studies reveal a lack of holistic security measures across existing frameworks. Only a handful of works integrate blockchain or federated techniques, highlighting a research gap in privacy-preserving AI-IoT systems.

6.2.4 Inclusivity and Affordability

Most high-performing solutions are developed for large-scale agribusinesses, leaving smallholder farmers underserved. Few studies address low-cost sensor kits or regional language interfaces, which are critical for wide adoption in developing regions.

6.4 Research Gaps Highlighted by Comparison

From the comparative analysis, several research gaps become evident: Lack of standardized datasets for benchmarking AI models across diverse crops and geographies. Insufficient focus on explainability and farmer-centric interpretability of AI outputs. Minimal integration of sustainability metrics (energy consumption, e-waste, carbon footprint) in evaluating IoT frameworks. Limited exploration of policy and governance frameworks in comparative works.

6.5 Toward an Integrated Framework

The synthesis of current research suggests the need for an integrated AI-IoT framework that balances: Scalability (via hybrid cloud–edge deployment),Trust (through blockchain and XAI),Affordability (low-cost, open-source hardware/software), and Sustainability (energy-efficient devices, green IoT).Such an integrated approach would accelerate the transition from isolated pilot projects to mainstream adoption in Agriculture 5.0.

7 CONCLUSIONS

This survey consolidates 35 representative studies on IoT in agriculture. Findings suggest that IoT has the potential to revolutionize food production by enabling precise, data-driven practices. To realize its full potential, future efforts must prioritize scalable architectures, standardized protocols, cost reduction, and inclusivity for smallholder farmers. IoT's role in transforming agriculture is undeniable, but its integration requires holistic strategies that balance productivity with sustainability.

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