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Integrating Artificial Intelligence and IoT for Precision Farming: A Review of Agriculture 4.0 Technologies, Applications, and Challenges

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Abstract: Agriculture 4.0 marks a decisive shift from mechanized and chemically intensive farming toward a data-driven, automated, and connected model of food production. At the center of this shift lies the convergence of artificial intelligence (AI) and the Internet of Things (IoT), which together allow farms to sense, interpret, and act on field conditions with a precision that manual methods cannot match. This review synthesizes the current body of literature on AI-IoT integration in precision farming, covering the core enabling technologies — smart sensors, unmanned aerial vehicles (UAVs), geographic information systems (GIS), edge and cloud computing, and block chain-based traceability — and the layered architecture through which they combine into functioning smart-farming systems. Drawing on peer-reviewed studies published largely between 2019 and 2025, the review examines representative applications in smart irrigation, crop-disease detection, yield prediction, and supply-chain traceability, consolidates the recurring barriers reported across this literature, and provides a detailed, year-ordered comparison of technique, dataset, performance metrics, and reported limitations across ten representative studies. The review concludes by outlining research gaps — particularly around affordable edge-AI models, interoperable data standards, and region-specific validation in smallholder contexts such as India — that merit attention in future work.

Keywords: *Precision Farming, Artificial Intelligence, Internet of Things, Agriculture 4.0, Smart Sensors, UAV, Machine Learning, Data Security.*

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Introduction

Agricultural production systems have passed through several distinct phases of transformation, from manual and animal-powered cultivation through the mechanization and chemical-input intensification of the 20th century to the current phase commonly termed Agriculture 4.0. Unlike earlier phases, which were centered on physical inputs and machinery, Agriculture 4.0 is defined by its reliance on data: continuous sensing of field conditions, algorithmic interpretation of that data, and automated or semi-automated responses [1], [5]. This shift is occurring against a backdrop of mounting pressure on food systems, including a growing global population, shrinking per-capita arable land, increasingly erratic weather patterns linked to climate change, and tightening constraints on water and other natural resources.

Precision farming is an operational expression of Agriculture 4.0. It replaces uniform, field-wide management practices with input applications that are tailored to the specific needs of small management zones or individual plants, based on real-time measurements rather than historical averages or visual inspection [3], [7]. Two technology families make this possible. The Internet of Things supplies the sensing and connectivity layer — soil-moisture probes, weather stations, connected machinery, and automated irrigation valves that continuously stream field data [8], [9]. Artificial intelligence supplies the interpretive layer — machine learning and deep learning models that convert this raw data stream into predictions, classifications, and recommendations, from forecasting yield to identifying an early-stage pest infestation from a drone image [16], [17].

The purpose of this review is to consolidate the fast-growing but fragmented literature on AI-IoT convergence in precision farming into a single, structured account: what the constituent technologies are, how they are architected together, where they have been applied with documented results, what obstacles recur across studies and geographies, and where the evidence base remains thin. The review is intended as a foundation for subsequent primary research within the broader doctoral project on AI-IoT integration for precision farming and is scoped accordingly, favoring depth on architecture, application, and challenge analysis over an exhaustive bibliometric count of all published work in the field.

Review Methodology

This is a narrative-cum-thematic review rather than a formal systematic review, reflecting its purpose as a scoping foundation for doctoral research rather than a standalone meta-analysis. Sources were identified through targeted searches of Scopus, Web of Science, IEEE Xplore, MDPI, Science Direct, and Frontiers, using combinations of the terms “precision agriculture,” “Agriculture 4.0,” “AI-IoT,” “smart farming,” “UAV crop monitoring,” and “block chain agriculture traceability.” Priority was given to peer-reviewed journal articles, systematic reviews, and conference papers published between 2017 and 2025, with an emphasis on the 2021–2025 windows to capture the most recent shifts in edge-AI, 5G/LPWAN connectivity, and deep-learning methods. Studies were organized thematically into five categories

— core AI applications, core IoT applications, UAV and remote sensing, GIS and spatial analytics, and block chain-based traceability — which form the structure of Sections 4 through 7. Where multiple studies converged on the same finding, the review reports the pattern rather than any single figure, to avoid over-reliance on one study's context-specific result. Figure 1 summarizes the identification-to-synthesis process.

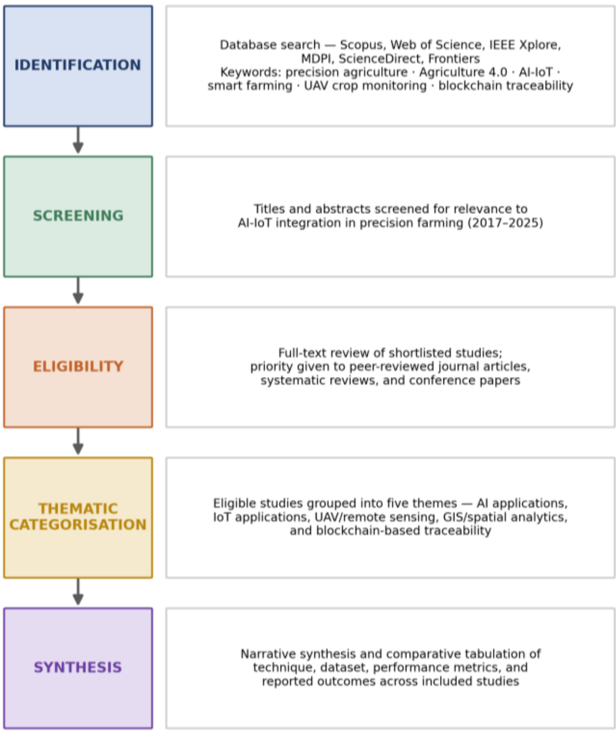

Figure 1. Review methodology flowchart.

Agriculture 4.0 and Precision Farming: Conceptual Overview

Precision farming can be understood as operating through a repeating sense-analyse-act cycle. In the sensing stage, IoT devices and remote-sensing platforms collect data on soil, crop, and atmospheric conditions. In the analysis stage, AI models process this data — often alongside historical records and satellite imagery — to detect patterns, anomalies, and forecasts that would not be evident from raw readings alone. In the action stage, the resulting insight is either delivered to the farmer as a recommendation or, increasingly, executed automatically through connected actuators such as irrigation valves or variable-rate applicators [1], [4].

This cycle distinguishes Agriculture 4.0 from earlier "precision agriculture" efforts of the 1990s and 2000s, which relied on GPS-guided machinery and static soil maps but lacked continuous, closed-loop feedback. The addition of AI and low-cost, networked IoT hardware over the past decade has made the cycle both continuous and adaptive: models can be retrained as new data arrives, and management zones can be redrawn in-season rather than only between growing cycles [5], [24].

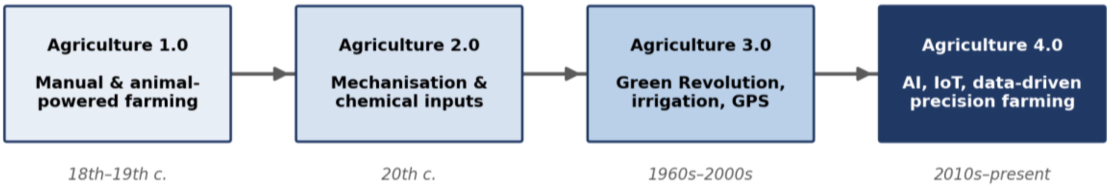

Figure 2. Evolution of agriculture from manual practice to Agriculture 4.0.

Core Enabling Technologies

Precision farming rests on a cluster of complementary technologies organized around the AI-IoT core. Figure 3 summarizes how the remaining enabling technologies discussed in this section — UAVs, GIS, cloud/edge computing, connectivity infrastructure, and block chain — relate to that core.

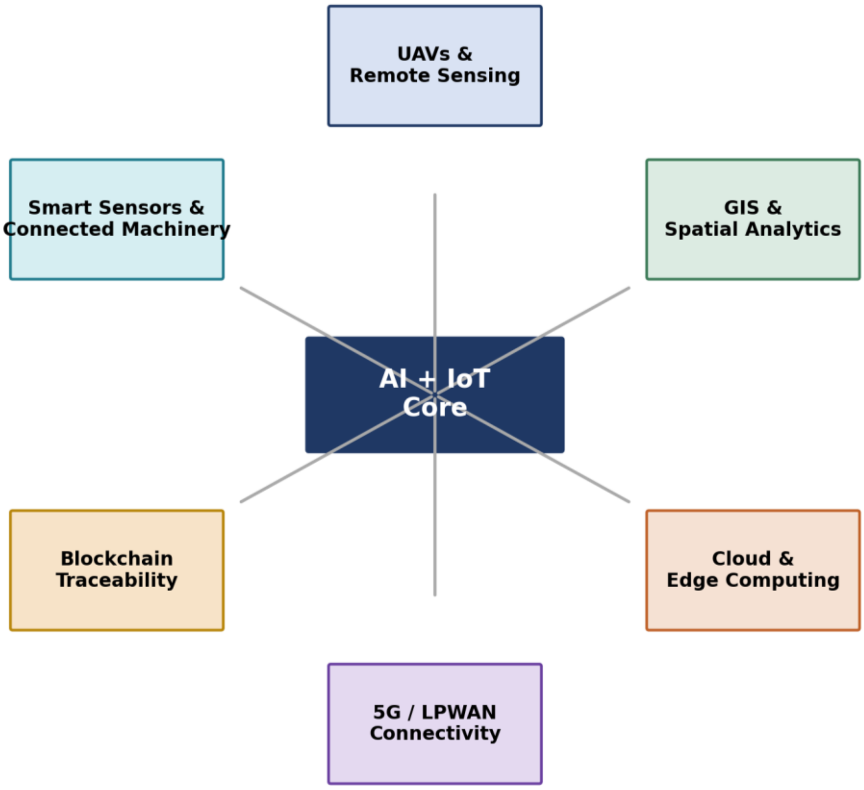

Figure 3. Precision farming technology ecosystem around the AI–IoT core.

Artificial Intelligence in Precision Farming

AI applications in precision farming fall broadly into three groups. Predictive analytics models — typically regression, ensemble, or deep-learning architectures — are trained on historical yield, weather, and soil data to forecast crop performance and anticipate disease or pest pressure before visible symptoms appear [3], [7]. Computer-vision models, most often convolutional neural networks, are applied to imagery from drones, satellites, or fixed field cameras to detect crop stress, weed presence, and specific pathogens; recent studies report classification accuracies in the mid-to-high 90th percentile for well-defined disease classes on curated datasets, though performance drops for rare classes and in field conditions that differ from the training data [17], [25]. Robotic and automation systems use AI-driven control to perform physical tasks — targeted weeding, selective harvesting, and variable-rate spraying — with less human labor and, where correctly calibrated, reduced chemical use.

A recurring theme across the reviewed literature is the gap between model accuracy reported in controlled research settings and performance under real farm conditions, where lighting, occlusion, sensor noise, and regional crop-variety differences are far less controlled. This gap is one of the central reasons AI adoption in agriculture continues to lag behind reported laboratory results, and is discussed further in Section 10 and quantified for a representative model family in Section 9.1.

Internet of Things in Precision Farming

IoT forms the sensing and connectivity backbone of precision farming. Smart sensors deployed in soil and canopy measure moisture, temperature, humidity, pH, and nutrient levels, transmitting readings at intervals ranging from minutes to hours depending on the application [8], [9], [15]. Connected machinery — tractors, harvesters, and irrigation controllers, along with autonomous field-monitoring robots — extends this network to include equipment status and usage data, supporting both real-time control and predictive maintenance [10]. Automated irrigation systems, one of the most mature IoT applications in agriculture, combine soil-moisture sensing with local weather forecasts to schedule watering, and studies report meaningful reductions in water use compared with fixed-schedule irrigation, though the magnitude varies by crop, soil type, and climate [2], [11].

The reliability of the IoT layer depends heavily on network infrastructure, which is the least mature part of the stack in most farming regions. This is addressed separately in Section 4.6.

Table 1: Summarizes the principal IoT components used in precision farming and their reported benefits.

IoT Component	Function	Reported Benefit
Smart Sensors	Measure soil moisture, pH, temperature, humidity and light intensity at the point of installation.	Enables targeted irrigation and fertilization instead of uniform, field-wide application.
Drones / UAVs	Capture RGB, multispectral, or hyperspectral imagery across large field areas.	Early detection of crop stress, pests, and disease before visible to the naked eye.
Automated Irrigation Systems	Combine soil-moisture data and weather forecasts to trigger or withhold irrigation automatically.	Reduced water wastage and more consistent crop hydration.
Connected Machinery	Tractors, harvesters and other equipment report usage, location and performance data.	It supports predictive maintenance and remote fleet coordination.
Weather Stations	Continuously log temperature, rainfall, humidity and wind data at the farm level.	Feeds short-term forecasts used to schedule irrigation and spraying.

Table 1: Core IoT components and their functions in precision farming.

Unmanned Aerial Vehicles and Remote Sensing

Drones equipped with RGB, multispectral, or hyperspectral cameras allow farmers to survey large areas quickly and at a spatial resolution finer than satellite imagery permits. Applications include vegetation-index mapping to flag stressed zones within a field, early pest and disease detection through spectral signatures invisible to the naked eye, and topographic mapping to support irrigation and drainage planning [12], [13]. Recent systematic reviews of UAV-based disease detection report a marked increase in publications after 2019, driven by falling drone hardware costs and the maturity of lightweight deep-learning architectures suitable for onboard or near-real-time processing [17]. Satellite-based remote sensing complements UAVs for large-scale, lower-frequency monitoring, such as regional yield estimation, where drone coverage would be impractical.

Geographic Information Systems

GIS provides the spatial-analysis layer that ties sensor, drone, and satellite data to specific locations within a farm. By overlaying soil maps, historical yield data, and real-time sensor readings, GIS tools allow farmers and agronomists to delineate management zones, plan crop-specific placement based on soil and micro-climate variation, and track long-term changes in field productivity [14]. GIS output is frequently the interface through which AI-generated recommendations are ultimately presented to the farmer, since spatial maps are more actionable than raw tabular data.

Block chain for Agricultural Traceability

Although not part of the original AI-IoT core, block chain has emerged as a complementary technology addressing a distinct problem: verifiable traceability of produce from farm to consumer. By recording each transaction or handling step on a distributed, tamper-resistant ledger, block chain systems aim to reduce fraud, support food-safety recalls, and give consumers verifiable information about origin and handling [18], [19], [21]. Several studies combine block chain with IoT sensor data specifically — for example, temperature logs during cold-chain transport — so that the recorded data is both immutable and independently verified at the point of capture [22]. Reported barriers mirror those seen elsewhere in agri-tech: implementation cost, the need for standardized data formats across supply-chain participants, and the practical challenge of ensuring the off-chain data entering the ledger is itself accurate.

Connectivity Infrastructure: 5G, LPWAN, and Edge Computing

Network connectivity is consistently identified as the weakest link in the AI-IoT stack for agriculture, because farms are disproportionately located in areas with poor cellular and broadband coverage. Low-Power Wide-Area Network (LPWAN) protocols such as LoRa WAN and NB-IoT are widely used for their long range and low power draw, suiting infrequent sensor readings across large areas, but they are unsuited to high-bandwidth applications such as video streaming from drones [20]. Where higher throughput is required, 5G offers substantially greater bandwidth and lower latency, but rural 5G coverage remains limited in most regions. Recent work evaluates hybrid LPWAN-5G architectures that route routine sensor traffic over LPWAN and reserve 5G for data-intensive tasks, reporting cost reductions of up to roughly 30% alongside improved reliability compared with either technology alone [20]. Edge computing — processing data locally on gateways or on-device rather than sending everything to the cloud — further mitigates connectivity constraints by reducing the volume of data that must travel over the network and by allowing time-critical decisions, such as irrigation triggers, to execute without waiting on a round trip to a remote server.

Table 2: Compares the connectivity options most frequently discussed in the reviewed literature across the dimensions that matter most for farm deployment: range, data rate, power consumption, and typical use case.

Technology	Frequency Band	Typical Range	Data Rate	Power Use	Typical Agricultural Use Case
LoRaWAN	Sub-GHz ISM (868 / 915 MHz)	5–20 km (rural, line-of-sight)	0.3–50 kbps	Very low	Soil/field sensor networks, remote monitoring
Sigfox	Sub-GHz ISM (868 / 902 MHz)	10–40 km	~0.1 kbps (100 bps)	Low	Simple periodic sensor bursts
NB-IoT	Licensed cellular band	1–10 km	Up to 250 kbps	Medium	Livestock tracking, higher-telemetry sensors
LTE-M	Licensed cellular band	~5 km	Up to 1 Mbps	Medium	Mobile machinery, real-time monitoring
Zigbee	2.4 GHz ISM (mesh)	~100 m (mesh-extendable)	Up to 250 kbps	Low–medium	Greenhouse and short-range sensor mesh networks
Wi-Fi	2.4 / 5 GHz ISM	~50–100 m	Up to several hundred Mbps	High	Farm-building connectivity, camera / video feeds
5G	Licensed cellular	Cell-dependent (~1–5 km macro cell)	Up to Gbps	Medium–high (device)	UAV video streaming, real-time robotics control

Table 2: Comparative analysis of IoT communication technologies for agricultural deployment.

AI-IoT Convergence: Smart Farming System Architecture

Across the reviewed literature, smart farming systems are consistently described using a three-layer architecture, even where the terminology differs slightly between sources.

The Data Collection Layer comprises the IoT sensors, drones, and connected equipment described in Section 4 that continuously capture soil, crop, weather, and machinery data at the field level. The accuracy and placement density of this layer set an upper bound on everything downstream — an AI model cannot compensate for systematically poor or sparse input data.

The Data Processing Layer handles storage, cleaning, and preliminary analysis, typically split between cloud platforms, which offer scalable storage and heavier analytical workloads across multiple farms or regions, and edge devices, which perform lightweight, latency-sensitive processing on-site. This split is what allows systems to remain functional, in a degraded but useful mode, when connectivity to the cloud is temporarily lost.

The Decision-Making Layer is where AI models operate on the processed data to produce yield forecasts, disease and pest alerts, and irrigation or fertilization recommendations. Outputs are typically surfaced to farmers through dashboards, mobile alerts, or GIS-based maps rather than raw model output, since usability research in this space consistently finds that actionable, visual recommendations are adopted far more readily than technical scores or probabilities.

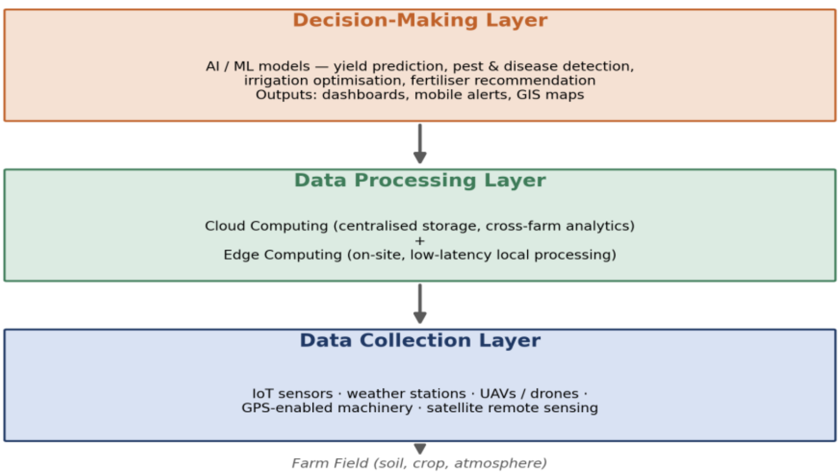

Figure 4. Architecture of the three-layer smart farming system

Underlying this layered architecture is a continuous sense-analyse-act cycle (Figure 5): IoT devices sense field conditions, AI models analyse the resulting data, and the system — or the farmer acting on its recommendation — acts on the field, generating new conditions for the next sensing pass.

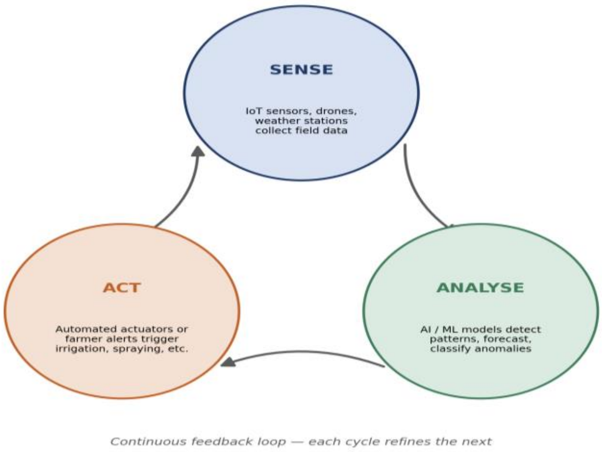

Figure 5. The AI–IoT sense–analyse–act cycle in precision farming.

Precision Farming Ecosystem — Stakeholder View

The technology architecture described in Section 5 sits inside a wider ecosystem of human and institutional actors, and adoption outcomes depend as much on this surrounding ecosystem as on the technology itself. Figure 6 places the farmer and field at the center of six interacting stakeholder groups: IoT and UAV sensing providers who supply the data-collection hardware; the AI/cloud analytics platforms that process it; input suppliers of seed, fertilizer, and equipment; agri-advisory and extension services that translate system output into actionable guidance; the market and supply chain that the farm's produce ultimately enters; and government bodies that shape policy, subsidies, and infrastructure investment. Data, decisions, goods, and support flow in both directions between the farmer and each of these groups — for example, extension services both receive field data and supply training back to the farmer — which is why technology-only interventions that ignore the surrounding ecosystem frequently under-perform relative to their technical potential [24].

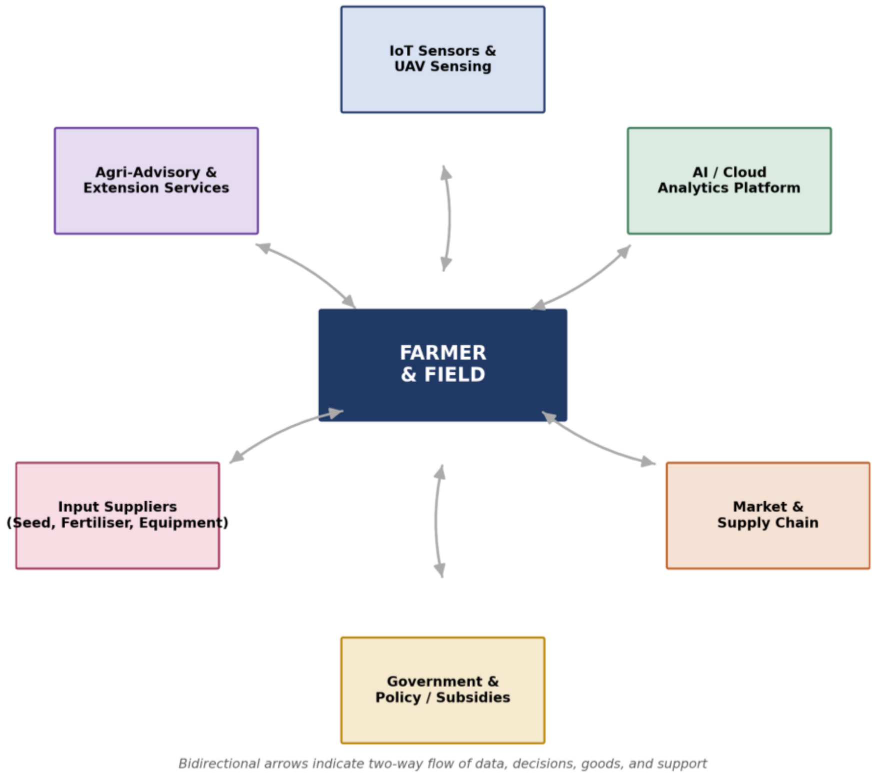

Figure 6. Precision farming ecosystem — stakeholder view.

Applications and Case Studies

The applications reviewed below span both staple food crops and high-value horticultural produce — from cereal and vegetable systems to specialty domains such as floriculture, where precision-farming techniques have also been applied to optimize growing conditions and post-harvest quality for ornamental crops [6].

Smart Irrigation

Smart irrigation is among the most widely deployed AI-IoT applications, combining soil-moisture sensing, weather forecasting, and crop-specific water-demand models to schedule irrigation automatically. Systems that incorporate short-term rainfall forecasts to postpone scheduled irrigation are reported to further reduce water use beyond what soil-moisture sensing alone achieves [11].

Pest and Disease Detection

Combining drone or fixed-camera imagery with deep-learning classifiers allows early detection of pest infestation and disease symptoms, often before they are visible during routine manual inspection. Multiple recent studies report classification accuracies above 90% for specific, well-represented disease classes, using architectures ranging from convolutional networks to lightweight mobile-optimized models suited to on-device deployment [17], [25]. Detection performance for underrepresented diseases or in field conditions differing from the training data remains a known weak point, as quantified in Section 9.1.

Crop Yield Prediction

Yield-prediction models integrate historical yield records, soil characteristics, weather data, and, increasingly, satellite or drone-derived vegetation indices. Model choice varies by crop and region, with gradient-boosting ensembles and deep-learning models both reported as effective depending on the size and structure of the available dataset [31]. Studies focused on Indian agricultural conditions specifically note that model performance depends heavily on the availability of localised, high-quality historical data, which remains uneven across states and crop types.

Supply-Chain Traceability

Block chain-based traceability systems, often paired with IoT sensors recording handling conditions such as temperature and humidity in transit, allow downstream participants and consumers to verify a product's provenance and handling history. Pilot deployments in rice and other staple-crop supply chains report improved data consistency and stakeholder trust, though scaling beyond pilot projects remains constrained by the cost of instrumenting every participant in the chain and by the absence of shared data standards across supply-chain actors [18], [21], [22].

Comparative Summary of Reviewed Studies

Table 3: Summarizes a representative cross-section of the studies reviewed, illustrating the range of technology focus and application area covered in the current literature. A more detailed, year-ordered comparison — including technique, dataset, performance metrics, advantages, limitations, and future scope for each study — follows in Section 9.

Author(s) / Year	Technology Focus	Application Area	Key Contribution / Finding
Liu et al., 2021 [1]	AI, IoT (Industry 4.0 lens)	Agriculture 4.0 enabling technologies	Maps the transition from Industry 4.0 to Agriculture 4.0 and identifies open research challenges in connectivity and interoperability.
Linaza et al., 2021 [3]	AI / Data analytics	Sustainable precision agriculture	Demonstrates AI-driven data pipelines improving sustainability outcomes across crop cycles.
Majeed, Fu & He, 2024 [16]	AI-of-Things (AIoT)	Precision agriculture, deep learning, machine vision	Frames AIoT as the convergence point of AI and IoT and highlights machine-vision-based field monitoring as a growth area.
Bouguettaya et al., 2023 [17]	UAV + Deep Learning	Plant and crop disease identification	Surveys CNN-based architectures for aerial disease detection and benchmarks their accuracy across crop types.
Bhattacharya et al., 2021 [11]	IoT sensors	Smart irrigation	Proposes a soil-moisture-driven IoT irrigation controller that reduces water wastage.

Author(s) / Year	Technology Focus	Application Area	Key Contribution / Finding
Mohamed Rafi et al., 2025 [20]	LPWAN, 5G, Hybrid connectivity	Rural network infrastructure	Shows hybrid LPWAN-5G architectures cut connectivity costs by up to 30% while improving reliability in remote farmland.
Rejeb, Keogh & Treiblmaier, 2019 [19]	Block chain + IoT	Supply chain management	Establishes a conceptual framework for combining block chain immutability with IoT sensing for traceability.
Chandan, John & Potdar, 2023 [18]	Block chain	Food-supply-chain sustainability (UN SDGs)	Links block chain-enabled traceability to measurable progress on UN Sustainable Development Goals in food systems.
Wolfert et al., 2017 [23]	Big Data	Smart farming decision support	Early foundational review positioning big-data analytics as the backbone of smart-farming decision support systems.
Klerkx, Jakku & Labarthe, 2019 [24]	Socio-technical systems	Adoption and governance of digital agriculture	Highlights that technology adoption barriers are as much social and institutional as they are technical.

Table 3: Representative studies on AI-IoT integration in precision farming.

Detailed Literature Review: Techniques, Datasets, and Performance

Table 4 extends the comparative summary in Section 8 with the technical detail needed to evaluate each study on its own terms: the specific technique or model used, the dataset it was evaluated on, the performance metrics reported, its stated advantages, its disadvantages or limitations, and the future work its authors identify. Studies are ordered by publication year, most recent first. Because studies differ in dataset, task, and evaluation protocol, the metrics in this table are not a like-for-like benchmark; they report what each study's authors measured under their own experimental conditions (see also the limitations noted in Section 12).

Year	Author(s)	Technique / Model	Dataset	Performance Metrics	Advantages	Disadvantages / Limitations	Future Scope
2025	Pal, Karmakar, Mukherjee & Chakrabarti [25]	Hybrid CNN (MobileNetV2 + residual blocks) with Grad-CAM / LIME explainability	Plant Disease Expert (199,644 img / 58 classes) & PlantVillage (54,305 img / 38 classes)	Accuracy 97.73% / 99.47%; F1 99.43%; inference 5.98 ms	Lightweight (3.51M params), explainable, validated across two datasets plus external field images	Benchmark datasets remain largely lab-captured; seasonal/field variation not fully modelled	Incorporate real multi-season field imagery to improve robustness
2025	Mohamed Rafi et al. [20]	Comparative simulation of LPWAN, 5G, and hybrid connectivity architectures	Literature review + simulated rural network case studies	Cost reduction ≈30%; improved reliability (qualitative)	Identifies a practical hybrid architecture balancing cost and reliability	Simulation-based; lacks a large-scale, multi-season field trial	Real-world pilot deployment across diverse farm terrains

Year	Author(s)	Technique / Model	Dataset	Performance Metrics	Advantages	Disadvantages / Limitations	Future Scope
2024	Mahesh & Soundrapandiyan [31]	Gradient-boosting ensembles (CatBoost, XGBoost, LightGBM, CART, AdaBoost, GB, RF, NN, SVM)	Crop-yield tabular dataset (agronomic and climate features)	CatBoost: R^2 0.996, RMSE 231.15, MAE 109.35, accuracy 99.12% (90:10 split)	CatBoost consistently outperforms other ensembles on tabular agricultural data	Performance sensitive to train/test split ratio; single-region dataset limits generalisation	Validate across multiple regions and crop types
2024	Majeed, Fu & He [16]	Editorial / agenda-setting review on AI-of-Things (AIoT)	N/A (editorial synthesis)	N/A (qualitative)	Frames deep learning and machine vision as the next AIoT growth area	No new empirical validation	Calls for stronger AI-IoT integration standards
2023	Bouguettaya, Zarzour, Kechida & Taberkit [17]	Survey of CNN architectures for UAV-based imagery	Multiple public UAV / aerial disease datasets (surveyed, not unified)	Reported accuracy ranges vary by architecture (survey-level)	Comprehensive taxonomy of UAV-DL disease-detection approaches	No unified benchmark across surveyed studies; direct comparison difficult	Calls for standard UAV benchmark datasets
2023	Chandan, John & Potdar [18]	Blockchain-enabled traceability mapped to UN SDGs	Conceptual / case-based (food supply chain)	Qualitative SDG-alignment assessment	Links traceability directly to measurable sustainability goals	No quantitative benchmarking of blockchain overhead	Empirical cost-benefit studies of blockchain traceability at scale
2021	Liu, Ma, Shu, Hancke & Abu-Mahfouz [1]	Conceptual / technology-mapping review	N/A	N/A (qualitative)	Foundational framing of the Industry 4.0 → Agriculture 4.0 transition	Pre-dates most recent (2023–2025) edge-AI and LPWAN-5G hybrid advances	Identifies interoperability and connectivity as priority research areas
2021	Bhattacharya, Roy & Pal [11]	IoT soil-moisture-driven irrigation controller	Field soil-moisture / weather sensor data (case study)	Reported reduction in water use (case-study level)	Demonstrable water savings over fixed-schedule irrigation	Case-study scale; not validated across multiple soil/climate types	Multi-site validation across soil and crop types
2019	Rejeb, Keogh & Treiblmaier [19]	Conceptual framework combining blockchain and IoT	N/A	N/A (qualitative)	Early, widely cited framework combining ledger immutability with IoT sensing	Conceptual only; no field implementation	Empirical validation of the proposed framework in live supply chains
2017	Wolfert, Ge, Verdouw & Bogaardt [23]	Foundational review of big-data analytics in farming	N/A	N/A (qualitative)	Established big data as the backbone of smart-farming decision support	Precedes deep-learning-era techniques now dominant in the field	Integration of big-data pipelines with real-time AI inference

Table 4: Detailed comparison of reviewed studies by technique, dataset, performance, and limitations (year descending).

Performance Comparison: A Worked Example

To illustrate how reported performance is typically compared within a single study rather than across the fragmented literature as a whole, Figure 7 reproduces the model-comparison table published by Pal et al. (2025) [25] for plant-disease classification on the PlantVillage benchmark. Because all values in this comparison were compiled and reported within one paper, they avoid the cross-study inconsistency that affects broader literature-wide comparisons, and illustrate the incremental accuracy gains achieved as architectures moved from earlier attention-based CNNs introduced in 2020 by Karthik et al. [26] and Chen et al. [27], through the teacher/student design of Brahimi et al. in 2019 [28], to the pruned-concatenation and lightweight architectures proposed by Arun and Umamaheswari [29] and Thakur et al. [30] in 2023, and finally to the lightweight hybrid model proposed by Pal et al. in 2025 [25].

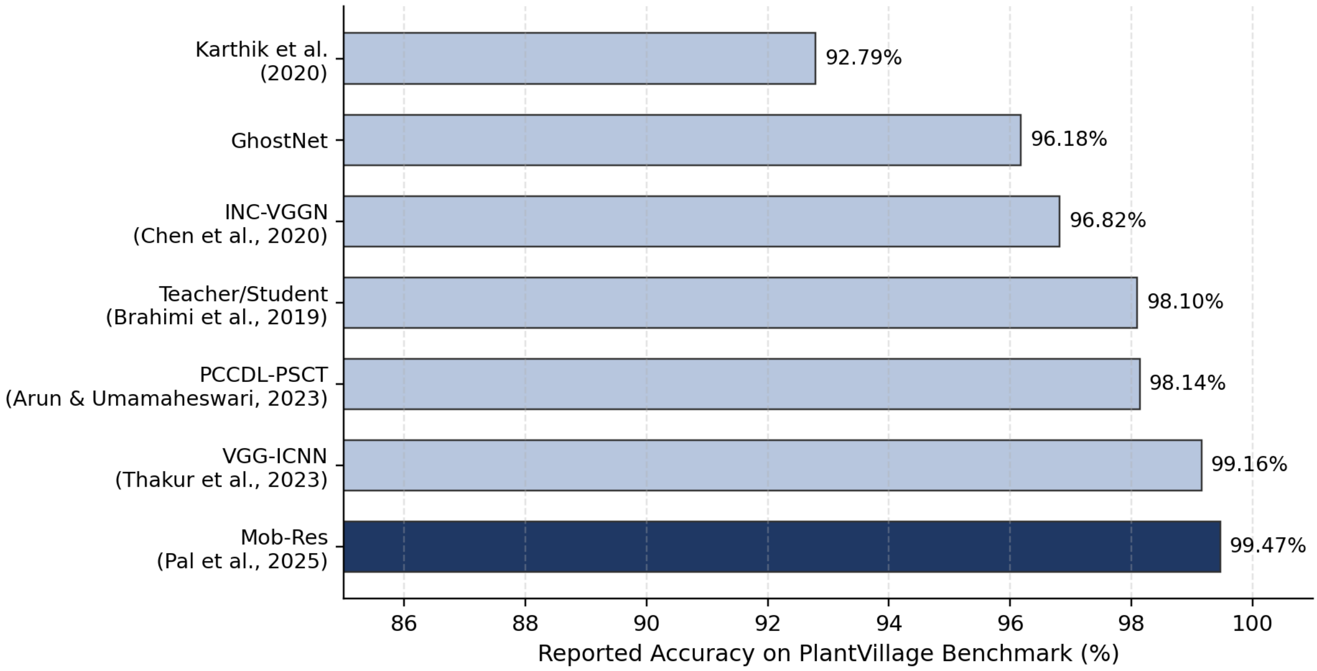

Figure 7. Reported accuracy of selected plant-disease-detection models on the PlantVillage benchmark, as compiled in Pal et al. (2025).

Challenges in AI-IoT Adoption

Connectivity and Network Infrastructure

Unreliable or absent rural connectivity remains the most frequently cited barrier across the reviewed literature, limiting real-time data transmission and, by extension, the responsiveness of automated systems. LPWAN, hybrid LPWAN-5G, and edge-computing approaches (Section 4.6) are the most actively researched mitigations, though deployment at scale requires infrastructure investment that individual smallholder farmers cannot make alone [20].

Data Security and Privacy

The growing volume of farm-level data — covering soil conditions, yields, and operational patterns — raises security and privacy concerns that are structurally similar to those in other IoT domains but carry agriculture-specific stakes, since compromised irrigation or supply-chain data could affect both crop outcomes and food safety. Reviewed studies consistently recommend encryption, secure authentication, and clearer data-ownership policies, though implementation lags recommendation in most deployed systems.

Cost and Scalability

The upfront cost of sensors, connectivity, and cloud or edge infrastructure remains prohibitive for many small and medium-sized farms, particularly in regions where digital agriculture would otherwise offer the largest relative productivity gains. Subscription-based and pay-as-you-go pricing models, along with government subsidy schemes, are proposed across the literature as partial solutions, but systematic evidence on their effectiveness at scale is still limited.

Data Quality and Interoperability

AI model performance is directly constrained by the quality, consistency, and volume of training data available, and agricultural datasets are frequently fragmented across proprietary platforms with incompatible formats. This interoperability gap slows both model development and the ability to transfer models trained in one region or crop context to another.

Digital Literacy and Adoption

Even where technology is accessible and affordable, adoption depends on farmers' familiarity with digital tools and trust in automated recommendations. Studies examining adoption barriers describe this as a socio-technical rather than purely technical problem, requiring training, extension support, and interface design suited to varying levels of digital literacy [24].

Table 5: Consolidates the challenges discussed in this section alongside the solutions most frequently proposed across the reviewed literature.

Challenge	Description	Proposed Solution(s) in Literature
Rural Connectivity	Weak or absent broadband/cellular coverage delays real-time data transmission from field devices.	LPWAN (LoRaWAN, NB-IoT), hybrid LPWAN-5G architectures, satellite internet, edge computing.
Data Security & Privacy	Sensitive farm data is vulnerable to unauthorised access, tampering or cyberattack.	Encryption, secure authentication protocols, blockchain-based tamper-resistant records.
Cost & Scalability	High upfront cost of sensors, connectivity and cloud services limits adoption by small farmers.	Pay-as-you-go pricing, government subsidies, shared/community IoT infrastructure.
Data Quality & Interoperability	Fragmented, inconsistent data formats across device makers and platforms hinder model transfer.	Standardised open data schemas, common APIs, shared regional datasets.
Digital Literacy & Adoption	Farmers may lack familiarity with, or trust in, automated digital recommendations.	Extension-service training, simplified dashboards, farmer-participatory system design.

Table 5: Key challenges in AI-IoT adoption and proposed solutions.

Research Gaps and Future Directions

- Affordable, low-power edge-AI models that can run reliably on inexpensive hardware in connectivity-constrained regions, reducing dependence on continuous cloud access.
- Standardized, interoperable data formats across IoT device manufacturers and agricultural platforms, to enable model transfer and multi-source data fusion.
- Region- and crop-specific validation studies, particularly for smallholder and sub-tropical farming contexts such as those in India, where most published model benchmarks originate from large-scale farms in other geographies.
- Longitudinal field studies measuring real-world model performance over multiple growing seasons, rather than single-season or laboratory-controlled evaluations.
- Integrated frameworks that combine AI-IoT precision farming with block chain traceability end-to-end, rather than treating them as separate research streams.
- Socio-technical research on adoption pathways, extension-service models, and financing mechanisms that could close the gap between technical feasibility and on-farm uptake.
- Standardized, cross-study benchmark datasets and evaluation protocols that would allow the kind of direct model comparison currently only possible within single studies (Section 9.1).

Limitations of this Review

This review has several limitations that should be considered when interpreting its findings. First, as a narrative-cum-thematic review rather than a formal systematic review conducted under PRISMA or a similar protocol, it does not apply quantitative inclusion/exclusion screening or formal risk-of-bias assessment, and the reference set — though spanning 2017 to 2025 — is not exhaustive of the rapidly growing literature in this field. Second, the detailed comparison in Table 4 and the worked example in Section 9.1 draw on metrics reported by the original authors under differing experimental conditions, datasets, and evaluation protocols; the figures are therefore illustrative of reported performance rather than the result of a standardized, head-to-head benchmark, and cross-study comparisons should be interpreted with this caveat in mind. Third, coverage of non-English-language literature and of grey literature was limited, which may under-represent region-specific work, particularly from non-English-speaking agricultural research communities. Fourth, the review's emphasis on peer-reviewed journal and conference sources means very recent developments may not yet be reflected. Finally, quantitative claims regarding cost reduction, water savings, and similar outcomes are drawn from the specific case-study contexts reported in the cited literature and may not generalize directly to other crops, regions, or farm scales without further validation.

Conclusion

The literature reviewed here indicates that AI and IoT convergence has moved from a conceptual proposition to a demonstrably functional set of technologies across irrigation, disease detection, yield forecasting, and supply-chain traceability. Reported gains in resource efficiency and early-warning capability are consistent across studies, even where the exact magnitude varies by crop, region, and system design, and the year-ordered comparison in Table 4 shows steady incremental improvement in reported model performance over the 2017–2025 period. At the same time, connectivity gaps, security concerns, cost barriers, data fragmentation, and uneven digital literacy continue to constrain adoption beyond pilot and research settings, particularly for smallholder farmers in regions with limited digital infrastructure. Closing this gap between demonstrated technical capability and real-world adoption — rather than further incremental gains in laboratory model accuracy — appears to be the central challenge for the next phase of research in this field, and is the direction this doctoral research programme intends to pursue.

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