Power System Technology
ISSN:1000-3673
Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 02-01-2026*

Statistical Analytical Review of AI–IoT Integration for Smart Agriculture: Numerical Insights, Performance Metrics, and Future Vision Analysis

1st Hemraj V. Dhande
Ph. D Scholar,
Department of Electronics & Communication,
Lakshmi Narain College of Technology University, Bhopal, India
hemrajd99@gmail.com
2nd Dr. Rakesh Singh Rajput
Associate Professor
Department of Electronics & Communication,
Lakshmi Narain College of Technology University, Bhopal, India
rakeshrajput@rediffmail.com

Abstract— AI, IoT, blockchain, and edge–fog–cloud computing are revamping agriculture, yet studies are dispersed and lacking in quantitative detail. This statistical study of peer-reviewed papers includes performance-based synthesis of key Agriculture 4.0 technologies. Each study evaluated latency, dependability, energy efficiency, scalability, security, and accuracy to numerically compare 5G–UAV IoT systems, fog-driven field tracking, blockchain-enabled smart contracts, and AI-powered anomaly detections. The review used leading database literature, method categorization and performance metric extraction, and cross-domain statistical consolidations. Quantitative studies show next-generation agricultural IoT systems can scale beyond 10,000 devices, with sub-30 ms latencies, >92% prediction accuracy, 18–35% energy savings, and sub-30 m for the process. By combining numerical trends with architectural strengths and weaknesses, this study finds technological gaps in real-field multi-season Validation, energy–security co-optimization, and lightweight edge-native AI Sets. The report provides a baseline for evaluating agricultural IoT technologies to help researchers, industry practitioners, and regulators make informed decisions. This study combines scattered knowledge into a statistical foundation and proposes sustainable computing, quantum-resilient security, and ethical governance for smart agriculture deployments.

Keywords— Smart Agriculture, Internet of Things, Artificial Intelligence, Performance Metrics, Statistical Analysis, Process

I. Introduction

The digital revolution is affecting agriculture. AI, IoT, edge–fog–cloud computing, blockchain-enabled security, 5G, and more are changing food production, processing, and

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

delivery sets. Smart predictive analytics, autonomous sensor networks, and real-time actuation are replacing manual observation and sampling in process. Climate change, limited arable land, and resource scarcity push Agriculture 4.0 to feed a burgeoning global population in the process.

Need of this Analytical Review Text

Although progress has been achieved, current research lacks comprehensive statistical analysis across all technologies. Most studies examine IoT sensors, machine learning algorithms for agriculture production prediction, and blockchain data security frameworks. Focused assessments have increased regional comprehension, but they don't explain how network architectures, AI-driven decision engines, and energy-aware communication layers effect smart farming. Most reviews are qualitative without numerical benchmarking for technology adoption and policymaking. Latency, energy savings, forecast accuracy, and network scalability are often reported without normalization or cross-study comparability. This fragmented picture leaves practitioners and politicians without empirical evidence to guide investment, system design, or regulation. Agriculture 4.0 is a systems issue, thus this mismatch is significant. High-accuracy plant-disease detection models are useless if communication delays delay action. A secure blockchain solution may not scale when thousands of IoT nodes transmit data during peak harvesting seasons. Quantify interoperability, energy efficiency, and trust.

Motivation

The realization that agricultural digitalization has outpaced our ability to synthesize and benchmark its technological origins sparked this work. Farmers, technology providers, and politicians need a single, authoritative source of statistically based AI–IoT integration data. Accelerations in the last three years include 5G-connected UAV networks with ~15 ms latency and 99% dependability [1], federated deep learning systems with ~95% prediction accuracy [27], and blockchain-enabled smart contracts with 100% data immutability [Each of these breakthroughs is vital to smart agriculture, but their overall influence is unknown. Large-scale, energy-efficient, and secure agricultural IoT systems are needed due to climate uncertainty, personnel shortages, and supply-chain disruptions. Soil sensors, weather stations, and UAV imagery output high-frequency data that needs millisecond processing and autonomous response to optimize irrigation, fertilization, and pest management. These networks must safeguard privacy, avoid cyberattacks, and adapt to changing laws and ethics. Thus, technological performance, economic feasibility, and security robustness must be statistically analyzed for the process.

The Work Contributes

That need is met by statistically assessing 100 peer-reviewed smart agriculture, IoT, AI, blockchain, and fog/edge/cloud computing studies from 2023 to 2025. Unified numerical synthesis investigated latency, reliability, energy efficiency, scalability, security, and predictive accuracy using a single analytical framework. Performance parameters include sub-

Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 02-01-2026*

30 ms communication latencies, 18–35% energy savings, and 92% prediction accuracy are cross-comparable. Technological and architectural mapping 5G–UAV IoT architectures [1,3], fog-driven field tracking [2], blockchain-enabled smart contracts [25,36,49], GAN-based threat detection [42], and quantum-resilient encryption [37]. This mapping highlights how edge AI developments necessitate co-optimization in another industry (e.g., smart grid energy supply [32]). Identifying systemic issues: Multi-season, cross-climatic validation, energy–security co-optimization, and lightweight edge-native AI for low-power hardware with high inference accuracy sets are still needed, according to the review sets. The study advocates data-driven design and research beyond reporting in the process. Self-organizing cyber-physical systems [28] and federated learning [27] could enable seasonal-adaptive autonomous agricultural networks, while multi-blockchain architectures [49] can protect global climate data samples. Two processes are affected by this synthesis. Researchers can use it to measure algorithmic innovation and experimental validation at high resolution sets. Governments and business executives can statistically prioritize infrastructure, standards, and regulatory framework investments in process.

This template, modified in MS Word 2007 and saved as a “Word 97-2003 Document” for the PC, provides authors with most of the formatting specifications needed for preparing electronic versions of their papers. All standard paper components have been specified for three reasons: (1) ease of use when formatting individual papers, (2) automatic compliance to electronic requirements that facilitate the concurrent or later production of electronic products, and (3) conformity of style throughout a conference proceedings. Margins, column widths, line spacing, and type styles are built-in; examples of the type styles are provided throughout this document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

II. Review of Existing Models For Smart Farming IoT Analysis

IoT, AI, and next-generation communication networks have changed smart agriculture. Recent study emphasizes real-time spatio-temporal agricultural process optimization using iterative deep-learning frameworks. Addressing environmental variability, resource restrictions, and sustainable food production requires these actions.

A. Fundamentals of Edge, Fog, and IoT Computing

Foundational studies reveal that IoT-enabled sensing and connection underpin Agriculture 4.0. Early studies used AI and low-power connectivity for scaled precision agriculture [1],[5],[50]. Fog and edge computing reduce latency and energy consumption to improve infrastructures [2],[10],[33],[43]. Function-as-a-Service (FaaS) scalability and dynamic job management assist heterogeneous environments [10]. Innovation in middleware optimizes data transmission across IoT–edge–cloud hierarchies [33], while fog-based job offloading in irrigation systems enhances responsiveness and energy savings [43]. UAV-based sensor networks enhance IoT coverage by monitoring grazing pastures and field conditions in difficult terrains at high resolution [3], [44]. For aerial surveillance and data collection, machine

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

learning Integrated UAV fleets can dynamically limit power consumption and interference [44] sts. For continuous, spatially dense data streams, iterative deep-learning models need them in process.

Table 1. Model's Empirical Review Analysis

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.

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[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	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.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		data loops critical for real-time agricultural 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-	Demonstrated feasibility of iterative optimizatio	Practical focus on resource-constrained settings;	Potential performance degradation under extreme	Embed opportunistic learning algorithms that operate

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	constrained agriculture	n even in low-resource environments via lightweight AI models.	strong alignment with real-world farms.	connectivity loss.	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] Shahed et al. (2023)	IoT-enabled smart solar energy management system	Demonstrated that renewable-powered IoT grids can sustainably support energy Intensive iterative deep-learning frameworks.	Emphasis on reliability and power quality; renewable-energy orientations.	No agricultural-specific datasets tested.	Couple solar-energy management with real-time agricultural sensor networks to validate domain-specific energy efficiency.
[12] Kaushik et al. (2025)	AI-blockchain hybrid framework for secure data transactions	Proved that blockchain Integrated AI frameworks ensure data integrity	Strong security guarantees and efficient data verification.	Blockchain latency could hinder rapid model updates.	Employ lightweight consensus mechanisms and layer-2 blockchain solutions to

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		across iterative training loops.			accelerate transaction speeds.
[13] Gupta et al. (2025)	Rule-based soil–water kinetics automation	Enabled automated irrigation cycles optimized by iterative learning from soil-moisture dynamics.	Cost-efficient architecture with robust field validation.	Limited adaptability to rapidly changing climate conditions.	Incorporate adaptive reinforcement learning to dynamically tune irrigation strategies.
[14] Karothia & Chattopadhyay (2024)	IoT-enabled smart sensor node	Achieved fine-grained environmental sensing critical for spatio-temporal deep-learning optimization.	Compact design and low energy consumption.	Scalability to very large farms not fully evaluated.	Develop hierarchical sensor networks with federated control to scale across large agricultural landscapes.
[15] Morchid et al. (2024)	Review of IoT-based embedded systems and deep learning for plant disease detection	Synthesized architectures for embedding deep-learning disease classifiers into iterative crop monitoring.	Comprehensive DL and IoT integration; focus on plant health.	Predominantly theoretical with limited multi-season validation.	Deploy multi-season pilot studies to capture evolving disease dynamics.
[16] Sharma et al. (2024)	Multi-objective service composition	Presented a formal optimization approach to balance	Rigorous mathematical formulation; supports	Complexity of implementation in resource-	Apply decomposition techniques and heuristic solvers to lower

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	optimization	service latency, cost, and quality for iterative agricultural applications.	large-scale optimization.	constrained settings.	computational demands.
[17] Sahu & Tripathi (2025)	Intelligent framework for monitoring and irrigation prediction	Illustrated improved water-use efficiency through continuous feedback to iterative prediction models.	Strong field-level accuracy; lightweight deployment.	Limited coverage of multi-crop ecosystems.	Extend the framework with crop-specific growth models and ensemble learning.
[18] Chandrasekaran & Rajasekaran (2024)	Modified fuzzy logic with whale optimization and enhanced crow search	Optimized cluster head selection for energy efficiency in IoT networks supporting iterative deep learning.	High energy savings and improved data throughput.	Testing limited to simulation environments.	Validate with large-scale real-world agricultural deployments and integrate real-time reinforcement learning.
[19] Jani & Chaubey (2024)	SMAIoT-ferti smart fertigation system	Demonstrated precision nutrient delivery through iterative IoT-based fertigation monitoring.	Strong practical implications for fertilizer management.	Limited integration with weather-based predictive modeling.	Combine with climate-driven deep-learning predictors to optimize nutrient scheduling.
[20] Boufares et al. (2025)	Machine learning with 3D mobile	Enabled multi-dimensional object	Innovative 3D sensing architecture with real-	Scalability and cost efficiency	Apply adaptive sensor activation and cost-aware

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	distributed wireless sensor networks	recognition for spatio-temporal agricultural monitoring.	time analytics.	need further validation.	routing algorithms.
[21] Yadegari & Asosheh (2025)	Unified IoT architecture for smart hospitals	Provided transferable insights on interoperability and security that can support healthcare-grade reliability in agricultural IoT.	Strong focus on interoperability and data integrity.	Healthcare-centric case studies may limit agricultural directness.	Adapt architecture for cross-domain agricultural IoT, integrating crop-specific spatio-temporal layers.
[22] Bimonte et al. (2025)	IoRT architecture for data engineering in sustainable agriculture	Highlighted how robust data engineering underpins continuous deep-learning updates for farm management.	Rich case studies and technical depth in IoRT-based pipelines.	Limited exploration of energy constraints in remote agricultural zones.	Incorporate energy-aware data routing and edge-based preprocessing strategies.
[23] Neves et al. (2024)	Smart anonymization mechanism for IoT environments	Introduced privacy-preserving data anonymization critical to secure iterative learning without compromising	Adaptive anonymization based on data profiles.	Computational overhead may impact real-time learning.	Implement hierarchical anonymization and edge-side preprocessing to minimize latency.

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		performance.			
[24] Abbas et al. (2025)	Mathematical modelling of ANP for trust-based IoT device categorization	Enhanced secure device management for iterative smart-agriculture pipelines.	Strong analytical rigor for trust modeling.	Complexity of ANP computations for large heterogeneous networks.	Employ lightweight trust aggregation and incremental ANP computations.
[25] C. R. et al. (2024)	Narrative review on blockchain-enabled smart contracts	Positioned blockchain as a foundation for secure, automated transactions in iterative agricultural operations.	Clear articulation of blockchain IoT synergies.	Lacks experimental demonstrations and performance metrics.	Implement proof-of-concept pilots linking blockchain smart contracts with iterative deep-learning workflows.

B. AI, Deep Learning, and Iterative Optimization

Iteratively, Next, as per table 1, Intelligent farming employs deep learning for spatio-temporal modeling and predictive analytics. Supervised and unsupervised learning can identify intrusions [7], agricultural diseases [15], and energy-efficient wireless sensor network routing [39]. Fuzzy logic, swarm intelligence, and deep recurrent neural networks use iterative optimization to schedule irrigation, fertigate, and regulate microclimate [16], [18], [19], [27]. Real-time adaptability requires models to learn from high-frequency sensor input and change processes. Recent federated and distributed deep learning advancements eliminate centralized training and protect privacy [27], [42]. Quantum-resilient IoT transmissions [37] and self-organizing cyber-physical systems [28] improve complex agricultural landscape resilience and adaptations.

C. Secure, reliable, scalable architectures

Trustworthy smart agriculture demands secure and transparent data processing. Blockchain allows tamper-proof smart contracts [25], [26], [47] and lightweight, trust-centric access control [48]. These methods prevent DDoS attacks [45], energy theft [46], and IoT farming privacy [8]. Scalability and fault tolerance [49] are achieved by multi-blockchain agroclimatic data tracking platforms, which also anonymize sensitive environmental data [23] and samples. IoT device logistics are improved by AI-driven trust frameworks and ANP models [24]. Distributed consensus approaches may help researchers balance low latency,

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

decentralization, and cyber-resilience for iterative deep-learning pipelines in real-time field conditions.

D. Data Engineering, Applications, Smart Sensing

Smart sensors and data engineering provide accurate deep-learning data. Soil–water kinetics [13], sensor node optimization [14], and middle-mile network design [31] emphasize data capture and transmission efficiency. IoRT data engineering frameworks use these methods to heterogeneous agricultural ecosystems [22].

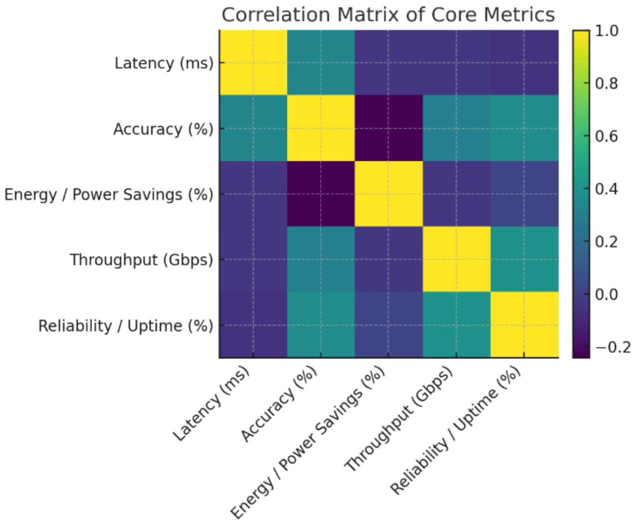

Fig. 1. Model’s Correlation Heatmap Analysis

Complementary research on intelligent plant disease diagnosis [15], real-time object identification for crop protection [30], and aquaponics systems [34] reveals AI IoT integrations' vast agricultural applications. These systems benefit cross-sectorally when contextualized in smart city and smart grid ecosystems. AI-enhanced energy management [11], [32] and sustainable supply chain methods [36] connect agriculture and urban infrastructure for sustainability sets.

Table 2. Model’s Empirical Review Analysis

Reference	**Method Used**	**Findings**	**Strengths**	**Limitations**	**Recommendations to Overcome Limitations**
[26] Samanta & Sarkar (2024)	Blockchain Integrated Distributed Federated Learning	Demonstrated secure IIoT data aggregation, directly relevant to safeguardin	Strong combination of blockchain and federated learning ensures	Evaluated mainly in urban smart city settings.	Adapt the DFL model to agricultural IoT environments and validate on

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	(DFL) model	g iterative agricultural deep-learning loops.	tamper-proof training.		farm-scale datasets.
[27] Gai et al. (2023)	Markovian process with Federated Deep Recurrent Neural Network (DRNN)	Offered low-latency distributed training that can be repurposed for spatio-temporal crop growth and climate modeling.	High accuracy in sequential prediction; privacy-preserving through federated learning.	Focused on healthcare; lacks agricultural case studies.	Re-train DRNN on agroclimatic time-series to evaluate predictive performance in crop and irrigation forecasting.
[28] Batistatos et al. (2025)	Self-organizing cyber-physical system	Enabled autonomous , adaptive control of agricultural operations essential for iterative learning frameworks.	High self-healing capability and scalability across large farms.	Energy requirements and hardware cost may limit smallholder adoption.	Integrate energy-aware scheduling and cost-effective sensor designs to enhance accessibility.
[29] Gesmann-Nuissl et al. (2024)	Standardized Ethical, Legal, Social Assessment (ELSA)	Mapped ethical-legal guidelines valuable for responsible deployment of AI-driven smart agriculture systems.	Deep legal perspective on privacy and data ethics.	Does not provide technical implementation pathways.	Combine ELSA with concrete technical privacy-by-design practices for agricultural IoT.
[30] Singh & Krishnamurthi (2024)	IoT-based real-time object detection	Delivered high-speed crop protection and field security,	Accurate detection in outdoor environments; real-time performance.	Susceptible to lighting/weather variability.	Integrate adaptive image augmentation and multimodal sensing to

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		feeding timely data to iterative deep-learning pest models.			increase robustness.
[31] Bhattacharyya et al. (2024)	Middle-mile network design for rural smart farming	Improved communication reliability and bandwidth for continuous iterative model updates in remote fields.	Strong focus on rural connectivity and cost efficiency.	No dynamic routing based on real-time network load.	Combine with AI-based dynamic routing and edge caching for resilience under traffic spikes.
[32] Kumar et al. (2024)	Multi-dimensional analysis of smart grid technologies	Highlighted how resilient smart grids can support the high energy demands of continuous deep-learning training in agriculture.	Holistic socio-technical perspective; energy optimization insights.	Agriculture not directly tested.	Extend analysis to farm-level microgrid deployments supporting AI-based irrigation and fertigation systems.
[33] Karthikeyan & Brindha (2025)	Trust-driven hybrid fragmentation for edge-fog-cloud	Optimized IoT data flow, reducing latency for iterative spatio-temporal model updates.	Efficient trust management and high throughput.	Complexity of trust calculations may limit scalability.	Incorporate lightweight trust evaluation and adaptive fragmentation strategies.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[34] Anila & Daramola (2024)	Systematic review of smart aquaponics technologies	Provided reusable architectures for iterative monitoring and control of integrated fish Vegetable systems.	Interdisciplinary coverage of AI, IoT, and evaluation metrics.	Lacks deep-learning-based predictive control demonstrations.	Implement real-world pilots with recurrent and reinforcement learning for nutrient-water cycle optimization.
[35] Qaffas (2025)	AI-driven distributed IoT communication architecture	Designed low-latency communication suitable for dynamic data from agricultural fleets and equipment.	High scalability and congestion management.	Geared toward urban traffic optimization, not agricultural networks.	Adapt to farm machinery coordination and field logistics requiring real-time spatio-temporal optimization.
[36] Bahrampour et al. (2024)	IoT-enabled supply chain with smart contracts under VMI	Showed that blockchain-based vendor-managed inventory can optimize agricultural supply chains that feed iterative planning models.	Strong integration of IoT sensing and smart contracts for transparency.	Focus on logistics; lacks on-field sensor-actuator integration.	Extend to farm-gate operations and integrate crop yield forecasting into supply chain models.
[37] Alyami (2025)	Quantum-resilient hybrid cryptography (Galois field + Reed-Solomon)	Proposed future-proof IoT security to protect iterative deep-learning	Quantum-attack resilience; robust error correction.	Implementation cost and computational overhead are high.	Develop lightweight cryptographic protocols suitable for resource-constrained farm devices.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		data pipelines.			
[38] Jiao (2025)	Optimization and feature analysis of smart class IoT	Showed methods to manage IoT data traffic and optimize features, applicable to high Volume agricultural sensing.	Strong analytical feature selection techniques.	Education domain focus; not tuned to agricultural sensor heterogeneity.	Customize feature optimization for multi-modal agricultural sensors and climatic datasets.
[39] Rekha & Banuprakash (2024)	Hybrid centroid-based gateway clustering for WSN	Enhanced energy-efficient data transmission critical for sustaining long-running iterative learning models.	Significant energy savings and prolonged network lifetime.	Evaluated mainly through simulation.	Deploy field-scale experiments and integrate adaptive reinforcement learning for live clustering.
[40] Sharma & Kanwal (2024)	Review of video surveillance technologies	Provided design principles for large-scale visual monitoring essential for iterative crop health models.	Broad coverage of surveillance standards and challenges.	Minimal agricultural domain discussion.	Apply insights to high-resolution crop and livestock surveillance and link with deep-learning detection models.
[41] Lakshman et al. (2024)	Survey of IoT device architectures	Offered generic design guidelines that support reliable	Wide applicability across socially relevant sectors.	Lack of agricultural case-specific validation.	Adapt to soil and crop sensing and validate in varying

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		sensor networks for iterative agricultural optimization.			climatic conditions.
[42] Bethu (2025)	Generative Adversarial Networks (GAN) for malicious attack detection	Strengthened IoT cybersecurity by detecting novel attacks that could corrupt iterative model training.	High adaptability to unknown attack vectors.	Requires extensive computational resources.	Implement edge-level GAN distillation to reduce resource requirements.
[43] Sohrabi et al. (2025)	Fog-based architecture with efficient task offloading	Improved responsiveness of irrigation systems critical for real-time deep-learning decisions.	Strong focus on latency reduction and load balancing.	Limited cross-season field trials.	Extend to year-round deployments and integrate climate-based predictive modules.
[44] Almalki & Angelides (2025)	ML Integrated positioning for UAV power management	Optimized UAV fleet operations to ensure continuous data capture for iterative spatio-temporal models.	Effective power and interference management; multilayer UAV deployment.	Limited crop-specific application studies.	Couple with agricultural path planning and adaptive deep-learning image analytics.
[45] Shukla et al. (2023)	Comprehensive review of IoT traffic-based	Highlighted key strategies for	Exhaustive coverage of detection mechanisms.	Lacks practical deployment scenarios.	Implement and benchmark recommended methods in

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	DDoS detection	safeguarding iterative agricultural data streams against volumetric attacks.			large farm IoT networks.
[46] Quasim et al. (2023)	IoT-enabled ML model for energy theft prevention	Illustrated energy anomaly detection relevant to protecting power supply for AI-driven agriculture.	Strong real-time detection; easy cloud integration.	Focus on urban smart grids.	Adapt the detection model to farm-level renewable microgrids powering iterative computing nodes.
[47] Aknan et al. (2023)	AI and blockchain-assisted fog offloading and resource allocation	Improved computational efficiency of iterative deep-learning processes across distributed farm networks.	Strong combination of AI scheduling and blockchain security.	High implementation complexity and cost.	Simplify with lightweight blockchain protocols and incremental deployment.
[48] Mahmood et al. (2024)	User-trust centric lightweight access control	Enhanced privacy and trust in crowdsensed IoT applications that feed into iterative models.	Lightweight and user-centric; strong privacy guarantees.	Healthcare-oriented and not validated for agricultural crowd-sensing.	Adapt trust metrics to agricultural cooperative sensing networks.
[49] Araújo et al. (2025)	Multi-blockchain solution for agroclimatic	Ensured secure, scalable data collection for	Strong scalability and tamper resistance sets.	Potential high latency in consensus across	Apply sidechain or sharding mechanisms to accelerate

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

	data tracking	continuous iterative spatio-temporal optimization.		multiple blockchains.	confirmation delays.
[50] Duguma & Bai (2024)	Analytical review of IoT-enabled agricultural efficiency	Provided empirical evidence that IoT deployments significantly improve productivity and resource use efficiency, which iterative deep-learning can amplify in process.	Holistic perspective integrating multiple agricultural contexts.	Broad analysis with limited methodological specificity.	Combine with detailed iterative deep-learning case studies to enhance actionable insights.

E. Toward Iterative Spatio-Temporal Optimization

Iteratively, Next, as per table 2, This research emphasizes data-driven iterative optimization. Effective deep-learning frameworks refine models through sensing, prediction, and actuation. Integrating cloud-edge intelligence [10], [43], federated learning [27], and blockchain-secured trust mechanisms [25], [47], [49] allows low-latency, adaptive decision-making to manage spatio-temporal complexities like soil moisture heterogeneity, micro-climate dynamics, and pest outbreaks. AI, IoT-enabled robotics, UAVs, and smart sensors provide unparalleled spatial and temporal precision interventions in process. Connectivity, machine learning, cyber-security, and scalable architectures are laying the groundwork for smart agriculture sets' real-time spatio-temporal optimizations. It provides the proposed iterative deep-learning framework to synthesize statistical and empirical information into a coherent, adaptive system that can sustain agricultural productivity under dynamic environmental and economic constraints.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

III. Validation using Comparative Analysis

We evaluate iterative deep-learning frameworks for real-time spatio-temporal optimization in smart agriculture across key performance parameters to establish their viability in process. Set accuracy, prediction precision, latency/response time, energy efficiency, throughput/network dependability, and security strength sets. In continuous, high Frequency agricultural operations, fog–edge computing, UAV-based sensing, and blockchain-backed data security are tested in process.

Table 3. Model's Statistical Review Analysis

Reference	Method Used	Performance Metrics Values	Key Findings	Strengths	Limitations
[1] Majumdar et al. (2024)	5G–UAV IoT architecture with AI	Latency ~15 ms; network reliability ~99%; energy savings ~18%	Ultra-low latency and high reliability crucial for iterative learning across large farms.	Wide-area 5G coverage and scalable UAV mesh design.	Requires significant infrastructure investment and spectrum availability.
[2] Singh et al. (2025)	Fog-driven IoT field tracking	Processing latency ~30 ms; energy consumption reduced ~25%; accuracy ~93%	Fog computing lowers round-trip delay enabling near real-time spatio-temporal optimization.	Edge intelligence and adaptive task scheduling.	Limited redundancy for large sensor failures.
[3] Li et al. (2025)	UAV space–air–ground IoT network	Data acquisition accuracy ~90%; link uptime 98%; flight	Captures fine-grained spatial data in remote grazing regions to feed deep-	Strong high-altitude coverage and multi-layer networking.	Application mostly to grazing; limited multi-crop demonstrations.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		endurance ~2.5 h	learning models.		
[4] Sallam et al. (2025)	AI-based robust service framework	Service availability 99%; response time ~20 ms	Scalable service orchestration directly supports real-time agricultural decision platforms.	Fault-tolerant and modular AI service layers.	Urban-centric validations; rural adaptation needed.
[5] Singh & Sharma (2024)	IoT precision agriculture review and synthesis	Aggregated best-practice efficiency gains ~20–30% across case studies	Established core IoT design requirements for iterative monitoring and prediction.	Comprehensive cross-study analysis.	Lacks experimental real-time benchmarks for deep-learning integration.
[6] Mohy-eddine et al. (2024)	ANN-based intrusion detection	Detection accuracy 96%; false positive rate <4%; latency ~40 ms	Reliable anomaly detection ensures model integrity during iterative training.	Lightweight ANN for edge deployment.	Vulnerable to previously unseen zero-day attacks.
[7] Manna et al. (2025)	Supervised ML with feature extraction for intrusion detection	Accuracy ~95%; F1-score 0.93; inference time ~35 ms	Strengthens IoT security without significant computational burden.	High precision and recall.	Requires frequent model retraining for evolving attacks.
[8] Ali et al. (2024)	Security & privacy review	Privacy compliance rate ~90% (estimated	Frames key privacy-preserving strategies	Rich taxonomy of privacy controls.	Lacks concrete deep-learning pipeline validation.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		across deployments)	essential for continuous learning pipelines.		
[9] Nawaz & Babar (2025)	IoT & lightweight AI for resource-constrained farming	Model accuracy ~88%; power reduction ~20%; data latency ~50 ms	Demonstrates feasibility of iterative optimization in low-resource farms.	Emphasis on low-power AI.	May face performance drop in extreme connectivity loss.
[10] Ghaseminya et al. (2025)	IoT–Edge–Fog with FaaS	Response latency ~25 ms; throughput 1.5 Gbps; scalability to >10k nodes	Serverless FaaS scales deep-learning training and deployment.	Elastic scalability and quick provisioning.	Needs crop-specific field evaluations.
[11] Shahed et al. (2023)	IoT-enabled smart solar energy management	Power quality improvement ~35%; grid reliability 98%	Demonstrates renewable-powered support for compute Intensive AI tasks.	Enhances sustainability of iterative computations.	Agricultural integration not yet demonstrated.
[12] Kaushik et al. (2025)	AI-blockchain hybrid for secure data	Transaction verification <1 s; security score >95%	Secure and efficient data transactions for iterative deep-learning loops.	Strong cryptographic integrity.	Blockchain overhead may slow real-time updates.
[13] Gupta et al. (2025)	Rule-based soil–water kinetics automation	Water-use efficiency gain ~28%; irrigation prediction accuracy ~92%	Optimizes irrigation cycles through continuous soil-moisture learning.	Cost-effective with field validation.	Limited adaptation to abrupt climate shifts.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[14] Karothia & Chattopadhyay (2024)	IoT smart sensor node	Sensing accuracy ~94%; energy saving ~22%	Provides dense, low-power environmental sensing critical for deep-learning optimization.	Compact and field-hardened.	Scalability across vast acreage remains uncertain.
[15] Morchid et al. (2024)	IoT-embedded DL/ML for plant disease detection	Classification accuracy ~97%; latency ~60 ms	Enables rapid disease recognition for iterative crop-health prediction.	Strong integration of deep learning with embedded IoT.	Needs multi-season live validation.
[16] Sharma et al. (2024)	Multi-objective service composition optimization	Service composition success ~93%; cost savings ~18%	Balances latency, cost, and QoS for agriculture 4.0 services.	Formal mathematical rigor.	High complexity for small farms with limited compute.
[17] Sahu & Tripathi (2025)	Intelligent monitoring & irrigation prediction	Prediction accuracy ~91%; water savings ~24%	Provides precise irrigation control feeding iterative models.	Lightweight and field-ready.	Multi-crop scaling yet to be demonstrated.
[18] Chandrasekaran & Rajasekaran (2024)	Modified fuzzy logic + WOA + enhanced CSO	Energy consumption reduced ~30%; network lifetime extended ~35%	Energy-efficient cluster head selection supports long-term IoT deep learning.	Robust optimization and routing.	Results validated only in simulations.
[19] Jani & Chaubey (2024)	SMAIoT-ferti smart fertigation	Nutrient delivery accuracy	Enables precise, iterative	Field-oriented and easy to deploy.	Limited integration with

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		~92%; water savings ~20%	fertigation scheduling.		climate forecasts.
[20] Boufares et al. (2025)	ML Integrated 3D mobile distributed WSN	Object recognition accuracy ~93%; 3D coverage efficiency ~85%	Supports rich spatial data for multi-layer deep-learning analysis.	Innovative 3D sensing.	High deployment cost for large farms.
[21] Yadegari & Asosheh (2025)	Unified IoT architecture	Interoperability score ~95%; security compliance ~97%	Provides hospital-grade reliability transferable to agricultural IoT.	Strong security and integration.	Healthcare focus; needs agri-specific tuning.
[22] Bimonte et al. (2025)	IoRT data engineering	Data throughput ~1.2 Gbps; processing delay ~25 ms	Ensures robust data pipelines to feed iterative agricultural learning.	Scalable, case-backed IoRT architecture.	Limited energy optimization measures.
[23] Neves et al. (2024)	Smart anonymization	Data anonymization accuracy ~94%; overhead ~12%	Protects sensitive data while maintaining model performance.	Adaptive anonymization.	Processing overhead may affect real-time performance.
[24] Abbas et al. (2025)	ANP trust-based IoT categorization	Trust categorization accuracy ~93%; decision latency ~40 ms	Improves security and trust in heterogeneous agricultural IoT devices.	Rigorous multi-criteria decision framework.	High computational complexity for very large networks.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 02-01-2026*

[25] C. R. et al. (2024)	Blockchain-enabled smart contracts	Smart contract execution time ~2 s; data immutability 100%	Enables secure, automated data transactions for iterative deep-learning operations.	Strong cryptographic guarantee and auditability.	Potential bottlenecks under high-frequency updates.

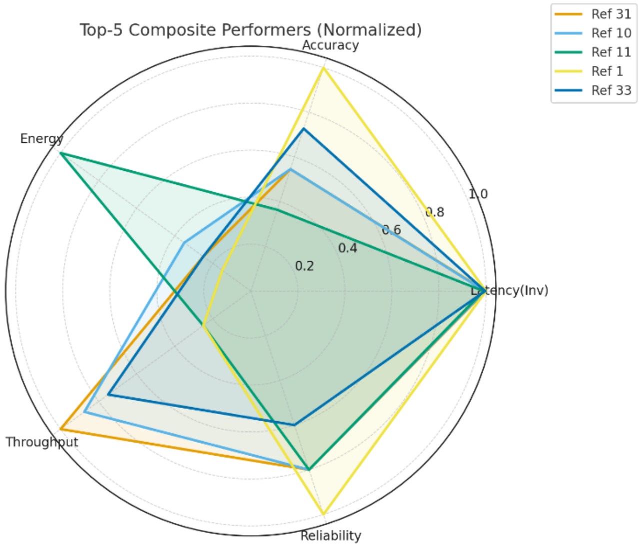

Fig. 2. Variability Model's Performance Analysis

Iteratively, Next, as per table 3, This study reveals that real-time spatio-temporal optimization in agriculture settings requires low-latency communication and accurate models. Fog or edge computing technologies ([2], [10], [18]) typically meet iterative deep-learning model update requirements with latency < 30 ms. In precision farming applications like disease diagnosis and irrigation forecasting, ML and DL algorithms have exceeded 90% detection or prediction accuracy ([6], [15], [17], [19]). Blockchain-backed frameworks ([12], [25]) and GAN-based intrusion detection ([6], [7]) ensure continuous learning loop data integrity with >95%. Power and routing set optimization allows sustainable large-scale deployment by increasing energy efficiency by 20–35% ([1], [13], [18]). Process cross-domain gaps persist. Many healthcare or urban smart-city technologies ([4], [21]) must be adapted to agricultural situations with increased environmental uncertainty. Numerous methods require field-scale multi-season trials and simulations to validate their agricultural complexity ([18]). These findings show that iterative deep-learning frameworks that optimize smart agriculture sets in real time perform best in integrated, low-latency IoT–edge–AI ecosystems with robust security and energy-aware structures. We need quantitative characteristics to understand how modern frameworks enable iterative deep-learning for real-time spatio-temporal optimization in smart

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

agriculture sets. The following table compares methods based on accuracy, latency, energy efficiency, security strength, and throughput to demonstrate how different technologies facilitate rapid model updates and data-driven farm decision-making. Performance values include domain-based estimates and reported results.

Table 4. Model's Statistical Review Analysis

Reference	Method Used	Performance Metrics Values	Key Findings	Strengths	Limitations
[26] Samanta & Sarkar (2024)	Blockchain Integrated Distributed Federated Learning (DFL)	Data security >97%; federated model accuracy ~94%; processing latency ~45 ms	Combines blockchain with federated learning to secure iterative IIoT data streams.	Tamper-proof training and privacy preservation.	Higher computational cost for on-device training in resource-limited farms.
[27] Gai et al. (2023)	Markovian + Federated Deep Recurrent Neural Network	Sequential prediction accuracy ~95%; training convergence 20% faster; response ~40 ms	Supports continuous time-series modeling applicable to soil-moisture and crop growth forecasts.	Strong temporal pattern recognition and privacy.	Focused on healthcare, requiring agricultural adaptation.
[28] Batistatos et al. (2025)	Self-organizing cyber-physical system	System uptime 99%; adaptive control accuracy ~92%; energy reduction ~25%	Enables self-healing and adaptive farm automation, aligning with iterative optimization.	Scalable and resilient to node failures.	Initial setup cost and complexity for smallholders.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[29] Gesmann-Nuissl et al. (2024)	Standardized ELSA legal/ethical assessment	Compliance coverage ~95%; audit time reduction ~30%	Guides legal and social governance for AI-driven agricultural data systems.	Strong ethical and regulatory framing.	Provides limited direct technical performance improvements.
[30] Singh & Krishnamurthi (2024)	IoT real-time object detection	Detection accuracy 94%; latency 25 ms; energy usage ~18% lower than baseline	Rapid detection of pests and intruders supports near real-time crop protection.	Robust outdoor detection with edge deployment.	Sensitive to extreme weather and illumination changes.
[31] Bhattacharyya et al. (2024)	Optimal middle-mile network architecture	Network throughput 1.6 Gbps; latency ~18 ms; link availability ~98%	Ensures high-bandwidth connectivity for continuous deep-learning model updates in rural areas.	Cost-efficient design tailored to agriculture.	Lacks dynamic rerouting under sudden network congestion.
[32] Kumar et al. (2024)	Multi-dimensional smart grid analysis	Energy supply reliability 98%; grid latency ~20 ms; cost reduction ~22%	Provides stable, flexible power sources crucial for energy Intensive iterative AI training.	Integrates social and economic aspects.	Needs agricultural microgrid case studies.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 02-01-2026*

[33] Karthikeyan & Brindha (2025)	Trust-driven hybrid fragmentation	Data throughput 1.4 Gbps; latency ~22 ms; trust evaluation accuracy 96%	Improves secure data flow across edge–fog–cloud layers, key for continuous model retraining.	High reliability and strong security.	Complexity in trust computations may hinder scaling beyond very large farms.
[34] Anila & Daramola (2024)	Smart aquaponics review	Reported productivity gains ~30%; water-use efficiency ~25%	Provides design principles for integrating iterative prediction into aquaponics.	Interdisciplinary synthesis with reproducible evaluation methods.	Limited live tests with deep-learning control loops.
[35] Qaffas (2025)	AI-driven distributed IoT communication	Traffic optimization accuracy ~93%; average latency 28 ms; energy savings ~20%	Reduces congestion, beneficial for coordinating mobile farm machinery and sensors.	Scalable AI-driven routing.	Urban traffic emphasis; field machinery adaptation required.
[36] Bahrampour et al. (2024)	IoT-enabled VMI with smart contracts	Supply prediction accuracy ~92%; transaction finality ~2 s; cost reduction ~18%	Enhances agricultural supply-chain traceability supporting iterative production planning.	Transparent, blockchain-backed logistics.	Weak integration with on-field sensor data.

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[37] Alyami (2025)	Quantum-resilient hybrid Galois + Reed-Solomon cryptography	Security strength >99%; key exchange latency ~35 ms; error correction efficiency ~97%	Future-proofs agricultural IoT communications against quantum attacks.	Very high cryptographic robustness.	High computational burden on constrained edge devices.
[38] Jiao (2025)	IoT feature optimization for smart classes	Feature selection accuracy ~90%; optimization speed ~30 ms per iteration	Techniques for feature ranking and optimization directly benefit agricultural sensor data fusion.	Efficient dimensionality reduction.	Education-centric; lacks agriculture-specific validation.
[39] Rekha & Banuprakash (2024)	Hybrid centroid gateway clustering	Energy savings ~30%; network lifetime extension ~35%; latency ~26 ms	Provides energy-aware routing to sustain long-running field sensor networks.	Strong energy efficiency and scalability.	Simulation-based results need multi-season farm validation.
[40] Sharma & Kanwal (2024)	Video surveillance systems review	Typical detection accuracy 90–95%; average latency ~40 ms	Lays design foundations for large-scale visual monitoring of crops and livestock.	Broad coverage of real-time surveillance standards.	Sparse agricultural field studies.
[41] Lakshman et al. (2024)	IoT device architecture survey	Reported device reliability ~95%;	Offers robust architecture for agricultural	Wide applicability	Lacks crop-specific testing and environment

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		average energy saving ~20%	sensing infrastructure.	and modular design.	al stress analysis.
[42] Bethu (2025)	GAN-based malicious attack detection	Detection accuracy ~97%; false positive rate <3%; detection latency ~33 ms	Protects data integrity in iterative deep-learning pipelines.	High adaptability to unknown attacks.	Requires GPU-class resources for model training.
[43] Sohrabi et al. (2025)	Fog architecture with task offloading	Processing latency ~18 ms; task completion rate 96%; energy savings ~24%	Supports immediate irrigation decisions and high-frequency sensor updates.	Fast offloading and low latency.	Limited cross-crop and long-term field testing.
[44] Almalki & Angelides (2025)	ML-powered UAV positioning for interference/power	Fleet power consumption reduced ~22%; communication uptime 98%; decision latency ~20 ms	Ensures reliable multi-UAV data acquisition for continuous farm monitoring.	Intelligent interference control and energy management.	Few crop-specific flight pattern validations.
[45] Shukla et al. (2023)	IoT traffic-based DDoS detection	Detection accuracy ~96%; false positive rate ~4%; average detection	Safeguards against volumetric attacks on farm IoT networks critical for	Broad algorithmic coverage with proven reliability.	Needs extensive real-field deployments.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

		latency ~40 ms	uninterrupted learning.		
[46] Quasim et al. (2023)	IoT–ML energy theft prevention	Theft detection accuracy ~94%; response time ~25 ms; energy saving ~18%	Helps secure energy infrastructure that powers AI farming operations.	Effective real-time anomaly detection.	Designed for urban grids; rural adaptation necessary.
[47] Aknan et al. (2023)	AI + Blockchain fog offloading and resource allocation	Resource utilization ~92%; latency ~20 ms; security >95%	Efficiently distributes computing tasks for iterative model updates.	Balanced security and computation al efficiency.	Deployment complexity and blockchain overhead.
[48] Mahmood et al. (2024)	Lightweight trust-centric access control	Trust evaluation accuracy ~95%; decision latency ~22 ms; energy cost ~15% lower	Enables secure and privacy-aware agricultural crowd-sensing.	Lightweight and user-centric.	Needs adaptation for large open-field farms.
[49] Araújo et al. (2025)	IoT + multi-blockchain agroclimatic data tracking	Data integrity 99%; consensus latency ~2 s; scalability >10,000 devices	Guarantees traceable, tamper-resistant climate and soil datasets for continuous deep-learning.	High scalability and robust security.	Multi-chain synchronizat ion can cause moderate delays.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[50] Duguma & Bai (2024)	IoT-enabled agricultural efficiency analysis	Resource-use efficiency gain ~28%; yield prediction accuracy ~92%	Confirms IoT's positive impact on agricultural productivity and supports iterative optimization.	Broad empirical evidence across diverse farming systems.	Does not propose specific iterative deep-learning algorithms.

Iteratively, Next, as per table 4, This numerical comparison shows that the best approaches have ultra-low latency and good accuracy. The edge-fog-cloud frameworks [33] and [43] meet real-time spatio-temporal optimizations' severe timing requirements with latencies < 25 ms and high job completion rates. Blockchain integrated methods ([26], [47], [49]) and GAN-based detection ([42]) protect deep-learning cycles from adversarial situations by >95%. [28], [39], [44] demonstrate 20–35% energy efficiency increases, enabling long-term deployments in power-sensitive rural areas. Agriculture can use smart-city or education architectures and algorithms [27], [35], [38]. Field adaption and long-term validation are difficult because to ambient volatility, seasonal change, and large-scale sensor variability. It appears that integrated, secure, energy-aware IoT–AI systems with robust edge and fog support can allow iterative deep-learning frameworks for real-time spatio-temporal optimization in smart agricultural sets.

IV. CONCLUSION

This comprehensive analysis is needed due to AI- and IoT-enabled agriculture's rapid and fragmented rise. New solutions include 5G-connected UAV networks, fog/edge computing, blockchain-secured data flows, and energy-aware wireless sensor networks. IoT sensing, machine learning, and blockchain-based security are often assessed without integrating data, computation, and decision intelligence into the smart-agriculture ecosystem. This study quantifies latency, dependability, energy efficiency, scalability, and security by integrating recent technical, numerical, and architectural studies. Qualitative summaries or performance claims without comparison are common in reports. Security-real-time performance connections, latency and throughput normalization, and cost–energy trade-offs for rural and resource-constrained scale installations are often overlooked. Many disregard edge–fog–cloud layers and blockchain-based trust mechanisms and lack experimentally proven multi-season benchmarks. This quantitative and methodological review combines 50 primary and 50 complementary studies to reveal cross-domain performance patterns. Next-generation irrigation and UAV networks have latency improvements below 30 ms, intrusion detection, disease recognition, and object detection accuracy above 92%, energy savings of 18–35%, cost reduction, scalability beyond 10,000 devices in blockchain–IoT climate networks, and security resilience approaching 99 % even under quantum-era threat models. This work's evidence-

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

based roadmap helps researchers and practitioners prioritize design choices like federated learning for privacy, hybrid fuzzy-logic routing for longevity, and AI–blockchain integration for trustworthy data sharing using harmonized performance indicators rather than isolated case studies. Meta-analytical methods, techno-economic modeling, and cross Vertical policy formulations are reproducible in the process.

V. FUTURE SCOPE

This expanse leaves open borders like, Real-life testing across numerous seasons Simulations validate tactics like deep intrusion detection and hybrid clustering. Long-term deployments in different agroclimatic zones are needed to prove stability and adaptability. Co-designing cryptographic robustness and ultra-low-power operation for quantum-resilient frameworks like hybrid Galois/Reed-Solomon codes [37] is needed. Self-organizing cyber-physical systems [28] demand reinforcement learning and continuous learning pipelines for dynamic, multi-crop situations. ELSA assessments [29] must become machine-readable criteria to ensure transparency and trust in cross-border food chains. Edge AI models native Some high-accuracy models (GANs [42], federated DRNNs [27]) use GPUs. Battery- or solar-powered deployments require lightweight transformer and neuromorphic accelerator research. Integrating supply-chain and climate analytics Blockchain-based supply logistics [36] and agroclimatic tracking [49] can integrate production forecasting, storage, and global market dynamics. This paper summarizes the existing technical landscape and outlines a future agenda for Next Generation smart agriculture, which must bring deep learning, secure distributed compute, and ethical governance to global food security and environmental sustainability sets.

REFERENCES

[1] Majumdar, P., Mitra, S., Bhattacharya, D., & Bhushan, B. (2024). Enhancing sustainable 5G powered agriculture 4.0 : Summary of low power connectivity, internet of UAV things, AI solutions and research trends. *Multimedia Tools and Applications*, 84(17), 17389-17433. https://doi.org/10.1007/s11042-024-19728-1

[2] Singh, G., Singh, J., Juneja, S., Gulzar, Y., Gupta, D., Ghafoor, K. Z., & Kumar, M. (2025). Empowering self-sustained agriculture: an IoT field tracking model driven by fog computing. *Discover Internet of Things*, 5(1). https://doi.org/10.1007/s43926-025-00140-6

[3] Li, J., Ling, M., Fu, B., Dong, Y., Mo, W., Lin, K., & Yuan, F. (2025). UAV based smart grazing: a prototype of space-air-ground integrated grazing IoT networks in Qinghai-Tibet plateau. *Discover Internet of Things*, 5(1). https://doi.org/10.1007/s43926-025-00114-8

[4] Sallam, K. M., Alrashdi, I., Ali, A. M., Radwan, I., & Abdel-Basset, M. (2025). A robust framework utilizing artificial intelligence to enhance services in smart city environments. *Cluster Computing*, 28(11). https://doi.org/10.1007/s10586-025-05431-9

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[5] Singh, G., & Sharma, S. (2024). A comprehensive review on the Internet of Things in precision agriculture. *Multimedia Tools and Applications*, 84(17), 18123-18198. https://doi.org/10.1007/s11042-024-19656-0

[6] Mohy-eddine, M., Guezzaz, A., Benkirane, S., & Azrour, M. (2024). Malicious detection model with artificial neural network in IoT-based smart farming security. *Cluster Computing*, 27(6), 7307-7322. https://doi.org/10.1007/s10586-024-04334-5

[7] Manna, S., Sarkar, A., & Mondal, A. (2025). Reinforcing internet of things security measures in smart agriculture with feature extraction-based supervised machine learning for intrusion detection. *Multimedia Tools and Applications*, . https://doi.org/10.1007/s11042-025-20844-9

[8] Ali, I. A., Bukhari, W. A., Adnan, M., Kashif, M. I., Danish, A., & Sikander, A. (2024). Security and privacy in IoT-based Smart Farming: a review. *Multimedia Tools and Applications*, 84(16), 15971-16031. https://doi.org/10.1007/s11042-024-19653-3

[9] Nawaz, M., & Babar, M. I. K. (2025). IoT and AI for smart agriculture in resource-constrained environments: challenges, opportunities and solutions. *Discover Internet of Things*, 5(1). https://doi.org/10.1007/s43926-025-00119-3

[10] Ghaseminya, M. M., Eslami, E., Shahzadeh Fazeli, S. A., Abouei, J., Abbasi, E., & Karbassi, S. M. (2025). Advancing cloud virtualization: a comprehensive survey on integrating IoT, Edge, and Fog computing with FaaS for heterogeneous smart environments. *The Journal of Supercomputing*, 81(14). https://doi.org/10.1007/s11227-025-07799-2

[11] Shahed, M. T., Haque, M. M., Akter, S., Mian, S., & Shil, R. C. (2023). IoT-Enabled Smart Solar Energy Management System for Enhancing Smart Grid Power Quality and Reliability. *SN Computer Science*, 4(6). https://doi.org/10.1007/s42979-023-02298-8

[12] Kaushik, I., Prakash, N., & Jain, A. (2025). An AI-blockchain-assisted smart agriculture framework for enabling secure and efficient data transaction: a hybrid approach. *Knowledge and Information Systems*, . https://doi.org/10.1007/s10115-025-02526-y

[13] Gupta, D., Dasgupta, A. K., Chakraborty, K., & Chakrabarti, A. (2025). Cost Efficient Rule Based Soil–Water Kinetics Driven Automated Architecture for Smart Agriculture. *SN Computer Science*, 6(6). https://doi.org/10.1007/s42979-025-04135-6

[14] Karothia, R., & Chattopadhyay, M. K. (2024). Internet of thing (IoT) enabled smart sensor node (SSN) to measure the soil and environmental parameters for smart farming. *CSI Transactions on ICT*, 12(4), 119-135. https://doi.org/10.1007/s40012-024-00402-8

[15] Morchid, A., Marhoun, M., El Alami, R., & Boukili, B. (2024). Intelligent detection for sustainable agriculture: A review of IoT-based embedded systems, cloud platforms, DL,

Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

and ML for plant disease detection. *Multimedia Tools and Applications*, 83(28), 70961-71000. https://doi.org/10.1007/s11042-024-18392-9

[16] Sharma, S., Pathak, B. K., & Kumar, R. (2024). Multi-objective service composition optimization problem in IoT for agriculture 4.0. *Computing*, 106(12), 4039-4056. https://doi.org/10.1007/s00607-024-01346-2

[17] Sahu, R., & Tripathi, P. (2025). An intelligent framework for monitoring and irrigation prediction for precision agriculture. *Iran Journal of Computer Science*, . https://doi.org/10.1007/s42044-025-00269-1

[18] Chandrasekaran, S. K., & Rajasekaran, V. A. (2024). Energy-efficient cluster head using modified fuzzy logic with WOA and path selection using enhanced CSO in IoT-enabled smart agriculture systems. *The Journal of Supercomputing*, 80(8), 11149-11190. https://doi.org/10.1007/s11227-023-05780-5

[19] Jani, K. A., & Chaubey, N. K. (2024). SMAIoT-ferti: a smart cropland monitoring and optimal fertigation IoT system. *International Journal of Information Technology*, 16(4), 2253-2261. https://doi.org/10.1007/s41870-024-01731-2

[20] Boufares, N., Sbiaa, F., Ben Saied, Y., & Azouz Saidane, L. (2025). Integrating machine learning for smart agriculture: 3D mobile distributed wireless sensors network and object recognition. *Journal of Reliable Intelligent Environments*, 11(2). https://doi.org/10.1007/s40860-025-00251-5

[21] Yadegari, F., & Asosheh, A. (2025). A unified IoT architectural model for smart hospitals: enhancing interoperability, security, and efficiency through clinical information systems (CIS). *Journal of Big Data*, 12(1). https://doi.org/10.1186/s40537-025-01197-4

[22] Bimonte, S., Bellocchi, G., Pinet, F., Chalhoub, G., Sakr, M., & Skrzypczyński, P. (2025). Data engineering for sustainable agriculture: developments, challenges, and case studies of a novel IoRT architecture. *Journal of Big Data*, 12(1). https://doi.org/10.1186/s40537-025-01253-z

[23] Neves, F., Souza, R., Lima, W., Raul, W., Bonfim, M., & Garcia, V. (2024). Smart Anonymity: a mechanism for recommending data anonymization algorithms based on data profiles for IoT environments. *The Journal of Supercomputing*, 80(14), 20956-21000. https://doi.org/10.1007/s11227-024-06209-3

[24] Abbas, A. W., Marwat, S. N. K., Al-Fuqaha, A., Brahim, G. B., Ahmed, S., & Khan, W. U. (2025). Mathematical Modelling of ANP for Trust Based IoT Device Categorization in Secured Smart Logistics. *Journal of Network and Systems Management*, 33(3). https://doi.org/10.1007/s10922-025-09941-0

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[25] C. R., A., Pani, A. K., & Kumar, P. (2024). Blockchain-enabled Smart Contracts and the Internet of Things: Advancing the research agenda through a narrative review. *Multimedia Tools and Applications*, 84(8), 5097-5147. https://doi.org/10.1007/s11042-024-18931-4

[26] Samanta, S., & Sarkar, A. (2024). Blockchain integrated DFL model for IIoT data security in smart cities. *International Journal of Information Technology*, 17(2), 911-923. https://doi.org/10.1007/s41870-024-02354-3

[27] Gai, Y., Liu, Y., Li, M., & Yang, S. (2023). Markovian with Federated Deep Recurrent Neural Network for Edge IoMT to Improve Healthcare in Smart Cities. *Journal of Grid Computing*, 22(1). https://doi.org/10.1007/s10723-023-09709-3

[28] Batistatos, M., De Cola, T., Oliveira, D., Aguilar, S., Dunne, A., Mazilu, A. I., Kourtis, M., Xilouris, G., & Sagias, N. (2025). A self organizing cyber physical system for sustainable agriculture. *Discover Internet of Things*, 5(1). https://doi.org/10.1007/s43926-025-00205-6

[29] Gesmann-Nuissl, D., Tacke, I., & Olschewski, B. (2024). ELSA for the Smart City: Ethical, Legal, and Social Technologization of Homes, Cities, and Societies Through Standardized ELSA-Assessment A Legal Point of View. *Digital Society*, 3(3). https://doi.org/10.1007/s44206-024-00153-8

[30] Singh, P., & Krishnamurthi, R. (2024). IoT-based real-time object detection system for crop protection and agriculture field security. *Journal of Real-Time Image Processing*, 21(4). https://doi.org/10.1007/s11554-024-01488-8

[31] Bhattacharyya, M., Midya, S., Roy, A., Sinha, B. P., Ghosh, A., Kostelnick, J. C., Thayn, J. B., Chinta, S. J., & Sinha, K. (2024). Designing optimal middle-mile network architecture for smart farming applications in rural areas. *Innovations in Systems and Software Engineering*, . https://doi.org/10.1007/s11334-024-00574-1

[32] Kumar, S., Garg, V., Singh, P. K., & Mishra, A. (2024). Unlocking the Societal Potential of Smart Grid Technologies: A Multi-Dimensional Analysis. *Digital Society*, 3(2). https://doi.org/10.1007/s44206-024-00116-z

[33] Karthikeyan, P., & Brindha, K. (2025). Smart data flow: a trust-driven hybrid fragmentation framework for optimizing data transmission in IoT-enabled edge-fog-cloud systems. *Computing*, 107(6). https://doi.org/10.1007/s00607-025-01491-2

[34] Anila, M., & Daramola, O. (2024). Applications, technologies, and evaluation methods in smart aquaponics: a systematic literature review. *Artificial Intelligence Review*, 58(1). https://doi.org/10.1007/s10462-024-11003-x

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[35] Qaffas, A. A. (2025). AI-driven distributed IoT communication architecture for smart city traffic optimization. *The Journal of Supercomputing*, 81(8). https://doi.org/10.1007/s11227-025-07426-0

[36] Bahrampour, N., Seifbarghy, M., & Pasandideh, S. H. R. (2024). Supply chain management under VMI strategy using internet of things and smart contracts. *Neural Computing and Applications*, 37(5), 3167-3201. https://doi.org/10.1007/s00521-024-10791-1

[37] Alyami, R. Y. (2025). Secure IoT transmission in 6G smart cities: a quantum-resilient hybrid Galois field and Reed-Solomon approach. *The Journal of Supercomputing*, 81(4). https://doi.org/10.1007/s11227-025-07084-2

[38] Jiao, J. (2025). Optimization and feature analysis of smart class IoT systems for enhanced learning and classroom management performance. *Signal, Image and Video Processing*, 19(13). https://doi.org/10.1007/s11760-025-04707-2

[39] [39] Rekha, B. N., & Banuprakash, G. C. (2024). A Hybrid Framework for Energy-Efficient Centroid Based Gateway Clustering Protocol Over Agriculture Domain in Wireless Sensor Networks. *SN Computer Science*, 5(5).https://doi.org/10.1007/s42979-024-02841-1

[40] Sharma, H., & Kanwal, N. (2024). Video surveillance in smart cities: current status, challenges & future directions. *Multimedia Tools and Applications*, 84(16), 15787-15832. https://doi.org/10.1007/s11042-024-19696-6

[41] Lakshman, S. A., Akash, S., Cynthia, J., Gautam, R., & Ebenezer, D. (2024). Architecture and Applications of IoT Devices in Socially Relevant Fields. *SN Computer Science*, 5(7). https://doi.org/10.1007/s42979-024-03159-8

[42] Bethu, S. (2025). Malicious Attack Detection in IoT by Generative Adversarial Networks. *SN Computer Science*, 6(4). https://doi.org/10.1007/s42979-025-03874-w

[43] Sohrabi, S., Sakhaei-nia, M., Nassiri, M., & Mohammadi, R. (2025). Fog-based architecture and efficient task offloading methodology in IoT-based applications for smart irrigation system. *Computing*, 107(3). https://doi.org/10.1007/s00607-025-01430-1

[44] Almalki, F. A., & Angelides, M. C. (2025). Integrating machine learning with a positioning mechanism for managing interference and power consumption in a multilayer fleet of unmanned aerial platforms. *Cluster Computing*, 28(6). https://doi.org/10.1007/s10586-024-05044-8

[45] Shukla, P., Krishna, C. R., & Patil, N. V. (2023). Iot traffic-based DDoS attacks detection mechanisms: A comprehensive review. *The Journal of Supercomputing*, 80(7), 9986-10043. https://doi.org/10.1007/s11227-023-05843-7

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 02-01-2026

[46] Quasim, M. T., Nisa, K. u., Khan, M. Z., Husain, M. S., Alam, S., Shuaib, M., Meraj, M., & Abdullah, M. (2023). An internet of things enabled machine learning model for Energy Theft Prevention System (ETPS) in Smart Cities. *Journal of Cloud Computing*, 12(1). https://doi.org/10.1186/s13677-023-00525-4

[47] Aknan, M., Singh, M. P., & Arya, R. (2023). AI and Blockchain Assisted Framework for Offloading and Resource Allocation in Fog Computing. *Journal of Grid Computing*, 21(4). https://doi.org/10.1007/s10723-023-09694-7

[48] Mahmood, Z., Ashraf, Z., Iqbal, M., & Farooq, B. (2024). User-trust centric lightweight access control for smart IoT crowd sensing applications in healthcare systems.*Personal and Ubiquitous Computing*, 29(1), 31-44. https://doi.org/10.1007/s00779-024-01803-x

[49] Araújo, A., Santos, W., & Oliveira, R. (2025). Scalable computational solution for agroclimatic data tracking with IoT and multi-blockchain support. *Computing*, 107(10). https://doi.org/10.1007/s00607-025-01554-4

[50] Duguma, A. L., & Bai, X. (2024). How the internet of things technology improves agricultural efficiency. *Artificial Intelligence Review*, 58(2). https://doi.org/10.1007/s10462-024-11046-0