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Systematic Review

From IoT to AIoT: Evolving Agricultural Systems Through Intelligent Connectivity in Low-Income Countries

Selain K. Kasereka [1,2,3,*], Alidor M. Mbayandjambe [3], Ibsen G. Bazie [4], Heriol F. Zeufack [4], Okurwoth V. Ocama [3], Esteve Hassan [5], Kyandoghere Kyamakya [6] and Tasho Tashev [1,*]

[1] Department of Information Measurement Systems, Technical University of Sofia, 1000 Sofia, Bulgaria
[2] Department of Environmental and Urban Geology, Natural Hazard Management Section, Centre de Recherches Géologiques et Minières (CRGM), Kinshasa P.O. Box 13275, Democratic Republic of the Congo
[3] Department of Mathematics, Statistics and Computer Science, University of Kinshasa, Kinshasa XI, Kinshasa P.O. Box 190, Democratic Republic of the Congo; alidor.mbayandjambe@unikin.ac.cd (A.M.M.); ocama.okurwoth@unikin.ac.cd (O.V.O.)
[4] ABIL Research Center, Kinshasa XI, Kinshasa P.O. Box 190, Democratic Republic of the Congo; ibsen.bazie@abil.ac.cd (I.G.B.)
[5] Jodrey School of Computer Science, Acadia University, Wolfville, NS B4P 2R6, Canada; esteve.hassan@acadiau.ca
[6] Institute of Smart Systems Technologies, University of Klagenfurt, 9220 Klagenfurt, Austria; kyandoghere.kyamakya@aau.at
* Correspondence: selain.kasereka@unikin.ac.cd (S.K.K.); t_tashev@tu-sofia.bg (T.T.); Tel.: +243-821-828-964 (S.K.K.)

Abstract

The convergence of Artificial Intelligence and the Internet of Things has given rise to the Artificial Intelligence of Things (AIoT), which enables connected systems to operate with greater autonomy, adaptability, and contextual awareness. In agriculture, this evolution supports precision farming, improves resource allocation, and strengthens climate resilience by enhancing the capacity of farming systems to anticipate, absorb, and recover from environmental shocks. This review provides a structured synthesis of the transition from IoT-based monitoring to AIoT-driven intelligent agriculture and examines key applications such as smart irrigation, pest and disease detection, soil and crop health assessment, yield prediction, and livestock management. To ensure methodological rigor and transparency, this study follows the PRISMA 2020 guidelines for systematic literature reviews. A comprehensive search and multi-stage screening procedure was conducted across major scholarly repositories, resulting in a curated selection of studies published between 2018 and 2025. These sources were analyzed thematically to identify technological enablers, implementation barriers, and contextual factors affecting adoption particularly within low-income countries where infrastructural constraints, limited digital capacity, and economic disparities shape AIoT deployment. Building on these insights, the article proposes an AIoT architecture tailored to resource-constrained agricultural environments. The architecture integrates sensing technologies, connectivity layers, edge intelligence, data processing pipelines, and decision-support mechanisms, and is supported by governance, data stewardship, and capacity-building frameworks. By combining systematic evidence with conceptual analysis, this review offers a comprehensive perspective on the transformative potential of AIoT in advancing sustainable, inclusive, and intelligent food production systems.

Keywords: Artificial Intelligence of Things (AIoT); smart agriculture; precision farming; IoT applications; machine learning; agricultural innovation in Africa

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1. Introduction

Agriculture constitutes the cornerstone of global food security, yet it is confronted with unprecedented challenges in the 21st century. The global population is projected to reach 9.7 billion by 2050, placing unprecedented pressure on food systems [1]. Climate change impacts, resource scarcity, and labor shortages further compound these challenges. These mounting pressures necessitate an urgent paradigm shift from traditional, input-intensive farming toward more efficient, sustainable, and data-driven agricultural practices. Conventional approaches rely heavily on manual labor and uniform field management, leading to significant inefficiencies. The overuse of water, fertilizers, and pesticides contributes to environmental degradation and biodiversity loss [2].

The proliferation of digital technologies has heralded the era of smart agriculture, offering a pathway to address these challenges. The Internet of Things (IoT) has emerged as a foundational pillar of this digital transformation. IoT systems deploy vast networks of interconnected sensors and devices to collect real-time data on soil moisture, microclimate, crop health, and livestock welfare [2]. These systems facilitate precision agriculture by providing actionable insights, such as automated irrigation based on soil moisture thresholds. However, conventional IoT frameworks have a significant limitation: they focus primarily on data acquisition and connectivity. They often lack the advanced analytical capabilities required for autonomous decision-making, predictive analytics, and complex pattern recognition in highly dynamic agricultural environments [3].

This limitation has catalyzed the evolution towards the Artificial Intelligence of Things (AIoT), a synergistic integration of AI algorithms, including machine learning (ML) and computer vision, with IoT infrastructure. AIoT represents the next frontier of "intelligent connectivity," where edge computing enables real-time, localized data processing, and cloud-based AI models deliver deep, long-term insights [4,5]. In agriculture, this convergence empowers transformative applications, from predictive crop yield modeling and automated pest detection to optimized nutrient management, thus improving sustainability through precise resource allocation and improved resilience to climatic uncertainties [6,7].

Despite its promising potential, the widespread adoption of AIoT in agriculture is not without significant hurdles. Key challenges include high initial implementation costs, persistent data quality and availability issues, connectivity limitations in rural areas, energy constraints for edge devices, and ethical concerns regarding data privacy and algorithmic transparency [8–10]. Furthermore, the adoption dynamics and contextual applicability of AIoT solutions, particularly in developing regions with unique infrastructural and socio-economic landscapes like Africa, warrant focused examination [1,11].

This paper employs various technical terms related to AIoT systems and agricultural technologies. For clarity, a glossary of key terminology is provided in Appendix A.

1.1. Research Questions

This paper is guided by two primary research questions. RQ1: How is the integration of AI with IoT transforming agricultural systems, and what are the key applications, enablers, and challenges driving this transition? RQ2: How can a flexible AIoT-based architecture be tailored to the specific needs of low- and middle-income countries, while addressing persistent constraints such as limited infrastructure, resource scarcity, and ethical considerations?

1.2. Research Objectives

To address these questions, the study pursues the following specific objectives:

- Examine the evolution of IoT toward AIoT in agriculture and its transformative impact.

- Identify and analyze key applications, enabling technologies, and challenges shaping this transition.
- Propose a flexible AIoT-based architecture adapted to the realities of low- and middle-income countries.
- Evaluate strategies to overcome persistent constraints, including infrastructural limitations, resource scarcity, and ethical concerns.
- Highlight pathways for building sustainable, resilient, and inclusive agricultural systems through intelligent connectivity.

1.3. Major Contributions of the Study

This study makes several original and complementary contributions to the literature on AIoT-enabled smart agriculture:

- Constraint-aware synthesis for low-income contexts: Unlike existing IoT–AIoT surveys that primarily emphasize technological performance and application benchmarking in high-resource settings, this review provides a systematic synthesis focused on low-income countries, with particular emphasis on African agricultural systems. It explicitly analyzes infrastructural, socio-economic, and digital capacity constraints that shape AIoT adoption, while highlighting opportunities for frugal innovation, participatory data generation, and leapfrogging deployment models.
- Structured analytical framework across AI pillars: The study introduces a conceptual framework centered on three interdependent AI pillars, Data, Features, and Models. By jointly examining challenges and opportunities across these dimensions, the review explains why conventional AIoT approaches often fail in resource-constrained environments and how context-adapted solutions can be designed.
- Context-adapted AIoT reference architecture: This work proposes a lightweight and modular AIoT reference architecture tailored to low-income agricultural contexts. The architecture integrates low-power sensing, long-range connectivity, edge intelligence (TinyML), and embedded governance mechanisms to address affordability, energy efficiency, intermittent connectivity, and data sovereignty.
- Integrated technical and governance perspective: Beyond technical considerations, the review explicitly incorporates governance, ethical, and sustainability dimensions, including data ownership, algorithmic transparency, and inclusive access. This integrated perspective responds to the limitations of technology-centric surveys and reflects the realities of AIoT deployment in vulnerable agricultural systems.
- Actionable insights for inclusive and sustainable agriculture: By bridging technological design, contextual constraints, and policy-relevant considerations, this study provides actionable guidance for researchers, policymakers, and practitioners seeking to develop resilient, equitable, and sustainable AIoT-enabled agricultural systems in the Global South.

Despite the rapid growth of AIoT research in agriculture, the majority of published studies continue to originate from high-income regions, resulting in limited empirical evidence and design guidance for low-income and African agricultural contexts. This review directly addresses this gap by re-centering AIoT research on deployment feasibility and contextual relevance.

1.4. Paper Organization

The remainder of this paper is structured as follows. Section 2 presents the study methodology following PRISMA 2020 guidelines. Section 3 reviews the evolution of smart farming systems from IoT to AIoT, including enablers, challenges, and a regional perspective on adoption in Africa. Section 4 synthesizes recent studies on key AIoT applications in smart farming. Section 5 introduces the proposed AIoT architecture tailored for low-income countries. Section 6 examines ethical considerations surrounding AIoT deployment in agriculture, including data sovereignty, algorithmic bias, and socio-economic equity. Section 7 provides a cohesive discussion of the findings. Finally, Section 8 offers concluding remarks and future research directions.

2. Research Methodology

This study is conducted as a systematic narrative review with thematic synthesis, following the PRISMA 2020 reporting guidelines [12]. While PRISMA is commonly associated with quantitative meta-analyses, its structured framework is equally applicable to ensure transparency, reproducibility, and methodological rigor in qualitative and technical reviews addressing heterogeneous bodies of literature.

A comprehensive literature search was conducted across major scholarly databases, including IEEE Xplore, MDPI, and Elsevier/ScienceDirect, among others. The search strategy employed standardized Boolean expressions adapted to each database. Core search strings included: (*"Internet of Things" OR "IoT"*) AND (*"agriculture" OR "farming"*) AND (*"artificial intelligence" OR "machine learning"*), as well as (*"AIoT" OR "Artificial Intelligence of Things"*) AND (*"smart agriculture" OR "precision farming"*). Additional keywords such as *"edge computing for farms"* were incorporated to capture emerging AIoT architectures.

The database search yielded a total of 1517 records. Prior to screening, approximately 09 records were removed due to duplication and the application of preliminary exclusion criteria. The remaining records were subjected to title and abstract screening and were segmented by source as follows: Elsevier/ScienceDirect (n = 513), IEEE Xplore (n = 347), MDPI (n = 286), and other academic repositories (n = 362). In total, 1508 records proceeded to the screening stage.

During the screening phase, approximately 1400 records were excluded based on title and abstract review due to duplication, lack of relevance to AIoT-enabled agricultural systems, non-agricultural application domains, or the absence of substantive artificial intelligence or Internet of Things components. From the 108 reports sought for retrieval, 30 full-text articles were unavailable, primarily due to restricted access, incomplete archival records, or conference abstracts without accompanying full manuscripts. The remaining 78 studies underwent eligibility assessment based on predefined inclusion criteria: (1) peer-reviewed publications published between 2018 and 2025, (2) explicit focus on AI–IoT integration within agricultural systems, (3) empirical, technical, or architectural contributions, and (4) English language. A total of 25 articles were excluded due to insufficient relevance to AIoT, limited agricultural scope, or methodological weaknesses.

The final corpus comprised studies, with particular emphasis on African and low-income country contexts to address persistent regional knowledge gaps. Rather than applying a formal quantitative risk-of-bias assessment, which is more appropriate for clinical or interventional meta-analyses, the selected studies were synthesized through thematic analysis. This approach enabled the identification and interpretation of recurring patterns, challenges, and opportunities across diverse study designs. Specifically, the thematic synthesis examined: (i) the technological evolution from IoT to AIoT in agriculture, (ii) domain-specific applications such as smart irrigation, pest and disease detection, crop yield prediction, and livestock management, (iii) proposed AIoT architectural frameworks, (iv) deployment challenges in resource-constrained environments, and (v) governance, ethical, and sustainability considerations.

Figure 1 presents the distribution of literature sources, while Figure 2 illustrates the PRISMA 2020 flow diagram detailing the multi-stage selection and screening process. Additional supporting details are provided in the Supplementary Materials.

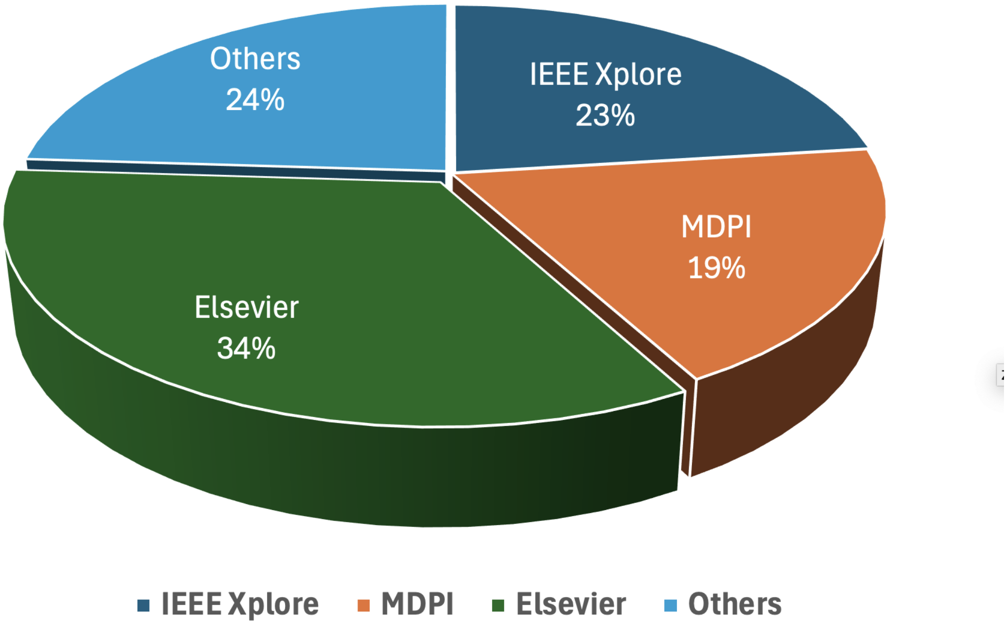

Figure 1. Distribution of acquisition sources supporting the literature base for the study. This chart illustrates the relative contribution of key academic platforms to the bibliographic foundation of the research, highlighting the proportions of Elsevier, IEEE Xplore, MDPI, and other sources in shaping the scientific corpus.

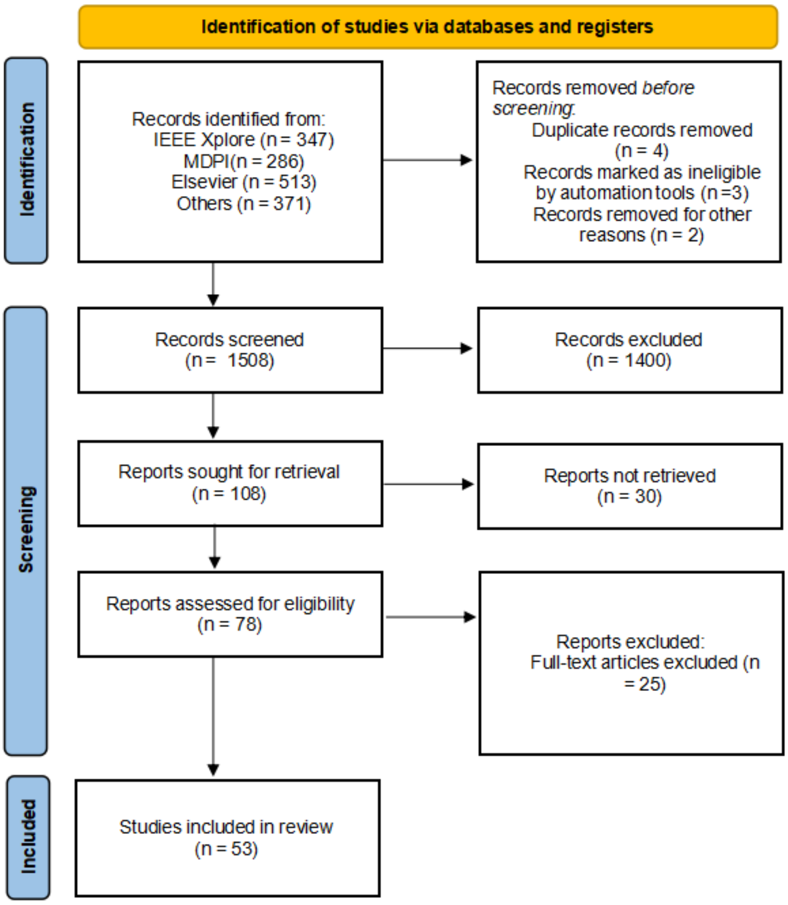

Figure 2. PRISMA 2020 flow diagram documenting the systematic selection process from 1508 initial records to included studies, following standardized reporting guidelines for transparent and reproducible literature reviews.

3. Technological Evolution of Smart Farming Systems

The agricultural sector is undergoing a profound transformation driven by digital technologies. The shift from conventional Internet of Things (IoT) frameworks to Artificial Intelligence of Things (AIoT) marks a new era of intelligent, adaptive, and data-driven farming. This section explores how agricultural systems are evolving through this transition, focusing on technological integration, practical applications, and emerging challenges.

3.1. Transition from IoT to AIoT in Agriculture

The transition from the Internet of Things (IoT) to the Artificial Intelligence of Things (AIoT) marks a significant evolution in digital farming systems. IoT refers to distributed networks of agricultural devices equipped with sensors, embedded software, and communication modules. These include soil moisture sensors, weather stations, GPS-enabled devices, and drone-based imaging systems that generate continuous streams of raw environmental data [13–15]. AIoT builds upon this infrastructure by integrating Artificial Intelligence (AI) capabilities to create intelligent, autonomous, and context-sensitive systems. Unlike traditional IoT, which focuses primarily on sensing and connectivity, AIoT leverages machine learning, predictive analytics, and edge computing. It transforms raw sensor data into actionable insights for optimized crop management, enabling advanced functions such as disease prediction, yield forecasting, irrigation automation, and multi-sensor fusion for real-time decision-making [14,16]. Embedding AI into connected agricultural devices provides substantial benefits. First, predictive capabilities move beyond real-time monitoring to forecast events such as pest outbreaks or yield volumes [3]. Second, autonomous control allows systems to act independently. For example, triggering irrigation only when AI models predict water stress. Third, enhanced efficiency is achieved through optimized resource use, with water and fertilizers applied precisely where and when needed [6]. Finally, anomaly detection identifies subtle, complex patterns indicative of disease or stress that remain invisible to simple threshold-based IoT systems [7]. Furthermore, the system architecture has evolved from a simple linear model to a complex and intelligent loop, with traditional IoT following a cloud-centric model, while AIoT leverages edge computing to distribute intelligence, enabling faster, localized decisions and reducing latency and bandwidth requirements [4]. Figure 3 illustrates the conceptual difference between IoT and AIoT within agricultural systems.

3.2. Technological Enablers

The technological enablers of AIoT in agriculture encompass several complementary dimensions. Edge computing enables on-site data processing for low-latency, bandwidth-efficient decision-making. Cloud platforms provide large-scale historical data analysis and model retraining. The synergy between edge and cloud computing is critical for scalable AIoT solutions [4]. Machine learning (ML) algorithms further enhance agricultural data analysis. These range from Random Forests and Support Vector Machines for classification tasks to Convolutional Neural Networks (CNNs) for image recognition and Long Short-Term Memory (LSTM) networks for time-series forecasting [3,17]. The integration of diverse data sources, including high-resolution drones for field-level detail, satellites for large-area coverage, and in situ sensors for ground-truthing, creates a comprehensive view of the farm and enriches AI models with multi-layered insights [18]. Finally, interoperability and data fusion are major enablers.

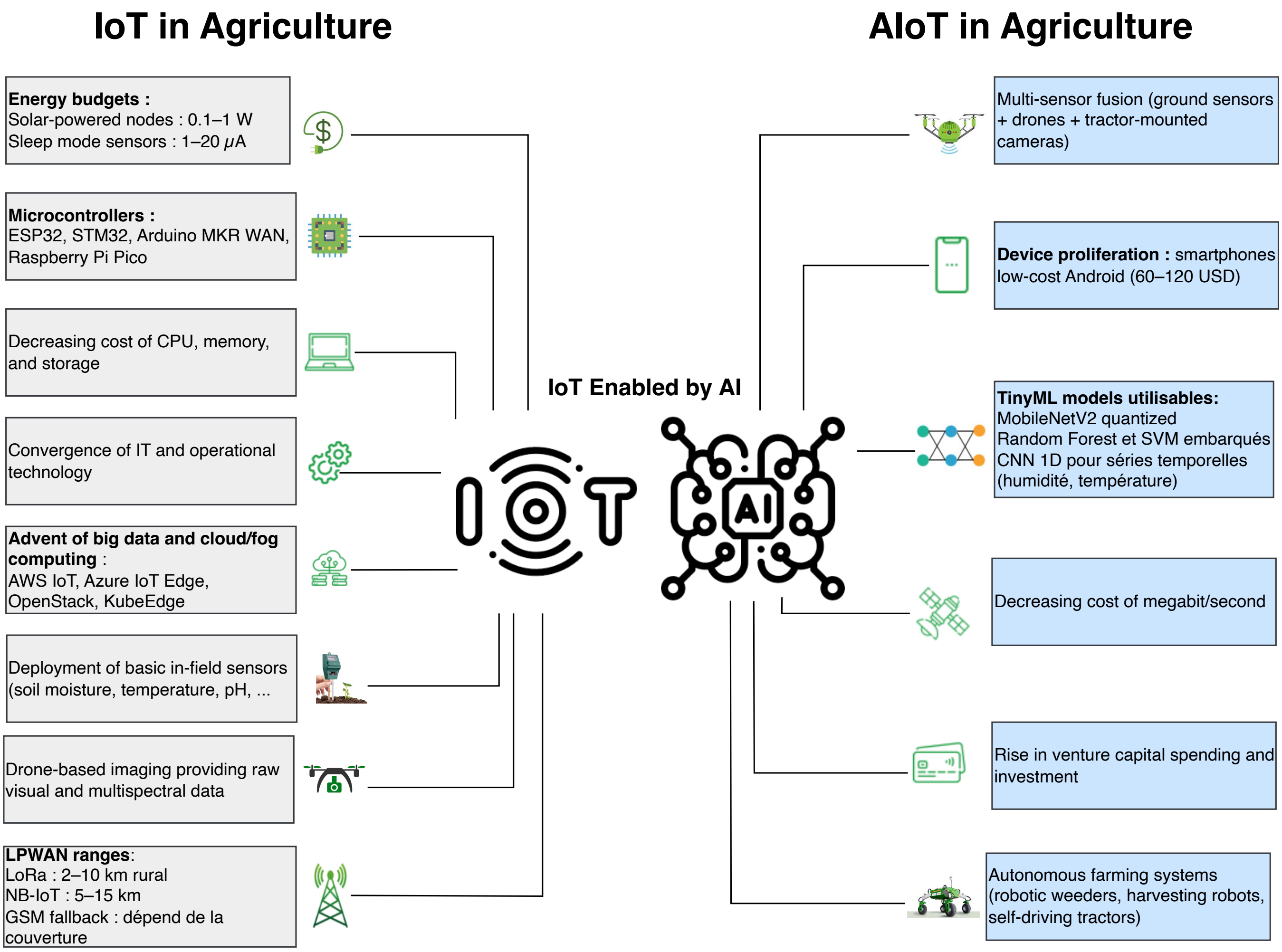

Figure 3. Comparative diagram presenting the shift from traditional Internet of Things (IoT) applications to Artificial Intelligence of Things (AIoT) in agriculture. The left section outlines core IoT components including low-power sensor nodes, microcontrollers, and cloud-based platforms for data aggregation. The right section illustrates how artificial intelligence enhances these systems through embedded machine learning models, sensor fusion, and autonomous machinery. The central element emphasizes the role of AI in transforming raw data into actionable insights for precision farming.

3.3. Challenges in System Evolution

AI models are often constrained by the principle of "garbage in, garbage out," meaning that inconsistent, noisy, or insufficient agricultural data can lead to poor model performance, while the creation of large, labeled datasets for training remains expensive and time-consuming [3]. In addition, many rural and remote farms lack reliable, high-bandwidth internet connectivity, which hinders real-time data transfer to the cloud and makes edge-based solutions a necessity [2,15]. Another challenge lies in energy efficiency and hardware constraints, as deploying sensors and edge devices in agricultural fields requires robust, low-power hardware; the energy demand for continuous data processing and transmission is significant, often mitigated through solar power but still a key design concern [9]. Ethical concerns and algorithmic transparency must be addressed, since the "black box" nature of complex AI models raises issues of trust and accountability, with farmers potentially reluctant to adopt systems whose recommendations they cannot interpret. Moreover, data privacy and ownership remain critical considerations in the evolution of such systems [1,10].

3.4. Regional Perspectives: Adoption in Africa

The adoption of AIoT in Africa presents a unique landscape characterized by leapfrogging potential, significant challenges, and context-driven innovation. Projects such as UjuziKilimo in Kenya demonstrate how simple sensors and machine learning can provide soil analysis and fertilizer recommendations via SMS to smallholder farmers, while in Nigeria, Hello Tractor leverages IoT and data analytics to connect tractor owners with farmers in need of mechanization services, thereby optimizing asset utilization [1]. Despite these promising initiatives, the pervasive lack of reliable electricity and internet connectivity in rural Africa remains a major barrier, which has spurred local innovation in solar-powered sensors and the adoption of Low-Power Wide-Area Network (LPWAN) technologies such as LoRaWAN that enable long-range connectivity with low power consumption [2]. Successful adoption also requires supportive policy frameworks that encourage investment in digital infrastructure, data governance, and skills development, with funding from international development agencies, public–private partnerships, and venture capital playing a crucial role in piloting and scaling solutions [11]. Moreover, AIoT offers significant opportunities for scalable, climate-resilient solutions, as AI-powered models can provide early warnings for droughts or floods tailored to local conditions [18], while the widespread use of mobile phones offers a ubiquitous platform for delivering these AI-driven insights to smallholder farmers, thereby enhancing food security and resilience [11]. Recent reviews highlight the integration of blockchain technology with AI-IoT systems for crop recommendation, emphasizing data integrity and transparency in agricultural supply chains, particularly relevant for developing regions [19,20].

3.5. Challenges in AIoT for African Agriculture: A Data, Feature, and Model Perspective

The successful deployment of Artificial Intelligence of Things (AIoT) in African agriculture hinges on overcoming a triad of interconnected challenges that span the AI development pipeline. These are not merely technical hurdles but are deeply intertwined with the socio-economic and infrastructural realities of the continent.

3.5.1. Data Study Challenges

The adage garbage in, garbage out is acutely relevant in contexts where data acquisition is fundamentally constrained.

- Scarcity and Sparsity: There is a pervasive lack of large-scale, historical, and digitized agricultural datasets. Data collection is often project-based, resulting in temporally and spatially sparse records insufficient for training robust, generalizable models.
- Heterogeneity and Inconsistency: Data streams originate from a mosaic of low-cost sensors, satellite platforms with varying resolutions, and manual entries. This leads to significant challenges in data fusion due to inconsistencies in format, calibration, sampling frequency, and accuracy.
- Ground Truth Acquisition: Supervised learning requires accurately labeled data. The process of obtaining ground truth for agronomic variables (e.g., pest species, soil nutrient levels, yield) is costly, time-consuming, and relies on scarce local expertise, creating a major bottleneck for model development.
- Privacy, Ownership, and Governance: Ambiguity surrounding data ownership can deter farmers from participating in data-sharing initiatives, particularly when coupled with fears of exploitation. The absence of clear, farmer-centric data governance frameworks undermines both trust and the ethical foundation of AIoT systems.

3.5.2. Feature Study Challenges

Transforming raw, often noisy data into informative features that capture complex agronomic phenomena presents specific difficulties.

- Domain-Specific Engineering: Identifying predictive features requires deep cross-disciplinary knowledge that bridges data science, agronomy, and local ecological understanding. This expertise gap can lead to the use of suboptimal or irrelevant features.
- Contextual Variability and Dimensionality: Agro-ecological conditions vary dramatically across Africa. Features that are predictive in one region may be irrelevant in another. Furthermore, multi-sensor fusion creates high-dimensional data, risking redundancy and increased computational load for edge processing.
- Real-Time Extraction Constraints: For edge-based intelligence, feature extraction algorithms must be extremely lightweight. Complex statistical or spectral features that are standard in cloud analytics may be infeasible on resource-constrained microcontrollers, necessitating significant innovation in efficient feature design.

3.5.3. Model Study Challenges

The development and deployment of AI models face acute challenges in low-resource, high-variability environments.

- Poor Generalization and Transferability: Models trained on data from one geographic or climatic context often fail to generalize to others due to differences in soil, crop varieties, weather patterns, and management practices. Developing adaptable or transferable models is a core research challenge.
- Computational and Energy Bottlenecks: Deploying state-of-the-art models on low-power edge devices (TinyML) requires aggressive model compression (pruning, quantization). This process involves a delicate trade-off between model accuracy, size, and inference speed, which is critical for real-time decision-making.
- The Black Box Problem and Trust Deficit: The opacity of complex models like deep neural networks erodes farmer trust. When recommendations cannot be intuitively explained or linked to observable field conditions, adoption is severely hindered.
- Model Maintenance and Concept Drift: Agricultural systems are non-stationary. Climate change, evolving pest biotypes, and changing soil conditions can cause model performance to degrade over time (concept drift). Establishing sustainable pipelines for model monitoring and retraining in off-grid settings is a significant operational challenge.

3.6. Opportunities in AIoT for African Agriculture: Innovating Within Constraints

The unique challenges of the African context are not merely obstacles but also catalysts for frugal and transformative innovation, opening distinct avenues for advancement in data, features, and models.

3.6.1. Opportunities in Data Study

Constraints are fostering novel, inclusive, and scalable approaches to data.

- Participatory and Crowdsourced Data Collection: The ubiquity of mobile phones enables farmer-centric data generation. Through structured apps, farmers can contribute labeled images, yield reports, and management logs. This approach builds rich, contextual datasets while enhancing digital literacy and engagement.
- Leveraging Open and Satellite Data: The proliferation of free, high-resolution earth observation data (e.g., Sentinel-2, NASA SERVIR) provides a foundational, continent-wide data layer. Fusing this data with sparse ground sensor measurements through advanced imputation and fusion techniques can mitigate initial data scarcity.

- Blockchain for Transparency and Equity: Blockchain and distributed ledger technologies can establish transparent data provenance, immutable usage records, and smart contracts for fair data valuation. These technologies can empower farmers by giving them control over their data and potential revenue streams.
- Synthetic Data Generation: For rare events (e.g., specific pest outbreaks) or to balance datasets, techniques like Generative Adversarial Networks (GANs) can create realistic synthetic agricultural data, safely augmenting training sets and improving model robustness.

3.6.2. Opportunities in Feature Study

Innovation in feature engineering is key to extracting maximum insight from limited data.

- Automated Feature Learning: Instead of manual engineering, deep learning architectures (e.g., autoencoders, 1D-CNNs for time-series) can be trained to automatically discover optimal, compressed feature representations directly from raw sensor data, even when noisy.
- Ethno-Computing and Domain Fusion: Collaborative design with farmers and agronomists can yield ethno-features computable representations of indigenous knowledge and observational cues. This fusion of local wisdom with data science ensures features are both interpretable and agronomically sound.
- Development of Transferable Feature Spaces: Research can focus on learning feature embeddings that are invariant to specific locales but sensitive to universal agricultural states (e.g., water-stressed, nutrient-deficient). This would enhance model portability across diverse African agro-ecologies.
- Ultra-Lightweight Feature Algorithms: There is a significant opportunity to design novel, computationally trivial algorithms for calculating key agronomic indices (e.g., vegetation indices, soil water content estimators) directly on edge devices, enabling sophisticated analytics without cloud dependence.

3.6.3. Opportunities in Model Study

The deployment environment is driving the creation of a new generation of AI models.

- Explainable AI (XAI) and Hybrid Models: The integration of XAI is imperative. Hybrid modeling, which combines data-driven ML with mechanistic crop models or rule-based expert systems, can enhance interpretability, improve performance with limited data, and build farmer trust by aligning with causal understanding.
- Federated Learning: This paradigm enables collaborative model training across multiple farms without centralizing raw data. It preserves data privacy, leverages diverse local data distributions, and builds collective intelligence ideal for cooperatives and farmer networks.
- Few-Shot and Meta-Learning: These approaches aim to create models that can rapidly adapt to new tasks (e.g., recognizing a new disease) with only a few examples. This is crucial for responsive pest and disease management in dynamic environments.
- Edge-Native Model Architectures: Beyond compressing cloud models, the future lies in designing edge-native models. This involves neural architecture search (NAS) for efficient topologies and training strategies that prioritize low-power inference, robustness to sensor noise, and adaptive learning from streaming data.

Moreover, the pathway to impactful AIoT in African agriculture is defined by a dialectic of challenge and opportunity. The constraints inherent in data, feature, and model studies are precisely what necessitate and inspire context-aware innovation. By embracing participatory approaches, frugal design, and transparent methodologies, the AIoT revolution can be steered towards building equitable, resilient, and intelligent agricultural systems across the continent.

4. Key AIoT Applications in Smart Farming

AIoT applications in smart farming encompass a wide range of innovations that enhance efficiency, sustainability, and productivity. Smart irrigation and water management systems integrate soil moisture, weather forecasts, and evapotranspiration data with machine learning models to predict crop water needs, moving beyond simple sensor thresholds to dynamic and predictive irrigation schedules that conserve water [21,22]. Pest and disease detection is increasingly supported by AI-enhanced sensors and computer vision models, often deployed on drones or mobile phones, which analyze crop images to identify early signs of pest damage or fungal infections, enabling targeted pesticide application [7]. Soil health monitoring and nutrient optimization rely on multi-parameter sensors that collect data on NPK levels, pH, and organic matter, with AI algorithms processing this information to generate precise variable-rate fertilizer application maps, thereby improving soil health and reducing chemical runoff [17]. Crop yield prediction and forecasting models combine historical yield data, real-time sensor inputs, and satellite imagery, using regression and neural networks to accurately estimate yields weeks before harvest, supporting supply chain planning and market strategies [1]. Livestock tracking and behavioral analysis leverage AI-powered collars or tags to monitor location, activity, and vital signs, with anomaly detection algorithms flagging early indicators of illness or estrus, ultimately improving herd health and productivity [23]. Figure 4 shows the distribution of AIoT-related research papers considered in the study, categorized by application area and contextual orientation.

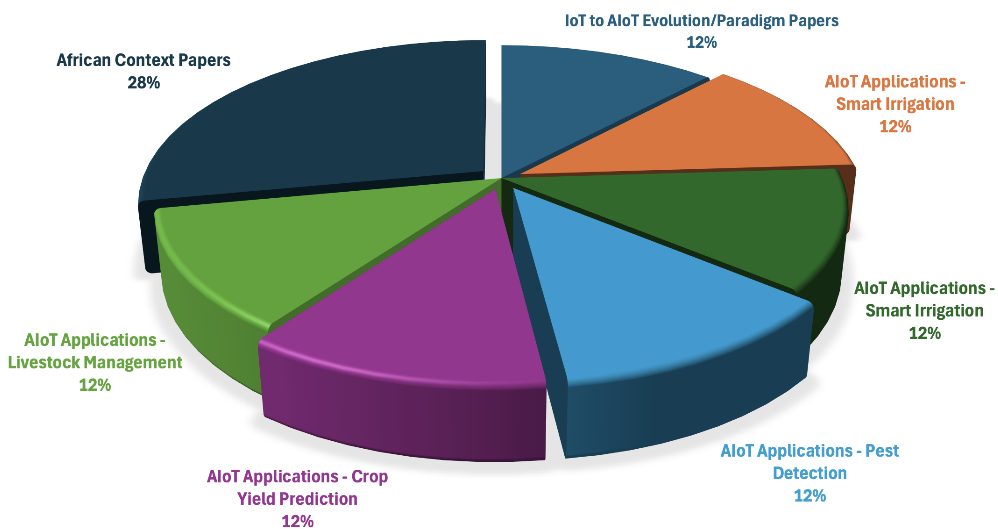

Figure 4. Categorization of AIoT-related research papers considered in the study by application domain and contextual focus. This chart illustrates the thematic distribution of the reviewed literature, highlighting the prominence of African-context studies (28%) and a balanced representation across key AIoT application areas, including smart irrigation, pest detection, crop yield prediction, and livestock management (each at 12%). The visualization reflects the evolving landscape of AIoT research, underscoring both regional relevance and the diversification of intelligent connectivity within agricultural systems.

Table 1 summarizes key studies examining AIoT applications across smart irrigation, pest detection, crop yield prediction, livestock management, and African agricultural contexts. The literature documents show significant technological achievements (>95% detection accuracy, 35% water savings) while highlighting persistent challenges in rural connectivity, implementation costs, and scalability for resource-constrained environments. It should be noted that the performance metrics reported are documented in the respective primary studies under specific experimental or field conditions. These results are context-dependent and should not be interpreted as universally guaranteed or directly comparable across different agricultural environments, crop varieties, or implementation scales.

Table 1. Summary of Literature on IoT to AIoT Evolution in Agriculture, and AIoT applications including smart irrigation, pest detection, crop yield prediction and livestock management. African context papers are also summarized.

Refs	Key Contributions	Study Scope	Technology Used	Dataset	Country	Limitations
			IoT to AIoT Evolution/Paradigm Papers			
[24]	Reviews edge-based AIoT deployment workflow for agricultural monitoring; Highlights data seasonality and power consumption challenges in edge AI.	IoT-AIoT evolution; Edge computing	Deep learning models, edge devices	Literature review	Global	Data seasonality limits model training; Power consumption concerns; Early development stage.
[25]	Systematic review tracking AIoT field growth from <5 papers (2017) to 50 papers (2023); Identifies AIoT as distinct paradigm beyond IoT+AI.	IoT-AIoT evolution; Smart agriculture	Deep learning, computer vision, IoT sensors	Literature review (37,230 AI/IoT agriculture articles)	Global	AIoT in infant stage; Adoption barriers; Data acquisition and connectivity challenges.
[26]	PRISMA 2020 systematic review demonstrating sharp publication increase 2022–2024; Comprehensive communication technology analysis.	IoT-AI integration; Precision agriculture	LoRa, NB-IoT, GSM/GPRS, IoT sensors	Literature review (PRISMA 2020)	Global	Rural connectivity challenges; Limited cellular coverage; Edge computing needs optimization.
			AIoT Applications-Smart Irrigation			
[27]	Reviews AIoT applications showing 35% water waste reduction; Integrates UAV technology with AI analytics for precision management.	Smart irrigation; Nutrient management	UAVs, AI analytics, soil moisture sensors	Literature review	Global	High setup costs; Rural connectivity issues; Inconsistent sensor reliability; Limited smallholder scalability.
[28]	Designs an IoT- and ML-based smart irrigation system to optimize water use through real-time sensing and predictive decision-making.	Smart irrigation; IoT–ML water management	Soil moisture sensors, micro-controller/IoT nodes, wireless communication, ML prediction models	Custom experimental sensor dataset	Morocco	Limited dataset size; field validation constrained; performance depends on sensor reliability; scalability and long-term deployment not fully assessed.
[29]	PRISMA review of 43 studies showing LSTM achieving R^2 0.76–0.91 for soil moisture prediction; Reports 20% pesticide reduction, 30% water savings.	Smart irrigation; Predictive analytics	LSTM networks, IoT sensors, ML algorithms	Literature review (43 studies 2017–2024)	Global	Field transferability issues; Manual steps required; High ML computational demands; Limited complex validation.
			AIoT Applications-Pest Detection			
[30]	Comprehensive review of CNN-based models achieving >95% classification accuracy and >90% detection precision for plant diseases.	Pest detection; Disease classification	CNNs, computer vision, deep learning	Literature review	Global	Environmental factors affect performance; Limited real-world validation; Large labeled datasets required; Occlusion challenges.
[31]	Develops portable edge device (Raspberry Pi 5) with Tiny-LiteNet CNN for resource-constrained African environments; Built-in explainability.	Pest detection; Edge AI	Raspberry Pi 5, Tiny-LiteNet CNN, lightweight models	Cereal crops dataset	Rwanda	Limited to cereal crops; HD camera required; Edge processing limitations; Climate change requires updates.
[32]	Novel IoT-based pest detection model with enhanced deep learning achieving higher accuracy than existing methods.	Pest detection; IoT classification	IoT sensors, enhanced deep learning, object detection	Custom IoT sensor data	India	Day/night pest hiding; Image quality sensor-dependent; High computational demands; Limited pest types.

Table 1. *Cont.*

Refs	Key Contributions	Study Scope	Technology Used	Dataset	Country	Limitations
			AIoT Applications-Crop Yield Prediction			
[33]	Integrates Explainable AI (XAI) with CNNs for transparent yield prediction using satellite/drone imagery for climate adaptation.	Crop yield prediction; XAI	CNNs, XAI, satellite/drone imagery, multispectral sensors	Satellite/drone imagery	Global	Requires high-resolution imagery; Complex training/validation; Limited developing region access; High computational needs.
[34]	Comprehensive review analyzing 115 articles on ML/DL methods for yield prediction; Notable advancement documented 2018–2023.	Crop yield prediction; ML/DL comparison	Random Forest, XGBoost, CNNs, LSTM	Literature review (115 articles)	Global	Data availability issues; Limited regional transferability; Substantial historical data needed; High computational resources.
[35]	Reviews AI integration with free Sentinel-2 satellite data for yield estimation; Continuous study increase 2017–2024.	Crop yield prediction; Satellite imagery	Random Forests, SVM, CNNs, Sentinel-2 multispectral	Sentinel-2 satellite data (wheat, maize, rice)	Global	Cloud cover affects quality; 5-day temporal limits; Ground truth validation required; Technical expertise needed.
			AIoT Applications-Livestock Management			
[36]	PRISMA systematic review covering sensors, actuators, controllers for multiple animal types; Addresses renewable energy integration.	Livestock management; IoT systems	IoT sensors, actuators, controllers, communication tech	Literature review (PRISMA)	Global	Single animal focus common; Limited scalability analysis; Stability/maintenance gaps; Economic feasibility unclear.
[37]	Reviews Precision Livestock Farming (PLF) device integration with edge/cloud computing and ML for dairy cattle real-time monitoring.	Livestock management; Dairy cattle	PLF devices, edge/cloud computing, ML, IoT sensors	Dairy cattle sensor data	Italy	High edge device costs; Regular updates required; Limited farm expertise; Heterogeneous adoption rates.
[38]	Examines precision livestock management integrating on-animal sensors, environmental monitoring, remote sensing for ranching.	Livestock management; Ranching	On-animal sensors, environmental monitoring, remote sensing, IoT	Rangeland sensor data	United States	Landscape connectivity challenges; Harsh conditions threaten devices; High implementation costs; Training requirements.
			African Context Papers			
[39]	Examines IoT irrigation solutions tailored for smallholder farmers in low-bandwidth Sub-Saharan Africa environments.	Smart irrigation; Smallholder focus	IoT sensors, low-bandwidth solutions	Not specified	Sub-Saharan Africa	Limited rural infrastructure; High upfront costs; Connectivity challenges; Limited technical support.
[40]	Explores ICT tools for sustainable agriculture and environmental protection among tropical Africa smallholder farmers.	ICT for sustainability; Environmental protection	ICT tools, digital agriculture technologies	Not specified	Tropical Africa	Rural infrastructure gaps; Digital literacy challenges; Affordability issues; Limited support networks.
[41]	Policy analysis demonstrating evidence-based livelihood improvements from digital agricultural solutions for African smallholders.	Digital agriculture policy; Livelihood improvement	Digital agricultural technologies	Not specified	Africa	Policy requires government action; Barriers not fully addressed; Scalability challenges; Funding concerns.
[42]	Industry overview of agri-tech transformation trends covering technological innovations and market opportunities in Africa for 2025.	Agri-tech trends; Market analysis	Various agricultural technologies	Not specified	Africa	May lack academic rigor; Limited peer review; May emphasize opportunities over challenges; Commercial bias.
[43]	Critical examination of AI's dual potential as sustainability enabler and complexity creator in African agriculture.	AI sustainability; Complexity analysis	AI technologies in agriculture	Not specified	Africa	Blog lacks peer review; May lack empirical data; Limited technical depth; Solutions underdeveloped.
[44]	Strategic analysis examining digitalization policy implications, infrastructure requirements, and socio-economic adoption factors in Africa.	Digitalization strategy; Policy analysis	Digital agricultural technologies	Not specified	Africa	Abstract-only access limits assessment; General roadmap; Regional diversity challenges; Funding unexplored.
[45]	Examines IoT farming applications emphasizing sustainability and future-oriented solutions for developing world contexts.	IoT sustainability; Future solutions	IoT sensors, smart farming technologies	Not specified	Nigeria	Limited impact factor; Review rigor uncertain; African-specific content unclear; Technical depth unspecified.

5. Proposed AIoT Architecture for African Agriculture

Figure 5 illustrates a lightweight and context-adapted AIoT architecture designed specifically for resource-constrained agricultural environments in sub-Saharan Africa. This architecture is intended as a reference design synthesizing validated components rather than as a fully integrated deployed system.

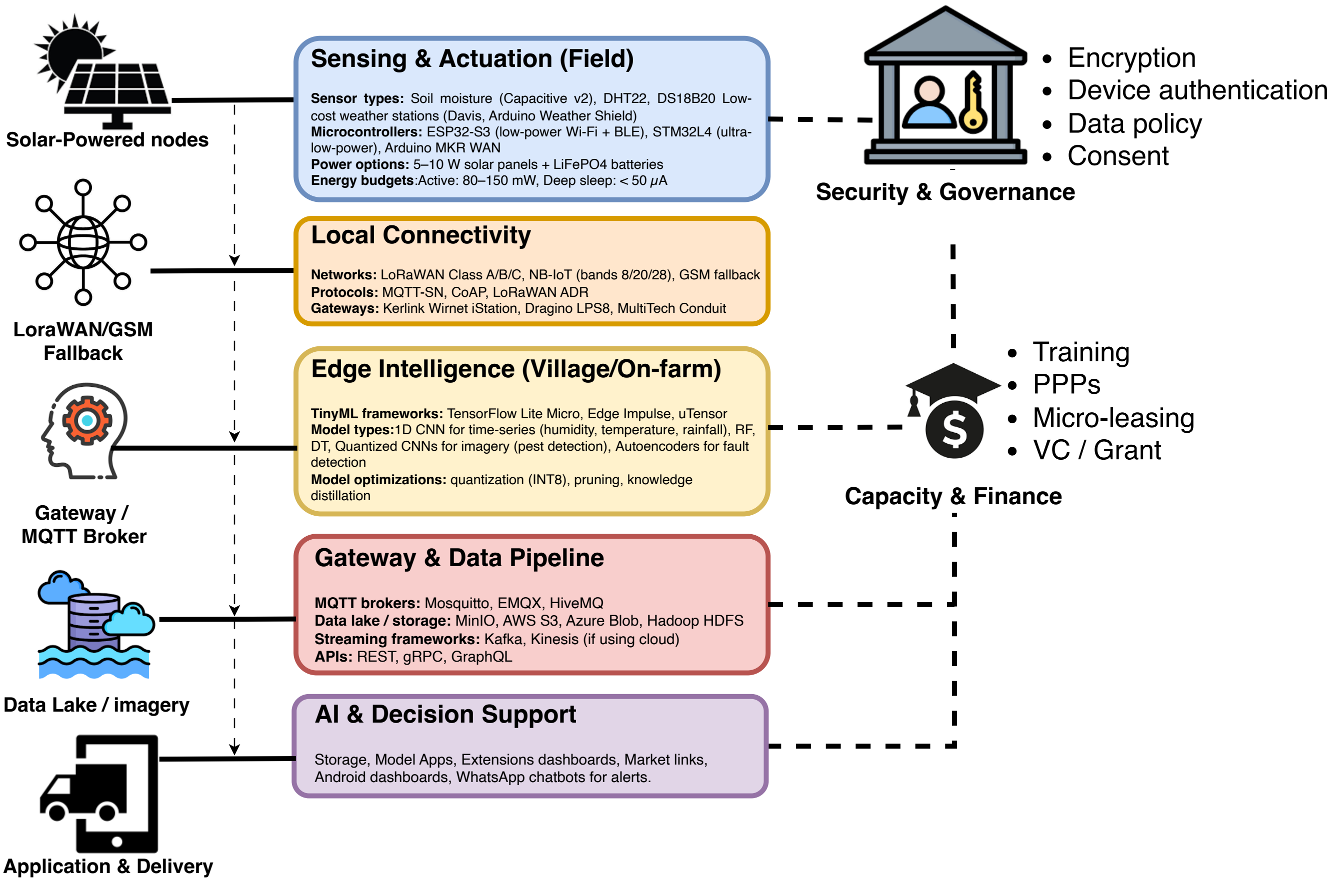

Figure 5. Modular AIoT architecture for African agriculture integrating field sensing, edge intelligence, and decision support.

The architecture is structured into five synergistic layers that collectively enable low-cost, reliable, and intelligent agricultural systems adapted to African constraints. Furthermore, this section details (i) the benefits of such an architecture for low-income and sub-Saharan contexts, (ii) key prerequisites for successful deployment, and (iii) the potential productivity gains documented in the literature.

5.1. Layered Architecture Overview

The proposed AIoT architecture for African agriculture (Figure 5) combines five essential layers to enable low-cost, reliable, and intelligent farming systems. It begins with solar-powered sensing and actuation nodes that collect soil, weather, and geolocation data while supporting basic automated functions. These devices connect via resilient low-power networks such as LoRaWAN, NB-IoT, or GSM fallback using lightweight MQTT messaging. Local edge units provide on-farm intelligence through tinyML-based inference, enabling timely decisions even where connectivity is intermittent. A gateway layer manages buffering, protocol translation, and secure data transmission toward backend systems, where AI-driven analytics, dashboards, and decision-support tools generate actionable recommendations. Cross-cutting elements including encryption and device authentication, data governance and consent, capacity building, and innovative financing mechanisms (e.g., PPPs, micro-leasing), ensure the system is trustworthy, sustainable, and suitable for resource-constrained agricultural contexts.

5.2. Benefits for Low-Income and Sub-Saharan Agriculture

The proposed AIoT architecture provides several benefits aligned with the needs and constraints of African smallholder farmers. IoT- and AI-enabled agriculture pilots in sub-Saharan Africa have demonstrated yield increases ranging from 10 to 25% compared to traditional practices [46,47], thereby improving crop productivity. In addition, early detection of pests, diseases, and crop stress using sensors and AI can significantly reduce losses and enhance resilience. Precision irrigation and fertilizer optimization further contribute to resource efficiency by decreasing water and agrochemical usage, supporting climate-smart agricultural goals [48]. The system's reliance on low-cost microcontrollers, modular sensors, and long-range low-power connectivity ensures scalability and affordability, making it economically viable for smallholders [49]. Ultimately, these combined benefits strengthen food security by increasing productivity and reducing losses, which directly supports national and regional food systems, particularly in rainfed farming contexts [50].

5.3. Prerequisites for Successful Deployment in Africa

To unlock the full potential of this architecture, several enabling conditions must be met. Reliable solar energy and at least intermittent network coverage through technologies such as LoRaWAN, NB-IoT, and GSM are essential outside urban centers to ensure basic infrastructure. Equally important is farmer training and digital literacy, as human capacity remains critical; farmers must be able to interpret dashboards, respond to alerts, and act on recommended interventions. An affordable cost model is also necessary, with mechanisms such as micro-leasing, cooperative ownership, and support from governments or NGOs helping to reduce entry barriers for smallholders. Institutional and policy support plays a key role, requiring clear data governance, incentives for digital agriculture, and supportive regulatory frameworks [51]. Finally, local adaptation through co-design with farmers ensures that solutions remain culturally, agronomically, and socio-economically relevant to the communities they serve.

5.4. Expected Productivity Gains

If widely adopted and supported by adequate infrastructure, AIoT-based systems could realistically increase agricultural productivity in Africa by 15–25%, consistent with results reported in digital agriculture initiatives across the continent [46,47,50]. Over a 5–10 year horizon, these gains could significantly improve food security, stabilize production, and strengthen rural livelihoods.

6. Ethical Aspects of AIoT in Agriculture

The adoption of Artificial Intelligence of Things (AIoT) in agriculture raises complex ethical issues that require special attention, particularly in resource-limited context [52]. These mechanisms enable operational enforcement of data sovereignty rather than reliance on policy-only instruments.

The massive collection of agricultural data by IoT sensors raises the fundamental question of data ownership and sovereignty: who owns the information on yields, farming practices and the characteristics of cultivated land [53]? This issue is all the more critical as small farmers, particularly in sub-Saharan Africa, risk losing control of their data to large technology companies, thus creating a new form of dependence and power asymmetry.

Furthermore, AI algorithms used to optimize agricultural practices are often trained on data from Western contexts, which can lead to algorithmic biases ill-suited to local realities, traditional practices, and the specific ecological characteristics of regions in the Global South [54,55].

In addition, the increasing automation driven by the AIoT risks exacerbating socio-economic inequalities by marginalizing small farmers who lack the financial resources to adopt these technologies, while threatening traditional agricultural jobs without offering viable alternatives [56]. Finally, the environmental sustainability of agricultural AIoT must be questioned: while these systems promise optimized resource use, their massive deployment implies significant energy consumption for the operation of sensors and cloud infrastructure, as well as the production of electronic waste in regions often lacking appropriate recycling systems [57].

These ethical considerations call for a human-centered approach, prioritizing the empowerment of local communities, algorithmic transparency, and the development of AIoT solutions co-created with farmers to respect their autonomy, traditional knowledge, and specific cultural contexts [58].

7. Discussion

This review demonstrates that the transition from IoT to AIoT marks not only a technological progression but a paradigm shift toward context-aware and cognitive farming systems. As evidenced throughout the literature, AIoT enables multisource sensing, distributed intelligence, and data-driven decision-support, allowing farms to operate with a degree of autonomy previously unattainable in low-resource environments. When effectively deployed, these systems can significantly improve yields, resource efficiency, and farm resilience, with documented productivity gains of 10–25% in African pilot deployments [46,47,50].

However, the findings also reveal that the pathway to AIoT adoption faces tightly coupled interdependencies. The "data–connectivity–computation" triad remains central. High-quality datasets are essential for trustworthy AI inference. Reliable and affordable connectivity enables timely data flows. Distributed computational capabilities determine whether critical inferences can occur autonomously at the edge [4]. In rural Africa, limited digital infrastructure, unstable power supply, and scarce technical expertise amplify these constraints.

The African context underscores that technological architectures cannot simply be transplanted from high-income regions to low-income settings. As discussed in Section 5, successful AIoT systems must be low-cost, energy-resilient, and robust to intermittent or low-bandwidth connectivity [2,59]. Edge intelligence and solar-powered sensing units reduce dependence on cloud services and grid electricity, while long-range low-power networks (e.g., LoRaWAN, NB-IoT) provide viable alternatives to high-cost cellular connectivity. These design considerations are not optional they are prerequisites for deployment in sub-Saharan rural environments.

Beyond technological barriers, this review highlights the critical importance of socio-economic and governance dimensions. The initial investment costs for sensors, gateways, analytics platforms, and maintenance risk deepening the digital divide. Without intervention, only commercial agribusinesses and well-resourced cooperatives may leverage AIoT capabilities [10]. Smallholder farmers, who produce up to 80% of food in many African countries, risk exclusion from the AIoT revolution without deliberate policy and financial innovation.

Therefore, future efforts must prioritize frugal innovation and inclusive financing mechanisms. Promising approaches include "AI-as-a-Service" subscription models, micro-leasing for sensor kits, cooperative-based ownership, and public–private partnerships that subsidize early adoption [1]. Furthermore, human capacity development remains a cornerstone: digital literacy programs, extension services, and community-based training are crucial to ensure farmers understand and act upon AI-driven recommendations.

Moreover, governance frameworks must define clear principles for data ownership, privacy, and ethical AI use. Without transparent data policies, farmers may be hesitant to adopt connected technologies, undermining trust in AIoT solutions. Establishing farmer-centered data governance; where users retain full control over their data is essential for long-term sustainability and equitable scaling.

Overall, the discussion shows that AIoT has the potential to transform African agriculture, but only if technological, socio-economic, and institutional prerequisites are addressed simultaneously. The transition toward sustainable, intelligent, and inclusive agricultural systems will rely on multi-stakeholder collaboration, context-driven system design, and the development of scalable business models that democratize access to AIoT innovations.

8. Concluding Remarks and Future Directions

This review has examined the progressive transition from data-centric Internet of Things (IoT) systems toward more autonomous and intelligent Artificial Intelligence of Things (AIoT) paradigms in agricultural applications. By synthesizing recent advances in sensing, connectivity, edge intelligence, and data-driven decision-making, the study highlights how AIoT can enhance agricultural productivity, resource efficiency, and climate resilience when appropriately adapted to contextual constraints.

A central finding of this review is that the transformative potential of AIoT in agriculture is not solely determined by algorithmic performance or technological sophistication. Successful deployment depends on aligning AI models, system architectures, and governance mechanisms with local infrastructural capacities, socio-economic conditions, and user needs. This alignment is particularly critical in low-income and resource-constrained environments. This insight reinforces the need to move beyond technology-centric approaches toward context-aware and human-centered AIoT designs.

Despite adherence to PRISMA 2020 guidelines, this study is subject to several limitations. The review primarily considers English-language peer-reviewed literature, which may exclude relevant regional studies or practitioner reports. Moreover, the heterogeneity of AIoT applications, datasets, and evaluation protocols limits the feasibility of quantitative comparison or meta-analysis. These limitations reflect structural characteristics of the field rather than methodological shortcomings and underscore the need for more standardized reporting and evaluation practices in future research.

Looking ahead, several research directions emerge as particularly promising. First, advances in TinyML and edge AI are expected to play a critical role in enabling low-power, low-latency intelligence directly at the sensor level, thereby reducing dependence on continuous connectivity and cloud infrastructure. Second, the integration of explainable artificial intelligence (XAI) techniques will be essential to improve model transparency, accountability, and trust among end users, particularly farmers and agricultural advisors. Third, the development of interoperable standards and open-source AIoT frameworks can lower adoption barriers, facilitate system integration, and support knowledge sharing across regions. Finally, participatory and human-centered design approaches should be prioritized to ensure that AIoT solutions complement local expertise, remain accessible to smallholder farmers, and contribute to inclusive and sustainable agricultural development.

Overall, the transition from IoT to AIoT represents an important technological evolution rather than a singular solution to agricultural challenges. When guided by contextual awareness, ethical governance, and inclusive design principles, AIoT has the potential to support more resilient, equitable, and sustainable agricultural systems, particularly in regions that have thus far remained underrepresented in the digital agriculture literature.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIoT	Artificial Intelligence of Things
AWS	Amazon Web Services
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DL	Deep Learning
GANs	Generative Adversarial Networks
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile Communications
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
LoRa	Long Range
LPWAN	Low Power Wide Area Network
LSTM	Long Short-Term Memory
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NB-IoT	Narrowband Internet of Things
NGO	Non-Governmental Organization
PLF	Precision Livestock Farming
PPP	Public–Private Partnerships
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
SMS	Short Message Service
SVM	Support Vector Machine
USD	United States Dollar
XAI	Explainable Artificial Intelligence

Appendix A. Key Terminology

Table A1. Glossary of Key Technical Terms.

Term	Definition
Artificial Intelligence of Things (AIoT)	Integration of artificial intelligence capabilities (machine learning, computer vision, predictive analytics) with IoT infrastructure to enable autonomous decision-making, pattern recognition, and intelligent responses in connected systems.
Climate Resilience	The capacity of agricultural systems to anticipate, absorb, adapt to, and recover from climate-related shocks and stresses (droughts, floods, temperature extremes) while maintaining productivity and sustainability.
Digital Divide	The gap in access to digital technologies, infrastructure, and literacy between well-resourced populations and resource-constrained communities, particularly affecting smallholder farmers in developing regions.
Edge Computing	Distributed computing paradigm where data processing occurs at or near the data source (the network edge) rather than in centralized cloud servers, enabling real-time decision-making with reduced latency and bandwidth requirements.
Governance Frameworks	Structured policies, regulations, and institutional arrangements that guide data ownership, privacy protection, algorithmic accountability, and ethical use of AI technologies in agricultural systems.
LPWAN (Low-Power Wide-Area Network)	Wireless communication technologies (e.g., LoRaWAN, NB-IoT, Sigfox) designed for long-range transmission (2–15 km) with minimal power consumption, ideal for connecting battery-powered IoT devices in remote agricultural areas.
Machine Learning (ML)	Computational methods and algorithms that enable systems to learn patterns from data and improve performance on specific tasks without being explicitly programmed, including techniques such as neural networks, decision trees, and support vector machines.
Precision Agriculture	Farming management approach that uses data-driven technologies to optimize field-level crop and livestock management with regard to spatial and temporal variability, minimizing resource waste while maximizing productivity.
Smart Livestock Management	Technology-enabled monitoring and management of animal health, welfare, behavior, and productivity using sensors, wearables, and AI analytics to optimize herd performance and detect early signs of illness or stress.
TinyML	Machine learning techniques optimized to run on resource-constrained microcontrollers and embedded devices with limited memory, processing power, and energy availability, typically consuming less than 1mW of power.

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