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Emerging AIoT Technologies for Efficient Data Collection and Decision Making in Smart Farming

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ABSTRACT

Traditional farming is being transformed into intelligent, data-driven agriculture by the confluence of Artificial Intelligence (AI) and the Internet of Things (IoT) into the AIoT paradigm. In order to increase agricultural output, optimize resource use, lessen environmental effects, and improve farmer decision-making, smart farming uses real-time data from distributed sensors, automated systems, and predictive models. The growing use of AIoT technology in agriculture addresses global issues such as resource limitations, population expansion, labor problems, and climate change. Wireless sensor networks (WSNs), drones and autonomous vehicles, edge computing, cloud analytics, and machine learning algorithms for predictive insights are key elements of AIoT systems in agriculture. In order to initiate automatic activities or offer decision assistance, these systems gather diverse data, including soil moisture, weather, crop health indicators, and equipment status. These data are then processed and analyzed. In order to improve data collection and decision-making in smart farming, this article examines new AIoT technologies. We look at the integration of various technologies, their advantages, real-world applications, issues with connectivity, security, data quality, and farmer adoption, as well as potential avenues for future research. This study uses an interdisciplinary approach to identify trends, gaps in existing practice, and tactics to optimize AIoT's influence in sustainable agriculture.
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Keywords: AIoT, Precision agriculture, Edge computing, Sensor networks, Decision support systems

1. INTRODUCTION

Rapid advancements in digital technologies and the increasing demand for sustainable food production are driving a fundamental shift in agriculture [1]. Climate variability, water scarcity, soil degradation, rising input costs, and labor shortages are just a few of the issues that traditional agricultural methods, which mostly rely on manual observation, experience, and reactive decision making, are finding it more and more difficult to handle. At the same time, population growth and shifting consumption habits are driving up the world's food demand [2]. The use of smart farming techniques, which leverage data and technology to increase production, resilience, and efficiency, has risen as a result of these challenges. A major technological enabler among these strategies is the combination of Artificial Intelligence (AI) with the Internet of Things (IoT), or AIoT [3].

IoT technologies enable large-scale, continuous data collection from agricultural surroundings, laying the groundwork for smart farming. Real-time data on soil moisture, temperature, humidity, nutrient levels, crop development, and animal health are collected by dispersed sensors positioned throughout fields, greenhouses, and livestock facilities [4]. While automated equipment and actuators capture operational data about irrigation, fertilization, and harvesting, drones and satellite imagery provide spatial and temporal perspectives. Often referred to as "agricultural big data," this sensor-rich environment produces enormous amounts of diverse data. However, unless it can be processed, analyzed, and converted into timely actions, raw data on its own has little value [5].

In order to transform agricultural data into information that can be put to use, artificial intelligence is essential. Based on past and present data, machine learning and deep learning algorithms can spot trends, forecast results, and suggest the best course of action. Artificial intelligence (AI) models are employed in smart farming settings to forecast yield, identify pests and diseases, schedule irrigation, optimize fertilizer, and guide agricultural machines autonomously. AI allows for automated and adaptive decision-making when paired with IoT technology, transforming farming operations from reactive to proactive and predictive. The AIoT paradigm is defined by this convergence of automation, intelligence, and sensing [6].

The importance of AIoT in agriculture is further enhanced by developments in communication and computer technology. Edge computing reduces latency and reliance on constant internet access by enabling data processing and AI inference to take place closer to the data source [3]. This is especially crucial in isolated and rural farming areas where network infrastructure might not be dependable. Simultaneously, cloud platforms offer scalable computing and storage resources for combining multi-season datasets, training intricate AI models, and providing decision support systems that may be accessed via web and mobile applications. Flexible architectures that strike a compromise between long-term analytics and real-time responsiveness are made possible by the combination of edge and cloud computing [7].

A key prerequisite for successful AIoT-based smart farming is efficient data collection. Weather, soil conditions, biological activities, and human activity all have an impact on agricultural ecosystems, which are quite dynamic [3]. Decisions that are not ideal or even detrimental can result from incomplete, inaccurate, or delayed data. Advanced sensors with improved durability and accuracy, low-power wide-area networks that facilitate long-range communication, and data fusion techniques that combine information from several sources are some of the emerging AIoT technologies that tackle this problem. These skills enhance situational awareness in farm management at both the macro and micro levels [8].

Agricultural decision-making is intrinsically complicated, involving trade-offs between risk, production, cost, and environmental impact. Farmers frequently have to make unclear decisions about when and how much to fertilize, water, or use crop protection measures. By evaluating data-driven insights and making recommendations unique to particular field circumstances, AIoT-based decision support systems help farmers [7]. AIoT systems can directly control actuators in more sophisticated implementations, allowing for robotic field activities, controlled watering, and greenhouse climate management. Particularly in large-scale or labor-constrained farming operations, such automation guarantees prompt interventions and lessens human effort [9].

AIoT implementation in agriculture confronts a number of obstacles despite its potential. These include the requirement for technical skills among farmers and farm managers, data security and privacy concerns, interoperability problems among diverse equipment, and expensive initial investment prices. Furthermore, a lot of AI models operate as "black boxes," which might reduce acceptance and confidence when recommendations are difficult to understand. Continued research, user-centered system design, supportive legislation, and capacity-building programs are needed to address these issues [10].

1.1 Scope

This study focuses on new AIoT technologies that make it possible for smart farming systems to collect data effectively and make wise decisions. Crop cultivation, precision irrigation, pest and disease control, soil and water monitoring, and some parts of animal monitoring when AIoT is used are all included in the scope [8]. It looks at data analytics, communication networks, sensing technologies, and AI-based decision support systems. System architectures, real-world applications, advantages, and drawbacks are highlighted in the paper. Only when they are directly related to on-farm AIoT deployment are post-harvest processing, supply chain management, and market-level analytics taken into account [11].

1.2 Objectives

This paper explores emerging AIoT technologies that improve data collection and decision-making in smart farming. Specific objectives include:

- Reviewing key AIoT components relevant to agriculture.
- Exploring how AI algorithms utilize IoT-collected data for predictive insights.
- Analyzing architectures that support real-time data processing.
- Identifying real-world applications, benefits, and limitations.
- Suggesting future research directions to address current gaps.

2. RELATED WORK

Over the past 20 years, a lot of research has been done on the use of digital technology in agriculture; early studies concentrated on sensor-based monitoring systems and precision agriculture. The utilization of wireless sensor networks to gather environmental data, including temperature, humidity, and soil moisture, was the main focus of early research [9]. When compared to traditional calendar-based methods, these investigations showed that continuous sensing might greatly enhance irrigation scheduling and resource usage. Nevertheless, the majority of early systems were limited in their capacity to adjust to changing field conditions since they depended on rule-based decision mechanisms and static thresholds [12].

Several researchers looked at large-scale IoT-enabled agricultural monitoring platforms due to the Internet of Things' explosive growth. These studies focused on long-range connectivity using technologies like Zigbee, LoRaWAN, and NB-IoT, low-power sensor design, and energy-efficient communication protocols [6]. Field deployments demonstrated that IoT devices could function for long stretches of time with no upkeep, making them appropriate for big, isolated agricultural fields. However, these platforms provided limited analytical capabilities for sophisticated decision making, primarily concentrating on data collection and visualization [13].

A major change in related research occurred when machine learning was introduced into agricultural applications. To forecast agricultural productivity, categorize soil types, and identify plant diseases, researchers started utilizing supervised learning methods, including support vector machines, decision trees, and random forests [8]. With the advent of inexpensive cameras and drones, image-based methods gained popularity since they allowed computer vision algorithms to automatically identify pests and nutrient deficits. Although these models outperformed conventional techniques in terms of accuracy, several of them lacked integration with real-time IoT data streams and were trained on offline datasets [14].

The confluence of AI and IoT into integrated AIoT frameworks for smart farming has been highlighted more and more in recent studies. In order to facilitate real-time analytics and long-term decision support, these studies suggest layered architectures that analyze sensor data via edge and cloud computing infrastructures [12]. By carrying out initial data filtering and inference close to the data source, edge computing has been emphasized as a way to lower latency and bandwidth consumption. According to experimental data, time-sensitive tasks like automated irrigation control and anomaly detection in greenhouse conditions can be successfully supported by edge-based AI models [15].

Deep learning methods for agricultural decision making are the subject of another substantial corpus of related work. Using multispectral and hyperspectral imaging, convolutional neural networks have been extensively used for crop disease detection, weed categorization, and crop growth monitoring. High classification accuracy has been reported by researchers, especially when deep learning models are trained on sizable and varied datasets [13]. Weather forecasting and yield estimation have made use of time-series models, such as recurrent neural networks and long short-term memory networks. Even though these models perform better, their deployment in resource-constrained farming situations may be limited since they frequently demand significant computational resources and huge labeled datasets [16].

Decision support systems that integrate AI models with agronomic information have been the subject of numerous studies. To increase robustness and interpretability, these hybrid techniques combine data-driven forecasts with expert guidelines. For instance, machine learning predictions based on sensor data have been integrated with evapotranspiration models in irrigation recommendation systems. Because the guidelines are in line with well-known agronomic concepts, these systems have demonstrated increased adoption among farmers. Scalability and customisation across many crops and geographical areas, however, continue to be unresolved issues [17].

AIoT-based research has also helped livestock farming, especially in the areas of behavior analysis and health monitoring. Anomalies in animal locomotion, feeding habits, and vital signs have been identified using wearable sensors and computer vision systems. Early disease and stress condition diagnosis is made possible by machine learning models built on these data streams. Although encouraging, many studies are restricted to small herds and controlled settings, underscoring the need for validation in diverse and large-scale farming situations [18].

Numerous related works have addressed security, privacy, and data management challenges. Unauthorized access, data manipulation, and denial-of-service attacks are among the vulnerabilities that researchers have found in IoT-based agricultural systems. Secure data storage methods, authentication systems, and lightweight encryption schemes are some of the suggested remedies. In order to guarantee data integrity and traceability, some research has recommended incorporating blockchain technologies. These methods add extra computational and energy overheads, even while they improve trust [19].

Table 1: Summarizing key aspects

Key Area	Key Technologies Used	Main Contributions	Limitations Identified
Sensor-based Precision Agriculture [20]	Wireless sensor networks, basic IoT nodes	Enabled real-time monitoring of soil and environmental parameters; improved irrigation scheduling	Relied on static thresholds; limited adaptability and intelligence
IoT-enabled Monitoring Platforms [21]	IoT sensors, LPWAN (LoRaWAN, NB-IoT), cloud dashboards	Large-scale data collection with low power consumption; long-term field deployment	Mostly focused on data acquisition and visualization; weak decision-making capabilities
Machine Learning in Agriculture [22]	SVM, Random Forest, Decision Trees	Improved yield prediction, soil classification, and disease detection accuracy	Often offline models, limited integration with real-time IoT data
Deep Learning for Crop Analysis [23]	CNNs, RNNs, multispectral imaging, drones	High accuracy in disease detection, weed identification, and crop monitoring	High computational cost; need for large labeled datasets
Edge Computing-based Smart Farming [24]	Edge AI, fog computing, sensor gateways	Reduced latency; enabled real-time control such as automated irrigation	Limited processing power at the edge; model complexity constraints
Hybrid Decision Support Systems [25]	AI models + agronomic rules	Improved interpretability and farmer acceptance of recommendations	Scalability and regional customization challenges
AIoT in Livestock Monitoring [26]	Wearable sensors, computer vision, ML models	Early detection of health issues and behavior anomalies	Mostly validated in small-scale or controlled environments
Security-focused Agricultural IoT [27]	Encryption, authentication, blockchain	Enhanced data integrity, privacy, and trust	Added computational and energy overhead; complexity
Integrated AIoT Frameworks [28]	IoT + AI + edge–cloud architectures	End-to-end data collection and intelligent decision making	Lack of holistic, cost-effective, and farmer-centric solutions

3. AIoT ARCHITECTURE FOR SMART FARMING

A well-designed AIoT architecture that can provide dependable data gathering, effective processing, intelligent analytics, and practical decision making is crucial to the success of smart farming systems. Because agricultural ecosystems are geographically dispersed and extremely dynamic, they need architectures that are resilient, scalable, energy-efficient, and able to function in situations with limited connectivity. To control complexity and guarantee a smooth connection between sensing devices, communication networks, computing resources, and end-user applications, a layered AIoT design is frequently used [29].

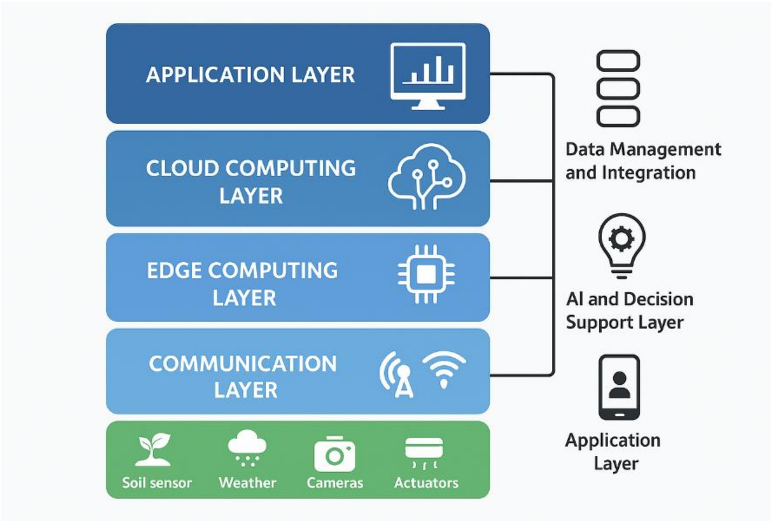

Fig. 1: AIoT Architecture for Smart Farming

3.1 Perception Layer: Data Acquisition and Actuation

By facilitating real-time data collection from the actual farming environment, the perception layer serves as the cornerstone of the AIoT architecture. It is made up of several sensing and actuation devices that are placed across aquaculture systems, greenhouses, fields, and animal shelters [30].

Important variables like temperature, pH, salinity, moisture content, and nutrient levels are measured via soil sensors. Rainfall, humidity, wind speed, and sun radiation are among the atmospheric variables that weather sensors record. Crop health, growth stages, and stress conditions are evaluated using optical sensors, cameras, and multispectral or hyperspectral imagers. Wearable sensors and vision-based systems are used in cattle husbandry to track animal movement, feeding habits, and physiological markers [31].

Actuators are equally significant parts of this layer. These include robotic tools for weeding or spraying, climate control systems, fertilizer dispensers, and irrigation valves. Actuators carry out physical tasks on the farm after receiving control signals produced by AI-driven decision modules. Because perception-layer devices are deployed outdoors and operate for extended periods of time, reliability, low power consumption, and environmental robustness are critical design requirements [32].

3.2 Communication Layer: Data Transmission and Connectivity

The communication layer is in charge of sending control commands back to actuators and conveying data from sensing devices to processing units. Connectivity is a major difficulty in smart agricultural systems since they frequently span broad and rural locations [33].

Because of its extended communication range, low energy consumption, and compatibility with tiny data packets, low-power wide-area network technologies like LoRaWAN and NB-IoT are frequently deployed. Wi-Fi, cellular networks, private LTE, and 5G networks are used for high-bandwidth applications such as picture and video transmission from drones or cameras. Gateways compile information from several sensor nodes and provide it to cloud platforms or edge servers [34].

This layer needs to guarantee secure communication, fault tolerance, and dependable data transmission. In dynamic agricultural contexts, adaptive routing, data compression, and scheduling techniques are frequently employed to maximize bandwidth utilization and minimize packet loss [35].

3.3 Edge Computing Layer: Local Processing and Real-Time Intelligence

By facilitating local processing and analysis, the edge computing layer brings intelligence closer to the data source. Data filtering, aggregation, anomaly detection, and real-time AI inference are among the functions carried out by edge devices, such as smart gateways or embedded controllers [36].

The edge layer lessens reliance on constant cloud connectivity and lowers latency by processing data locally. For time-sensitive processes like automated irrigation control, greenhouse climate regulation, and safety-related choices, this is especially crucial. In order to address memory, processing, and energy constraints, lightweight machine learning models or compressed deep learning networks are frequently implemented at the edge [37].

By reducing the quantity of raw data sent to the cloud, edge computing also improves data privacy. By forwarding only pertinent features, summaries, or alerts, communication overhead and exposure to possible security risks are decreased [38].

3.4 Cloud Computing Layer: Centralized Analytics and Model Training

High-performance processing, scalable storage, and sophisticated analytics are all offered by the cloud computing layer. It acts as the focal point for combining data gathered over extended periods of time, from various sources, and over several fields or farms [39].

This layer uses both historical and current data to train sophisticated AI models. The cloud is usually used for tasks like yield forecasts, long-term climate effect assessments, and seasonal resource allocation optimization. Additionally, cloud platforms facilitate data fusion, which combines sensor data with other datasets, including market data, weather forecasts, and satellite imagery [40].

Through recurring retraining and validation, the cloud layer allows AI models to be continuously improved. A closed-loop learning system that adjusts to shifting operational and environmental variables can be created by deploying updated models back to edge devices [41].

3.5 Data Management and Integration Layer

The success of AIoT-based smart farming depends on efficient data handling. Data ingestion, storage, preprocessing, labeling, and retrieval are all handled by this layer. Robust data cleaning and normalization procedures are necessary because agricultural data are frequently heterogeneous, noisy, and incomplete [42].

Semantic data models, time synchronization, and metadata management all contribute to interoperability and consistency across many platforms and devices. In order to facilitate more precise and context-aware decision making, data integration frameworks allow sensor data to be combined with agronomic knowledge, historical records, and other information sources [43].

3.6 AI and Decision Support Layer

Converting processed data into useful insights is the responsibility of the AI and decision support layer. It houses algorithms for machine learning, deep learning, and optimization that examine trends, forecast results, and produce suggestions [44].

Irrigation schedules, fertilizer application rates, pest control alerts, and equipment maintenance recommendations are examples of decision outputs. By directly activating actuators, this layer also facilitates autonomous decision execution in sophisticated systems. For farmers to successfully implement AI-generated recommendations, explainability and transparency are crucial factors [45].

3.7 Application Layer: User Interaction and Visualization

Farmers, agronomists, and farm managers can communicate with the AIoT system via interfaces provided by the application layer. Real-time sensor data, analytical results, alerts, and recommendations are presented in an intuitive way using web dashboards and mobile applications [46].

Maps, charts, and trend analysis are examples of visualization tools that aid users in comprehending temporal and spatial differences in farm conditions. Strategic planning and well-informed decision-making are supported by customizable warnings and reporting tools. To guarantee usability across all technical skill levels, user-centric design is essential [47].

3.8 Security and Management Layer

All levels of the AIoT architecture are covered by security and system management functionalities. This covers system monitoring, access control, secure data transmission, and device authentication. The smart farming infrastructure's long-term dependability and robustness are guaranteed by frequent upgrades, fault detection, and remote device management [48].

Sensing, communication, intelligence, and action may all be seamlessly coordinated with a well-integrated core AIoT architecture. These designs serve as the foundation for next-generation smart farming systems that are productive, sustainable, and able to adapt to new challenges by facilitating effective data collection and intelligent decision making [49].

4. EMERGING TECHNOLOGIES FOR DATA COLLECTION

The foundation of AIoT-enabled smart farming is effective and trustworthy data collection. Due to the complexity, spatial dispersion, and high degree of dynamic nature of agricultural environments, data collection solutions must be precise, reliable, scalable, and energy-efficient. The quality, granularity, and timeliness of agricultural data have been greatly improved by recent developments in sensing, imaging, robotics, and connectivity. Important new technologies that facilitate sophisticated data collection in smart agricultural systems are covered in this section [50].

Fig. 2: Smart Farming AIoT Infographic

4.1 Smart Soil and Environmental Sensors

Data-driven agriculture relies heavily on environmental and soil sensors. Numerous factors, including soil moisture, temperature, electrical conductivity, pH, salinity, and nutrient concentrations, can be measured simultaneously by contemporary smart sensors. Microcontrollers that carry out local preprocessing, calibration, and fault detection are frequently integrated into these sensors [51].

Sensor accuracy and durability under challenging field circumstances have improved thanks to developments in material science and sensor manufacture. When paired with solar or energy-harvesting devices, energy-efficient designs enable long-term deployment with low maintenance. Precise irrigation and fertilization decisions are made possible by real-time soil data, which minimizes water waste and nutrient runoff while preserving ideal crop development conditions [52].

4.2 Weather Monitoring Stations and Microclimate Sensing

Crop growth, insect dynamics, and irrigation needs are all directly impacted by weather conditions. Compact and inexpensive, emerging AIoT-based weather stations can record localized microclimate data, such as rainfall, humidity, wind speed, sun radiation, and air pressure [53].

Distributed microclimate sensors offer fine-grained spatial data that represents fluctuations within a single farm, in contrast to conventional centralized weather stations. AI models for illness prediction, yield forecasting, and evapotranspiration calculation are more accurate thanks to this localized data. Predictive performance is further improved by integration with external meteorological data [54].

4.3 Remote Sensing and Satellite-Based Data Collection

For extensive agricultural surveillance, satellite remote sensing has emerged as a crucial data source. Higher spatial, temporal, and spectral resolution made possible by satellite imaging advancements allows for frequent monitoring of agricultural conditions across large regions [55].

Crop vigor, biomass, and stress levels are frequently evaluated using vegetation indices like NDVI and EVI that are generated from satellite data. AIoT platforms combine sensor readings from the ground with satellite data to offer multi-scale insights. Although cloud cover and revisit intervals may have an impact on satellite data, its extensive coverage makes it useful for strategic planning and regional monitoring [56].

4.4 Unmanned Aerial Vehicles for High-Resolution Sensing

Drones, also referred to as unmanned aerial vehicles, offer versatile and high-resolution data collection capabilities. Drones with RGB, multispectral, hyperspectral, and thermal cameras may take precise pictures of crops at crucial growth stages [57].

Early diagnosis of crop diseases, water stress, nutritional deficits, and insect infestations is made possible by drone-based sensing. Aerial imagery is processed by AI algorithms to create field maps that identify trouble spots and allow for focused actions. Drones are appropriate for precision agricultural applications because they provide superior spatial resolution and on-demand data collection when compared to satellite imaging [58].

4.5 Autonomous Ground Robots and Field Rovers

In smart farming, autonomous field rovers and ground robots are becoming mobile platforms for data collection. These devices collect in-situ and close-range data using cameras, LiDAR, soil probes, and environmental sensors [59].

In situations where aerial platforms have restricted visibility, ground robots can function beneath crop canopies. They simultaneously carry out duties like scouting, weeding, or sampling while gathering comprehensive data on plant morphology, weed density, and soil conditions. Real-time monitoring and adaptive decision making are supported by ground robots' constant data collection [60].

4.6 Computer Vision and Imaging Sensors

In order to collect visual data for crop and livestock monitoring, computer vision technologies are essential. Images and videos reflecting plant health, growth stages, and animal activity are gathered by mobile cameras on drones and robots, as well as fixed cameras in greenhouses and barns [61].

Diseases, weeds, and pests can now be automatically identified thanks to developments in image sensors and AI-based vision algorithms. By detecting temperature changes linked to illness or a lack of water, thermal imaging sensors help detect stress. In addition to numerical sensor measurements, these visual data sources offer rich contextual information [62].

4.7 Wearable and Biometric Sensors for Livestock

Wearable sensors have become a dependable method of ongoing data collection in animal production. These devices are affixed to animals and track many data, including feeding behavior, activity levels, heart rate, and body temperature [63].

The information gathered aids in identifying early indicators of disease, stress, or reproductive cycles. Automated alarms and health evaluations are made possible by integration with AI models, which enhances animal production and welfare. Additionally, wearable sensors provide position tracking, which helps prevent theft and manage pastures [64].

4.8 Aquaculture and Water Quality Sensors

Water quality factors like dissolved oxygen, pH, temperature, turbidity, and ammonia levels are monitored by smart aquaculture systems using both surface and underwater sensors. Maintaining healthy aquatic habitats requires accurate and ongoing monitoring [65].

New sensor technologies provide increased biofouling resistance and sensitivity. AI models are used to assess the data gathered from these sensors in order to optimize water exchange, aeration, and feeding schedules, hence lowering operating costs and environmental impact [66].

Table 2: Emerging Technologies for Data Collection in Smart Farming

Technology	Data Collected	Key Sensors / Tools	Coverage Area	Advantages	Limitations
Smart Soil Sensors [67]	Soil moisture, temperature, pH, nutrients	Capacitive sensors, EC sensors, pH probes	Localized (field/plot level)	Real-time, high accuracy, low power consumption	Limited spatial coverage, maintenance required
Weather Stations [68]	Rainfall, humidity, temperature, wind speed, solar radiation	Rain gauges, anemometers, hygrometers	Farm or regional level	Supports climate-aware decisions, continuous monitoring	Installation cost, calibration needed
UAVs (Drones) [69]	Crop health, NDVI, canopy cover, pest stress	RGB, multispectral, thermal cameras	Medium to large farms	High-resolution imagery, flexible deployment	Weather dependent, limited battery life

Satellite Remote Sensing [70]	Vegetation indices, soil moisture, land use	Multispectral and hyperspectral sensors	Large-scale and regional	Wide coverage, historical data availability	Lower resolution, data latency
Smart Imaging Systems [71]	Leaf color, growth patterns, pest presence	AI-enabled cameras	Plant-level	Early disease detection, automated analysis	High data volume, processing overhead
Wearable Livestock Sensors [72]	Body temperature, movement, and feeding behavior	RFID, accelerometers, biosensors	Individual animals	Improves animal health monitoring	Device cost, battery replacement
IoT-Enabled Machinery Sensors [73]	Equipment performance, fuel use, soil compaction	GPS, pressure, vibration sensors	Field operations	Enhances operational efficiency	Integration complexity
Environmental Gas Sensors [74]	CO_2, NH_3, methane levels	Gas sensors	Greenhouses/farms	Supports climate-controlled farming	Sensor drift, calibration needs

5. AI TECHNIQUES FOR DECISION MAKING

In order to convert unprocessed agricultural data gathered by AIoT devices into insightful analysis and practical choices, artificial intelligence is essential. Uncertainty, non-linearity, and a heavy reliance on biological and environmental variables define farming ecosystems. By identifying patterns in both historical and current data, AI methods assist in modeling this complexity and facilitate autonomous, predictive, and prescriptive decision-making. The main AI methods for making decisions in smart farming are covered in this section, along with their functions and benefits [75].

5.1 Supervised Machine Learning for Predictive Analytics

When labeled datasets are available, agricultural decision support systems frequently employ supervised machine learning algorithms. These models discover correlations between input variables, including crop characteristics, weather, and soil parameters, and output variables, like yield, the presence of disease, or water requirements [76].

Support vector machines, decision trees, random forests, linear regression, and gradient boosting models are among the frequently utilized techniques. These methods are used for tasks including disease categorization, soil fertility assessment, and agricultural yield prediction. Supervised models are prized for their robust performance on structured data and comparatively easy implementation. However, the quality and representativeness of labeled training data have a significant impact on their accuracy [77].

5.2 Unsupervised Learning for Pattern Discovery

When labeled data is scarce or unavailable, as is frequently the case in agriculture, unsupervised learning techniques are used. Without predetermined outputs, these techniques find hidden patterns, similarities, or anomalies in data [78].

Fields are divided according to crop growth patterns, soil characteristics, or moisture levels using clustering techniques like DBSCAN, k-means, and hierarchical clustering. Abnormal sensor readings, early indicators of disease outbreaks, or equipment failures can all be found with the use of anomaly detection tools. Unsupervised learning facilitates exploratory analysis and aids agronomists and farmers in comprehending field variability [79].

5.3 Deep Learning for Complex Data Analysis

Because deep learning approaches can handle complicated, high-dimensional data like photos, movies, and time-series sensor streams, they have attracted a lot of attention. Convolutional neural networks are widely utilized for image-based decision making, such as crop stage categorization using camera or drone imagery, weed identification, and plant disease detection [80].

Sequential data is used for irrigation planning, yield estimates, and weather forecasting using recurrent neural networks and long short-term memory models. Transformer-based designs for multi-modal agricultural data have been investigated more recently. Although deep learning models are very accurate, their deployment in resource-constrained situations may be limited due to their high computing resources and huge dataset requirements [81].

5.4 Reinforcement Learning for Adaptive Control

For decision-making tasks involving sequential actions and dynamic contexts, reinforcement learning is especially well-suited. By interacting with their surroundings and getting feedback in the form of rewards, reinforcement learning agents in smart farming discover the best tactics [82].

Robotic navigation, greenhouse climate control, and adaptive irrigation scheduling are examples of applications. An RL-based irrigation system, for instance, balances crop health and water usage to determine when and how much to irrigate. In order to guarantee stable and secure functioning, reinforcement learning necessitates lengthy training and careful reward function design [83].

5.5 Edge AI for Real-Time Decisions

Using AI models directly on edge devices, including gateways, microcontrollers, or embedded systems, is known as "edge AI." By processing data close to the source, this method lowers latency and dependence on cloud connectivity, enabling real-time decision making [84].

Edge AI is utilized in agriculture for things like automated actuator control, local anomaly detection, and quick pest detection. To overcome hardware limitations, lightweight models, model compression, and quantization techniques are frequently used. Particularly in isolated farming regions with poor network connectivity, edge AI improves responsiveness and resilience [85].

5.6 Hybrid AI Models and Knowledge-Based Systems

Hybrid AI techniques integrate rule-based systems, domain expertise, and data-driven models. To increase robustness and interpretability, these systems combine machine learning predictions with expert rules, crop growth models, and agronomic knowledge [86].

For example, machine learning predictions based on sensor data can be combined with evapotranspiration equations to create irrigation recommendations. By coordinating AI decisions with conventional farming methods, hybrid systems boost farmer confidence and promote adoption. However, strong cooperation between AI specialists and agriculture experts is necessary for the development and upkeep of such systems [87].

5.7 Explainable AI for Trustworthy Decision Making

Because farmers must comprehend the reasoning behind recommendations, explainability is a crucial prerequisite for agricultural decision support. Through the identification of influential elements, the visualization of decision paths, or the generation of human-readable explanations, explainable AI techniques offer insights into model behavior [88].

Predictions about yield, disease risk, or resource allocation are interpreted by users with the aid of techniques like feature importance analysis, saliency mapping, and rule extraction. Explainable AI enhances user confidence, accountability, and transparency—all of which are critical for the broad adoption of AIoT-based systems [89].

5.8 Digital Twins and Simulation-Based Decision Support

By combining sensor data, artificial intelligence models, and simulation tools, digital twin technology generates virtual replicas of actual farming systems. Before implementing them in the actual world, these virtual settings enable farmers to assess various situations, such as modifications to planting dates or irrigation tactics [90].

Digital twins powered by AI facilitate long-term planning, risk assessment, and predictive analysis. Digital twins facilitate more proactive and informed decision-making by modeling crop growth and environmental interactions [91].

5.9 Continuous Learning and Model Adaptation

Seasonal fluctuations, climatic trends, and management techniques all cause agricultural ecosystems to vary throughout time. AI models can adapt by changing their parameters in response to fresh input thanks to continuous learning techniques.

While maintaining data privacy, online learning, transfer learning, and federated learning techniques facilitate model evolution. Over several growth seasons, decision-making systems are kept correct and pertinent through constant change [92].

Table 3: AI Techniques for Decision Making in Smart Farming

AI Technique	Decision-Making Role	Input Data Types	Key Advantages	Limitations	Typical Smart Farming Applications
Rule-Based Systems [93]	Threshold-based decisions	Sensor readings, expert rules	Simple, transparent, easy to implement	Rigid, not adaptive to changing conditions	Basic irrigation control, alerts
Machine Learning (Supervised) [94]	Predictive and classification decisions	Historical sensor data, weather data	High accuracy, data-driven	Requires labeled data, retraining	Yield prediction, disease

			insights	needed	classification
Unsupervised Learning [95]	Pattern discovery and anomaly detection	Multivariate sensor data	No labeled data needed, detects unknown patterns	Limited interpretability	Stress detection, anomaly identification
Deep Learning [96]	Complex decision inference	Images, videos, multispectral data	High precision in image-based analysis	High computational cost, low explainability	Crop disease detection, weed recognition
Reinforcement Learning [97]	Sequential decision optimization	State-action-reward data	Learns optimal policies over time	Training complexity, exploration risk	Irrigation scheduling, greenhouse control
Fuzzy Logic Systems [98]	Decision making under uncertainty	Imprecise sensor data	Handles uncertainty well, interpretable	Rule tuning required	Climate control, irrigation management
Bayesian Networks [99]	Probabilistic reasoning	Sensor data, prior knowledge	Manages uncertainty, supports reasoning	Computational complexity	Pest outbreak prediction, risk assessment
Ensemble Learning [3]	Robust decision support	Multiple model outputs	Improved accuracy and reliability	Higher computation cost	Crop yield estimation, disease diagnosis
Edge AI Models [7]	Real-time local decisions	Streaming sensor data	Low latency, reduced bandwidth usage	Limited model complexity	Automated irrigation, real-time alerts
Hybrid AI Models [11]	Integrated decision frameworks	AI models + agronomic rules	Balanced accuracy and interpretability	Design complexity	Precision farming decision support

6. BENEFITS AND IMPACTS

The productivity, sustainability, and resilience of agriculture are significantly impacted by the use of AIoT technology in smart farming. AIoT-based solutions convert conventional farming methods into precision-driven operations by facilitating ongoing data collection, intelligent analysis, and prompt decision-making. The main advantages and effects of AIoT in agriculture from an economic, environmental, and social perspective are covered in this section [7].

6.1 Enhanced Resource Efficiency

Increased efficiency in the use of vital resources like water, fertilizer, energy, and agrochemicals is one of the biggest advantages of AIoT in smart farming. Based on current soil moisture and meteorological circumstances, sensor-driven irrigation systems only provide water when and where it is required. In a similar vein, AI-guided precision fertilization eliminates fertilizer waste and lowers runoff into nearby ecosystems [13].

In addition to reducing input costs, optimal resource usage increases the availability of limited resources, especially in water-stressed areas. Long-term agricultural sustainability and better environmental stewardship are facilitated by this efficiency [15].

6.2 Increased Crop Yield and Quality

By facilitating the early detection of stress factors, including pests, illnesses, nutrient deficits, and water limitations, AIoT-enabled decision support systems increase crop production. Farmers can reduce production losses and improve crop health by intervening at the best time through continuous monitoring and predictive analytics [17].

Furthermore, consistent crop development and higher quality are the results of exact control over growing circumstances. This leads to lower post-harvest losses and higher market prices for high-value commodities like fruits and vegetables [19].

6.3 Cost Reduction and Economic Gains

Automation and smart decision-making cut operational inefficiencies and lessen reliance on manual labor. AI-guided spraying, robotic weeding, and autonomous irrigation all lower labor needs and related expenses. Additionally, early problem discovery avoids costly large-scale interventions later in the growth cycle [88].

These efficiencies result in increased profitability and a higher return on investment for farmers. Adoption of AIoT on a larger scale boosts rural development and agriculture's economic viability [21].

6.4 Risk Mitigation and Climate Resilience

Extreme weather events and climatic variability pose a serious threat to agriculture. By offering real-time monitoring and forecasting insights regarding weather patterns, soil conditions, and crop responses, AIoT systems increase resilience [87].

AI-driven forecasting models provide proactive planning and mitigation methods by assisting farmers in anticipating risks like disease outbreaks, floods, and droughts. In the face of shifting climatic conditions, this risk-aware decision-making helps stabilize agricultural output by lowering uncertainty [23].

6.5 Environmental Sustainability

AIoT technologies greatly lessen farming's environmental impact by making it possible to apply water, fertilizer, and pesticides precisely. Reduced use of chemicals reduces biodiversity loss, water pollution, and soil degradation [28].

AIoT-enabled sustainable farming methods enhance soil health, lower greenhouse gas emissions, and promote resource conservation. Long-term ecological balance and agricultural productivity are matched by these environmental advantages [85].

6.6 Improved Farm Management and Decision Transparency

AIoT technologies give farmers access to extensive dashboards that display historical and real-time data from various aspects of agricultural operations. Strategic planning, performance evaluation, and well-informed decision making are all supported by this holistic perspective [30].

Transparent statistics and explainable AI boost confidence in automated suggestions. More adoption and efficient use of AI-driven technologies result from farmers having a better knowledge of how decisions are made [83].

6.7 Support for Smallholder and Precision Farming

AIoT technologies that are affordable and easy to use can help small and medium-sized farmers by giving them access to precision agricultural methods that were previously only available to large commercial enterprises [80].

Localized AI models, mobile-based decision support, and inexpensive sensors assist smallholders in increasing yields and optimizing inputs. This democratization of technology lessens inequalities in agricultural output and promotes food security [33].

6.8 Social and Labor Impacts

Adoption of AIoT reduces physically taxing and repetitive chores, changing the character of agricultural labor. Farmers may concentrate on higher-level management tasks thanks to automation, which also enhances working conditions [35].

Simultaneously, the need for digital skills in agriculture opens up new job, training, and innovation opportunities in rural areas. Future generations will find the agriculture sector more appealing and modern as a result of these societal effects [79].

7. CHALLENGES AND LIMITATIONS

Even though AIoT-based smart agricultural systems have many advantages, there are a number of technological, financial, and societal obstacles that limit their widespread use and long-term efficacy. Unlike conventional industrial or urban IoT contexts, agricultural ecosystems have particular limitations. The main obstacles and restrictions related to implementing AIoT technology in smart farming are covered in this section [36].

7.1 Connectivity and Infrastructure Constraints

Reliable network access is still a significant problem, especially in rural and isolated agricultural areas. Real-time data transfer to cloud platforms is limited in many farms because they lack reliable cellphone service or high-speed internet. Despite offering long-range connectivity, low-power wide-area networks like LoRaWAN and NB-IoT may not be appropriate for bandwidth-intensive applications like drone video streaming due to their restricted data rate support [78].

Reduced system responsiveness, information loss, and data delays can result from infrastructure constraints. These limitations make it more difficult to implement cloud-dependent AI models and emphasize the necessity of reliable edge computing solutions [38].

7.2 Data Quality, Reliability, and Sensor Limitations

The accuracy and dependability of gathered data are critical to AI-driven decision-making. Sensors are subjected to severe environmental factors in agricultural environments, including dust, wetness, extremely high or low temperatures, and physical harm. Inaccurate or missing data might result from hardware malfunctions, sensor drift, and calibration mistakes [40].

7.3 Scalability and System Integration

Heterogeneous equipment from many suppliers, each utilizing distinct data formats and communication protocols, is frequently used in smart agricultural systems. It is very difficult to integrate sensors, drones, robotics, edge devices, and cloud platforms seamlessly [77].

Managing thousands of connected devices is harder as farms get bigger or more complicated. System flexibility and scalability might be hampered by vendor lock-in, interoperability problems, and a lack of defined data models [75].

7.4 Computational and Energy Constraints

Many AIoT components, especially sensor nodes and edge devices, are subject to stringent computational and energy limitations. Advanced AI models must be simplified, compressed, or offloaded to the cloud to be deployed on low-power hardware []39.

System lifetime and maintenance needs are also impacted by energy constraints. Although energy harvesting methods present viable options, they are not yet consistently dependable in all agricultural settings. A crucial problem is still striking a balance between model accuracy, computational load, and energy usage [41].

7.5 Security and Privacy Risks

Cybersecurity risks, such as illegal access, data manipulation, and denial-of-service attacks, can affect AIoT-based smart farming systems. Compromised systems may cause equipment damage, interfere with farm operations, or result in poor decision-making [43].

Another issue is data privacy, especially when sensitive farm data is handled or kept in the cloud. Concerns about data ownership, misuse, or commercial exploitation may make farmers hesitant to provide operational data. System complexity and operating expenses rise when strong security measures are put in place [74].

7.6 High Initial Investment and Cost Barriers

AIoT technology deployment frequently necessitates a sizable upfront investment in software platforms, sensors, communication infrastructure, and computational power. These expenses may be unaffordable for small and medium-sized farmers [71].

Adoption is further constrained by continuing maintenance, data services, and system upgrade costs in addition to the original outlay. Many farmers could be reluctant to invest in AIoT solutions in the absence of clear short-term economic rewards or financial support methods [77].

7.7 Model Generalization and Adaptability

AI models that were trained on data from particular areas, crops, or seasons might not adapt well to other settings. Model performance can be greatly impacted by variations in crop kinds, agricultural methods, climate, and soil type [65].

To maintain accuracy, frequent retraining and modification are frequently necessary, which increases operational complexity. A persistent research challenge is ensuring model adaptability while minimizing retraining costs [66].

Table 4: Challenges and Limitations of AIoT-based Smart Farming Systems

Category [49]	**Challenge / Limitation**	**Description**	**Impact on Smart Farming**	**Possible Mitigation Approaches**
Infrastructure [53]	Limited connectivity	Poor internet and cellular coverage in rural areas	Delayed data transmission and decision making	LPWAN, edge computing, hybrid networks
Data Quality [67]	Sensor noise and failures	Harsh field conditions affect sensor accuracy	Incorrect AI predictions	Sensor redundancy, data validation
Scalability [2]	Heterogeneous devices	Multiple vendors and protocols	Integration and management complexity	Standardized protocols, middleware

Computation [11]	Limited edge resources	Low processing power and memory	Restricts advanced AI deployment	Model compression, edge–cloud offloading
Energy [89]	Power constraints	Battery-operated devices require frequent maintenance	Reduced system reliability	Energy harvesting, low-power AI models
Security [44]	Cyber threats	Unauthorized access and data manipulation	Operational disruptions and data loss	Encryption, authentication, secure firmware
Privacy [34]	Data ownership concerns	Fear of misuse of farm data	Low farmer trust and adoption	Clear data governance policies
Cost [33]	High initial investment	Sensors, drones, AI platforms are expensive	Barrier for small-scale farmers	Subsidies, low-cost AIoT solutions
AI Models [19]	Poor generalization	Models trained for specific regions	Reduced accuracy in new environments	Transfer learning, localized training
Explainability [35]	Black-box decisions	Lack of transparency in AI outputs	Low user trust	Explainable AI techniques
Skills [88]	Technical skill gap	Limited digital literacy among farmers	Improper system usage	Training and extension services
Regulatory [99]	Policy uncertainty	Lack of standards and regulations	Slows adoption	Regulatory frameworks and guidelines

8. CONCLUSION

A strong technological basis for the development of smart farming has been introduced by the combination of artificial intelligence and the Internet of Things. Many of the drawbacks of conventional agricultural methods are addressed by AIoT-based systems, which allow for ongoing data collection, intelligent analysis, and prompt decision-making. Farmers may monitor field conditions with high precision and take proactive measures to address operational and environmental concerns by utilizing a variety of AI methodologies, edge and cloud computing, and advanced sensing technology.

This study demonstrates how new AIoT technologies assist sustainable agricultural methods, increase crop output and quality, lower operating costs, and improve resource efficiency. AIoT systems reduce risks associated with resource scarcity, pest outbreaks, and climatic unpredictability by enabling data-driven and automated decisions. The analysis also shows that the implementation of AIoT has wider effects, strengthening food security, enhancing agricultural management, and conserving the environment.

Notwithstanding these benefits, there are still a number of obstacles to overcome, such as infrastructure constraints, problems with data quality, security difficulties, high upfront expenses, and the requirement for explainable and flexible AI models. Continued research, standardization, and cooperation between technologists, agricultural specialists, legislators, and farmers are necessary to address these issues. To guarantee widespread adoption, especially among small and medium-sized farmers, an emphasis on user-centric design, cost, and capacity building is crucial.

All things considered, AIoT is a revolutionary approach to contemporary agriculture. AIoT-enabled smart farming can be crucial in creating resilient, effective, and sustainable agricultural systems that can fulfill future global food demands with further innovation and supportive frameworks.

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