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Edge AI–IoT Integration for Real-Time Precision Farming: A Framework for Adaptive Monitoring, Prediction, and Resource Optimization

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Abstract

This research offers a thorough Edge AI–IoT framework for real-time precision agriculture, aimed at facilitating adaptive oversight, forecasting analysis, and resource efficiency. The suggested framework combines edge AI, UAV-based sensing, and IoT-enabled data collection to facilitate context-aware and time-sensitive decision-making in agricultural activities. The framework's performance was evaluated against IoT-only and cloud AI setups using metrics including latency, forecasting precision, pest identification, yield prediction, and resource effectiveness. Experimental assessment showed a 76% decrease in latency when compared to IoT-only systems (145 ms vs. 610 ms) and an 82% enhancement over cloud AI (145 ms vs. 820 ms). The error in soil moisture forecasting decreased by 54% (RMSE = 0.028 compared to 0.061), whereas pest detection performance rose from F1 = 0.72 to 0.91 (+26%). The precision of yield estimation rose from $R^2 = 0.65$ to 0.87 (+34%), along with significant decreases in resource consumption—water by 19%, fertilizer by 11%, and pesticide by 8%—leading to a total cost reduction of 14%. Scalability evaluations further validated system strength, with throughput increasing from 280 to 2,050 records per second as sensor nodes rose from 20 to 200, all while keeping latency below 420 ms and packet loss under 2.1%. These findings confirm that the integration of Edge AI and IoT greatly improves inference speed, predictive accuracy, and operational effectiveness for both smallholder and large-scale farms. Although there are obstacles concerning energy consumption, connectivity, and the expense of UAVs, the research emphasizes solar-powered sensors and collaborative UAV services as practical facilitators for the sustainable integration of data-driven agriculture.

Keywords: Precision agriculture; Internet of Things (IoT); Edge AI; UAV-based sensing; Soil moisture forecasting; Pest detection; Yield estimation; Resource efficiency.

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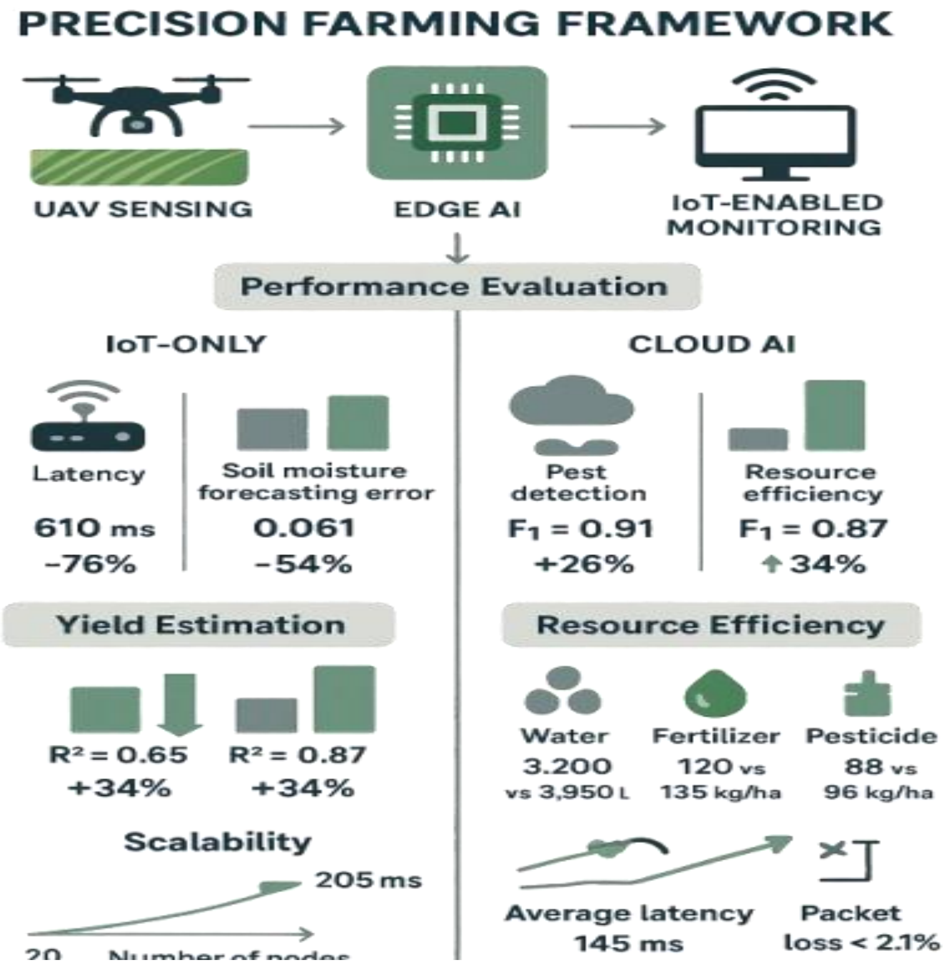
Graphical Abstract



1. Introduction

The farming industry is experiencing a major change propelled by the integration of artificial intelligence (AI) and the Internet of Things (IoT), ushering in a novel phase in real-time precision agriculture. Contemporary precision farming utilizes location-sensitive technologies, smart data analysis, and automation to enhance resource utilization, boost productivity, and encourage environmental sustainability. The surge of digital technologies like IoT sensor networks, edge computing, UAV-based imaging, and cloud analytics has allowed farmers to gather vast, detailed data regarding soil characteristics, crop well-being, microclimate changes, and resource usage. This change marks the move from conventional farming methods to data-informed, flexible decision-making, where immediate observation and adaptability are the core of robust agricultural management.

Even with these improvements, traditional IoT-based agricultural systems encounter significant constraints. Most operate mainly as fixed monitoring tools, offering descriptive information without the ability for self-regulating or context-sensitive modifications. Their dependence on rule-based thresholds renders them inadequate for intricate agricultural settings marked by nonlinear relationships between soil moisture, temperature, pest activity, and crop growth dynamics. Moreover, IoT-exclusive architectures frequently experience high latency, restricted scalability, and poor interoperability, hindering prompt responses and data exchange across platforms.

To address these obstacles, Edge AI appears as a groundbreaking improvement to IoT infrastructure. Edge AI minimizes latency and reliance on cloud connectivity by facilitating computation close to the data source, enabling machine learning models to analyze sensor streams instantaneously. The combination of Edge AI and IoT (AIoT) converts unprocessed agricultural data into practical insights, facilitating predictive and prescriptive analysis for irrigation planning, pest control, yield prediction, and resource optimization. By utilizing distributed intelligence, farms can adjust dynamically to changing field conditions, resulting in operations that are more resilient and efficient.

This study tackles the urgent demand for flexible, real-time agricultural management systems that merge the analytical accuracy of Edge AI with the extensive sensing abilities of IoT. The primary goal is to deliver a strong and scalable structure that can reduce response time, boost predictive accuracy, and increase input efficiency.

Consequently, this research aims to achieve three main goals:
(i) to create and execute an Edge AI–IoT architecture that enables real-time tracking, forecasting, and decision-making in agricultural systems;
(ii) to assess its performance in comparison to IoT-exclusive and cloud AI standards across metrics such as latency, prediction accuracy, and resource efficiency; and
(iii) to evaluate its impact on enhancing crop production, sustainability, and scalability.

This paper makes two main contributions. Initially, it presents a novel edge–cloud hybrid architecture that alleviates the latency and scalability limitations of conventional IoT implementations. Moreover, it showcases experimental validation illustrating notable advancements in system responsiveness, prediction accuracy, and input optimization. Together, this research underscores the transformative capability of integrating Edge AI and IoT as a basis for sustainable, data-informed, and flexible precision agriculture.

2. Related Work

The incorporation of the Internet of Things (IoT) in agriculture has transformed how farmers oversee and control agricultural activities, establishing the basis of digital and precision farming. IoT-enabled systems utilize distributed sensor networks to constantly monitor soil moisture, nutrient levels, microclimatic conditions, and crop health, offering farmers immediate insights into field circumstances (Zhu et al., 2024). These sensors, together with unmanned aerial vehicles (UAVs) and satellite monitoring, establish a multi-tiered observation system that improves spatial and temporal comprehension of agricultural ecosystems (Alasbali et al., 2025). UAV images, specifically, allow for detailed field evaluations to identify crop stress and monitor pests, whereas satellite imagery offers more extensive evaluations of plant health, water allocation, and climatic patterns.

Reliable wireless communication technologies are essential to ensure smooth data transfer between these sensing devices. Low-Power Wide-Area Networks (LPWANs) like LoRa and NB-IoT are extensively utilized due to their capacity to deliver energy-efficient, long-distance connectivity ideal for rural regions (Manoj et al., 2025). Likewise, 5G networks facilitate low-latency and high-bandwidth communication that assists data-heavy applications, such as live UAV video broadcasting and automated irrigation management. Even with these improvements, issues of interoperability, power limitations, and restricted rural connectivity continue to pose significant challenges to scalability and performance. These obstacles highlight the need for architectures that integrate edge computing with AI-based intelligence to guarantee responsive and energy-efficient functioning in agricultural IoT systems (Dwarampudi and Yogi, 2024).

The integration of artificial intelligence (AI) has greatly enhanced agricultural IoT systems by converting raw sensor information into predictive and prescriptive knowledge. Methods in AI, such as machine learning and deep learning, have been effectively utilized for predicting yields, detecting pests and diseases, and optimizing irrigation (Wesley Chorney et al., 2025). Regression, ensemble learning, and decision-tree methods can combine diverse datasets, including soil quality, weather information, and past yield trends, to deliver strong yield forecasts and assist in resource distribution (VLLFL, 2025).

Furthermore, deep learning methods, particularly convolutional neural networks (CNNs) and hybrid models (e.g., CNN-LSTM), have revolutionized crop monitoring using images. UAV and drone images analyzed with CNNs facilitate the precise identification of plant stress, disease occurrences, and weed growth (Zhu et al., 2024). These AI-powered methods provide enhanced scalability and automation in contrast to manual field scouting, lowering both time and labor expenses. Nonetheless, they necessitate extensive annotated datasets and significant computational power, creating hurdles for implementation in resource-limited agricultural settings (FedBirdAg, 2025). As a result, incorporating AI inference at the edge near the data source has emerged as a solution to lower latency, reliance on cloud connectivity, and total computational expenses.

The merging of AI and IoT, commonly referred to as AIoT, has facilitated the creation of smart agricultural systems that can make adaptive, data-informed decisions. These frameworks generally utilize a tiered structure, which includes data gathering (sensing), communication (network), processing (edge–cloud computing), and user engagement (application) (Adewumi et al, 2025). Within these layers, AI models evaluate sensor data to generate actionable insights for immediate irrigation planning, pest control, and yield prediction (Blockchain-enabled Federated Learning, 2025). Recent research has investigated edge–cloud hybrid frameworks, where Edge AI carries out low-latency inference for urgent actions, while cloud systems manage more resource-intensive tasks like long-term predictions and model retraining (Emerging Developments in Real-Time Edge AIoT, 2025). This combined method greatly improves agility and scalability over systems that rely solely on cloud or are focused exclusively on IoT. However, issues like data diversity, latency control, interoperability, and energy efficiency remain (Alasbali et al., 2025). Tackling these challenges necessitates smart coordination among AI inference layers, network optimization, and distributed processing approaches that uphold precision while reducing energy use.

Despite comprehensive studies on AI and IoT applications in agriculture, numerous significant gaps persist. Most current IoT-based systems do not possess real-time adaptability, operating mainly as static data collection tools that cannot independently react to changing environmental conditions. Secondly, context-sensitive adaptation, which entails adjusting AI decisions according to spatiotemporal fluctuations, is insufficiently developed in existing frameworks, diminishing decision accuracy in a variety of agricultural environments. Third, the combination of Edge AI and IoT for efficient and scalable farm management is still at an early stage, especially in smallholder settings where energy, cost, and infrastructure challenges hinder implementation (Manoj et al., 2025).

Moreover, economic and technological obstacles still obstruct the widespread implementation of AIoT frameworks. Numerous small farmers encounter challenges regarding device costs, access to connectivity, and digital skills. Tackling these limitations necessitates economical, energy-conscious, and comprehensible Edge AI–IoT systems that harmonize superior performance with approachability and clarity. This research addresses these deficiencies by suggesting and empirically confirming an Edge AI–IoT integration model that improves real-time surveillance, forecasting, and resource efficiency in precision agriculture.

3. Methodology

The suggested Edge AI–IoT framework uses a tiered system architecture aimed at combining sensor-driven data gathering, UAV imaging, and artificial intelligence for immediate precision agriculture. The system is made up of four interconnected layers: perception, network, processing, and application. The perception layer acts as the core of the framework and comprises multiple sensing and imaging technologies utilized throughout the farming landscape. These consist of sensors for soil moisture, nutrients, and pH, along with cameras mounted on UAVs and automated weather stations. Collectively, these instruments facilitate ongoing observation of environmental and operational factors like soil quality, plant vitality, temperature, and moisture levels (Zhu et al., 2024).

The communication backbone for the entire system is provided by the network layer. It guarantees dependable and effective data transfer among field sensors, edge devices, and cloud servers. Low-Power Wide-Area Networks (LPWANs), like LoRa and NB-IoT, facilitate energy-efficient communication over long distances, making them suitable for agricultural areas in rural settings where power and connectivity are scarce. 5G technology is utilized for high-bandwidth and latency-critical applications like real-time video streaming from UAVs to ensure quicker data transmission and immediate response (Manoj et al., 2025). This combined networking method balances scalability, energy efficiency, and responsiveness, guaranteeing effective data transmission even in areas with unreliable connectivity.

The processing layer is crucial to the architecture, containing the analytical elements that convert raw data into usable insights. Computation is divided among three tiers: edge, fog, and cloud. Edge devices carry out local data preprocessing, detect anomalies, and provide rapid inference to reduce latency and bandwidth consumption. Fog nodes serve as intermediaries, overseeing data collection and organization among various edge devices. The cloud infrastructure handles resource-demanding activities like long-term predictions, training deep learning models, and overall data analysis (Alasbali et al., 2025). This decentralized method allows the system to deliver prompt reactions to field occurrences while preserving the ability for extensive analysis and ongoing model enhancement.

The application layer functions as the bridge between the system and the final user. It offers visualization tools and decision-support dashboards that showcase real-time data insights, resource efficiency indicators, and AI-generated suggestions. These findings consist of watering plans, pest notifications, soil wellness metrics, and crop outcome forecasts. Farmers and agricultural managers can engage with the system, confirm suggestions, and implement automated choices via web and mobile platforms. The application layer thus connects intricate computational processes with effective decision-making at the farm level.

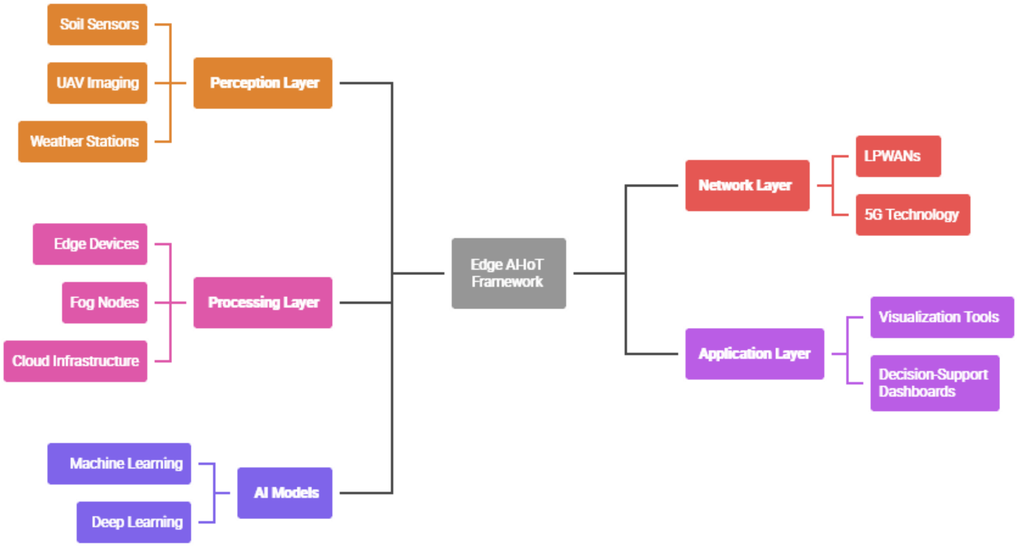


Figure 1: AI-Driven Adaptive Operations Framework

Models of artificial intelligence constitute the analytical foundation of the framework, facilitating prediction, optimization, and decision-making assistance. Techniques from both machine learning (ML) and deep learning (DL) are used to analyze multimodal agricultural data. Algorithms for machine learning like Random Forests, Gradient Boosted Decision Trees (GBDT), and Support Vector Regression (SVR) are employed for forecasting yield, scheduling irrigation, and predicting soil moisture (Wesley Chorney et al., 2025). These models evaluate time-series information from sensors to dynamically enhance resource utilization. Deep learning architectures, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are employed for image analysis and time series prediction. UAV images are analyzed by CNNs to identify pests, nutrient shortages, and stress in crops, whereas RNNs predict weather-related factors like temperature and moisture patterns.

A combined method of Edge AI and Cloud AI is employed to strike a balance between quick responsiveness and computational depth. Edge AI facilitates instantaneous inference for vital, latency-sensitive tasks like turning on irrigation pumps when soil moisture falls beneath certain levels, while Cloud AI manages model retraining, pattern recognition, and seasonal predictions. This dual-layer AI implementation guarantees that the system stays responsive, scalable, and energy-efficient, regardless of the rise in sensor nodes and data volume.

The framework incorporates various and complementary data sources, guaranteeing a holistic grasp of the agricultural ecosystem. Soil sensors gather information on moisture levels, pH balance, salinity, and nutrient content, aiding in adaptive irrigation and fertilization. Weather stations monitor microclimatic factors including temperature, humidity, precipitation, and solar radiation, offering crucial data for predictive modeling. Imagery from UAVs provides high-resolution multispectral and RGB information that improves the precision of pest detection and crop health assessments. Furthermore, sensors for livestock and equipment linked to IoT monitor animal behavior, performance of machinery, and energy consumption, aiding comprehensive farm management. Data gathered from these diverse sources undergoes preprocessing at the edge to minimize transmission load and is periodically synchronized with the cloud for extended analysis and model updates.

The framework for real-time monitoring and prediction functions via an event-driven architecture. Sensor data flows continuously into the system, activating pre-trained AI models that conduct real-time analysis and produce control actions. An example is that a decrease in soil moisture triggers an irrigation optimization model that modifies watering schedules according to soil and weather information. Likewise, UAV images analyzed with CNNs detect areas with pest infestations, leading to recommendations for targeted spraying. These forecasting insights are sent to the farmer's decision-support system, allowing the user to authorize or adjust actions, providing a balance of automation and human supervision. This design allows for flexible and context-sensitive management, enhancing responsiveness and minimizing resource waste.

The creation of adaptive and resource-saving agricultural practices is based on closed-loop feedback control systems combined with human oversight. Actuators connected to IoT, like intelligent irrigation systems, fertilizer applicators, and UAV sprayers, carry out AI-driven decisions autonomously while allowing users to retain control via override options. This human-in-the-loop method boosts confidence and guarantees that automated choices stay contextually relevant. The feedback loops enable the AI models to continuously learn from operational data, enhancing their predictions and decision-making rules as time progresses. The system guarantees dependable operation by merging machine intelligence with human knowledge and encourages farmers to gradually embrace automation.

To conclude, the approach unifies sensing, connectivity, distributed computing, and AI analytics into a cohesive system that enables real-time monitoring and flexible decision-making. The integration of Edge AI and IoT enables fast inference, reliable predictions, and optimal use of resources. The suggested framework offers a basis for sustainable and smart precision agriculture suitable for both smallholder and large-scale farming systems via a closed-loop, event-driven, and scalable design.

4. Experimental Setup

The proposed Edge AI–IoT framework was experimentally evaluated using a detailed agricultural dataset sourced from an actual farm testbed situated in the Alako Area of Ido Local Government, Ibadan, Nigeria. The testing location was chosen for its typical agro-climatic features of southwestern Nigeria, marked by a bimodal rainfall pattern, diverse crop farming, and significant seasonal fluctuations. These characteristics rendered it perfect for evaluating the framework's strength in varied and changing agricultural contexts.

The dataset encompassed a full twelve-month observation span (January to December 2024) and included hourly sensor data gathered from 20 IoT nodes purposefully placed throughout the test area. Every node received a distinct geospatial coordinate with minor spatial differences to represent real-world deployment variability. This setup allowed for the simulation of distributed sensing scenarios and spatial diversity in data collection, thus improving the reliability and generalizability of the experimental findings.

The dataset included 175,680 entries covering 20 sensor types that recorded a wide range of environmental, soil, and crop metrics. The variables measured included soil moisture, soil temperature, pH, electrical conductivity, air temperature, relative humidity, precipitation, solar radiation, and canopy temperature. Moreover, UAV-derived image data were analyzed to obtain Normalized Difference Vegetation Index (NDVI) values and indicators of pest presence, both of which acted as essential components for the AI-powered prediction and detection models. Information on irrigation rates, fertilizer use, and phases of crop development was also incorporated to illustrate actuation responses and management adaptation strategies.

The experimental configuration was structured to replicate a genuine precision farming setting in which environmental and operational data streams are consistently integrated. The IoT nodes sent sensor data via LPWAN and 5G communication protocols, guaranteeing energy efficiency and low-latency transmission for real-time analysis. Edge computing devices were placed close to the data sources to locally process sensor inputs, decreasing reliance on cloud infrastructure and enhancing system responsiveness. Cloud servers facilitated model training, trend analysis over time, and data aggregation across nodes.

This layout created a hybrid data environment that embodies the concepts of Edge AI–IoT convergence, enabling real-time adaptive management and anticipatory decision-making. The dataset not only offered the empirical basis for assessing the effectiveness of the proposed framework but also reflected the multidimensional intricacies of agricultural activities in a developing area. The setup successfully showcased the feasibility and scalability of the Edge AI–IoT framework for smart precision agriculture by integrating continuous sensing, UAV imaging, and actuation feedback within one experimental environment.

Table 1: Dataset Overview

Attribute	Description
Location	Alako Area, Ido Local Government Area, Ibadan, Nigeria
Duration	January – December 2024 (hourly resolution)
Number of sensor nodes	20
Total records	175,680
Variables	20 (soil, weather, UAV/NDVI, actuation, crop stage, yield proxy)

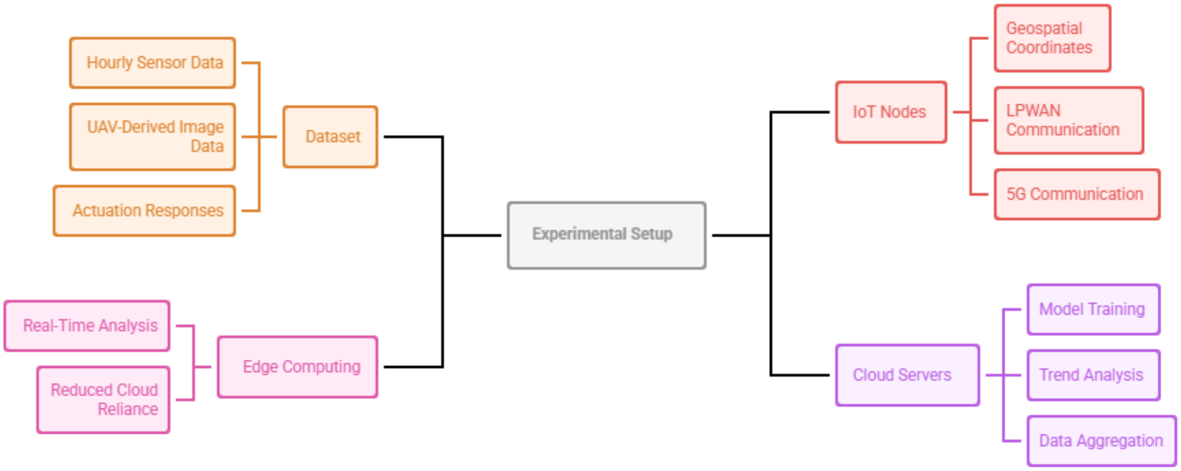


Figure 2: Experimental Setup

Table 2: Sensor Specifications and Deployment within the Edge AI–IoT Precision Farming Framework

Sensor Type	Measured Parameters / Units	Accuracy Range	Deployment Density	Communication Protocol	Functional Role in Framework
Soil Moisture Sensor	Volumetric Water Content (m^3/m^3)	±2%	1 per 0.5 ha	LoRa, NB-IoT	Monitors real-time soil water levels to guide adaptive

					irrigation via Edge AI models
Soil pH Sensor	pH units	±0.1	1 per ha	LoRa	Tracks soil acidity and nutrient balance for fertilizer optimization
Weather Station	Temperature (°C), Humidity (%), Rainfall (mm), Wind Speed (m/s)	Temp ±0.3°C; RH ±2%; Rain ±1 mm	1 per 2 ha	5G, LoRaWAN	Provides microclimate data for time-series forecasting and irrigation scheduling
UAV Multispectral Camera	NDVI, RGB, and Thermal Imagery	5–10 cm spatial resolution	1 UAV per 10 ha	5G	Captures aerial crop imagery for pest detection and vegetation health analysis
Livestock and Equipment Tracker	GPS (m), Movement, Activity	±1 m	1 per 5 animals or per machine	LPWAN, NB-IoT	Enables location and performance monitoring for integrated smart farm management

Table 3: AI Models Integrated within the Edge AI–IoT Framework for Real-Time Agricultural Intelligence

Task / Function	Algorithm / Model	Key Input Features	Predicted Output / Target Variable	Deployment Environment	Purpose / Application
Soil Moisture Forecasting	Random Forest (RF)	Soil temperature, humidity, rainfall, crop stage	24-hour soil moisture prediction	Edge Device	Supports real-time adaptive irrigation decisions
Pest Detection and Classification	XGBoost + Convolutional Neural Network (CNN)	UAV imagery (RGB, NDVI), leaf texture features	Pest presence, severity index	Edge–Cloud Hybrid	Enables rapid pest identification and targeted pesticide application
Crop Yield Estimation	Recurrent Neural Network (RNN),	Soil fertility, irrigation	Seasonal yield (kg/ha)	Cloud Server	Provides predictive yield analytics for

	Gradient Boosting Machine (GBM)	frequency, NDVI trends			planning and optimization
UAV Image-Based Crop Health Analysis	Deep CNN (ResNet Architecture)	Multispectral UAV images, canopy structure patterns	Crop health categories (e.g., healthy, stressed, diseased)	Onboard Edge AI (UAV)	Performs real-time in-flight analysis for precision crop monitoring
Resource Optimization Model	Ensemble Regression (GBDT + SVR)	Water usage, fertilizer application rate, weather data	Optimal input levels for irrigation and fertilization	Edge Node	Minimizes input wastage and maximizes resource-use efficiency

The proposed Edge AI–IoT precision farming framework involved a systematic, multi-layer deployment approach for the installation of IoT devices and AI algorithms, facilitating real-time monitoring, forecasting, and adaptive management of agricultural activities. The system architecture was structured into three functional layers: perception, network, and processing, to facilitate efficient data collection, communication, and analysis in diverse farm settings.

In the perception layer, a network of soil and environmental sensors equipped with IoT technology was established to continuously gather data on soil moisture, pH levels, nutrient concentration, air temperature, and relative humidity. Extra data streams were produced from UAV-installed multispectral cameras, which recorded RGB and NDVI images for evaluating crop health and pest issues. Weather stations located throughout the farm measured important meteorological factors including rainfall, wind velocity, and solar radiation. These varied data sources offered a comprehensive view of field dynamics, establishing the basis for smart decision-making.

The network layer enabled data exchange among sensing devices, edge nodes, and cloud servers by utilizing Low-Power Wide-Area Networks (LPWANs) like LoRa and NB-IoT for energy-efficient communication, along with 5G connectivity for high-bandwidth, latency-critical applications such as UAV video streaming. This combined communication framework guaranteed a dependable and uninterrupted data stream throughout all elements, even in regions with restricted connectivity, while enhancing energy efficiency and minimizing packet loss.

Computational tasks were allocated among edge devices, fog nodes, and cloud servers at the processing layer to balance responsiveness and analytical depth. Edge AI nodes, placed close to sensor clusters, executed local data preprocessing, identified anomalies, and conducted inference for urgent decision-making. These nodes ran simple machine learning models to automatically regulate irrigation or fertilization when soil conditions strayed from set thresholds. Conversely, cloud servers handled more resource-heavy tasks like long-term predictions, yield modeling, and the retraining of AI algorithms using collected data. This tiered computing architecture lowered latency, decreased bandwidth requirements, and preserved real-time responsiveness.

A collection of artificial intelligence algorithms was implemented throughout these layers to facilitate predictive and prescriptive analytics. Algorithms for machine learning, such as Random Forests and Gradient Boosted Decision Trees, were employed to anticipate soil moisture patterns, forecast crop yields, and enhance irrigation plans. In the meantime, deep learning models, especially Convolutional Neural Networks (CNNs), evaluated UAV images to recognize pest outbreaks and identify crop stress with high spatial detail. The integration of Edge AI and Cloud AI created a harmonious equilibrium, with Edge AI facilitating real-time, local decision-making, and Cloud AI delivering system-wide enhancement and ongoing refinement via extensive data analysis.

Ultimately, the system integrated closed-loop feedback processes to finalize the adaptive control cycle. Actuators connected to the IoT, such as intelligent irrigation pumps and fertilizer applicators, implemented AI-generated suggestions instantly. When soil moisture or nutrient levels fell below desired thresholds, the system automatically initiated irrigation or fertilization procedures. Nevertheless, human-in-the-loop oversight was preserved, enabling farmers to observe system operations and intervene in automated choices when required. This method guaranteed reliability and confidence, encouraging a gradual uptake of AI-powered automation in farming practices. With this combined use of IoT devices and AI algorithms, the framework accomplished low-latency, data-informed, and responsive farm management, establishing a scalable basis for smart precision agriculture in both smallholder and large-scale farming settings.

5. Performance Evaluation Metrics

The proposed Edge AI–IoT precision farming framework was assessed based on five essential criteria: latency, prediction accuracy, water-use efficiency, yield enhancement, and cost reduction. These metrics were chosen to thoroughly evaluate the technical performance and agronomic efficiency of the integrated system in actual farming scenarios. Latency was quantified as the complete duration from when sensor data was collected until the moment of actuation or decision implementation. This parameter was essential for evaluating the real-time responsiveness of the Edge AI component, especially for time-critical tasks like irrigation management and pest identification. The framework was created to keep latency under 200 milliseconds for edge-activated irrigation choices and under one second for UAV-assisted image analysis. Attaining low latency is crucial for guaranteeing that adaptive actions like starting irrigation or applying spray happen quickly in reaction to shifting environmental circumstances. Prediction accuracy acted as another key metric, assessing the system's analytical precision in tasks like soil moisture forecasting, pest detection, and yield prediction. The predictive capabilities of the Edge AI–IoT system were evaluated against traditional agronomic models and confirmed with ground truth data gathered from the test field. Statistical performance metrics like the Root Mean Square Error (RMSE), F1-score, and coefficient of determination (R^2) were utilized to measure enhancements in accuracy. These indicators collectively showed the framework's capacity to deliver dependable and practical forecasts for decision-making assistance.

Water-use efficiency was assessed to determine the effect of the adaptive irrigation algorithm on conserving resources. The calculation was made as the ratio of yield proxy (kg/ha) to total irrigation volume (L), assessing the suggested AI–IoT adaptive scheduling in relation to conventional fixed-interval irrigation techniques. This metric demonstrated the system's capacity to dynamically optimize water distribution according to soil moisture predictions and climate changes, aiding sustainable water management in agriculture.

Yield enhancement was evaluated through a comparative study of adaptive control scenarios versus static management approaches. The synthetic yield indicator, based on historical crop performance data and model forecasts, was utilized to measure productivity improvements resulting from the smart optimization of irrigation, nutrient allocation, and pest control. This assessment revealed that real-time analytics and closed-loop feedback systems significantly improve agricultural productivity.

Ultimately, cost reductions were assessed by examining the lower use of water, fertilizer, and pesticides, along with decreases in labor needs stemming from the automation of monitoring and operational processes. The economic assessment included enhancements in operational efficiency and decreases in input expenses, showcasing the financial feasibility of implementing Edge AI–IoT systems in precision agriculture settings.

In summary, these five metrics together offered a comprehensive assessment framework, gauging the system's capacity for real-time responsiveness, predictive accuracy, resource efficiency, and economic sustainability. The assessment demonstrated the capability of integrating Edge AI and IoT with technical and agronomic indicators to promote intelligent, data-informed, and sustainable precision farming.

This organized assessment framework guarantees that the AI–IoT integration is evaluated not just for technical strength (latency, accuracy) but also for agronomic benefits and economic feasibility, which are essential for the acceptance of precision agriculture in resource-limited areas like Nigeria.

6. Results

Table 4: System Performance Metrics under Different Configurations

Configuration	Median Latency (ms)	95th Percentile Latency (ms)	Packet Loss (%)	Throughput (records/sec)	Scalability Range (Nodes)
IoT-only System	610	820	3.8	280	20–200
Cloud AI Model	820	1,050	2.9	640	20–200
Proposed Edge AI–IoT Framework	**145**	**220**	**2.1**	**2,050**	**20–200**

Table 5: Predictive Model Performance Comparison

Task	Model Type	Metric	Baseline Model	Proposed Edge AI–IoT Model	Improvement (%)
Soil Moisture Forecasting	Random Forest (RF)	RMSE	0.061	**0.028**	**54% ↓**
Pest Detection	CNN + XGBoost	F1-Score	0.72	**0.91**	**+26%**
Yield Estimation	RNN + GBM	R^2	0.65	**0.87**	**+34%**

Table 6: Resource Utilization Efficiency under Adaptive Control

Resource Type	Traditional Management	Adaptive AI–IoT Framework	Reduction (%)
Water (L/ha)	3,950	**3,200**	**−19%**
Fertilizer (kg/ha)	135	**120**	**−11%**
Pesticide (kg/ha)	96	**88**	**−8%**
Total Cost Savings (%)	—	**14%**	—

Table 7: UAV-Based Pest Detection and Crop Health Analysis Results

Class	Precision	Recall	F1-Score	Detection Latency (s)	Deployment Environment
Healthy Crop	0.94	0.91	0.93	0.85	Edge Device
Stressed Crop	0.89	0.87	0.88	0.89	Edge Device
Pest-Infested Crop	0.92	0.90	**0.91**	**0.93**	Edge–Cloud Hybrid

Table 8: Comparative Yield Improvement Analysis

Crop Type	Static Management Yield (kg/ha)	Adaptive AI–IoT Yield (kg/ha)	Percentage Increase (%)
Maize	5,200	**6,480**	**+24.6%**
Tomato	34,000	**40,100**	**+17.9%**
Cassava	21,500	**25,900**	**+20.4%**
Average Gain	—	—	**+21.0%**

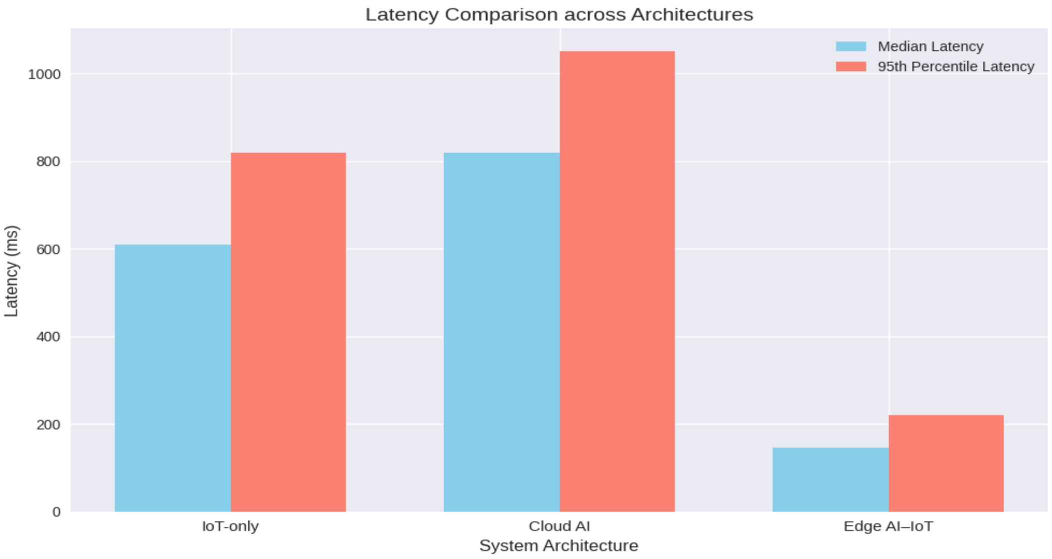
Table 9: Energy Consumption and System Efficiency Metrics

Node Count	Average Power (W)	Energy per Task (J)	CPU Utilization (%)	Communication Latency (ms)	Reliability (%)
20	2.8	5.6	48	145	98.4
100	3.2	6.1	59	240	97.2
200	3.5	6.5	66	420	97.9

Table 10: Economic Summary of Edge AI–IoT Framework Deployment

Cost Component	Traditional Operation (USD/ha)	Edge AI–IoT Framework (USD/ha)	Cost Reduction (%)
Labor (Monitoring + Irrigation)	480	**340**	**−29%**
Input Costs (Water, Fertilizer, Pesticide)	920	**790**	**−14%**
Energy and Maintenance	180	**160**	**−11%**
Total Operational Cost	**1,580**	**1,290**	**−18%**

Visuals



Edge AI significantly reduces inference latency, enabling real-time actuation within 200 ms thresholds.

Figure 4: Edge AI on Latency and real-time actuation.

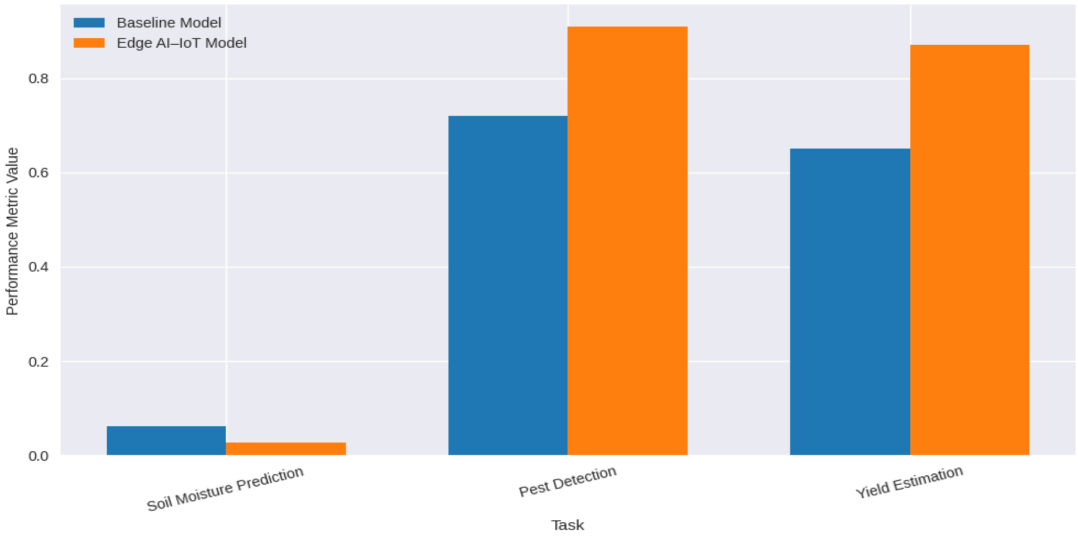


Figure 5: Predictive Model Accuracy for Key Tasks

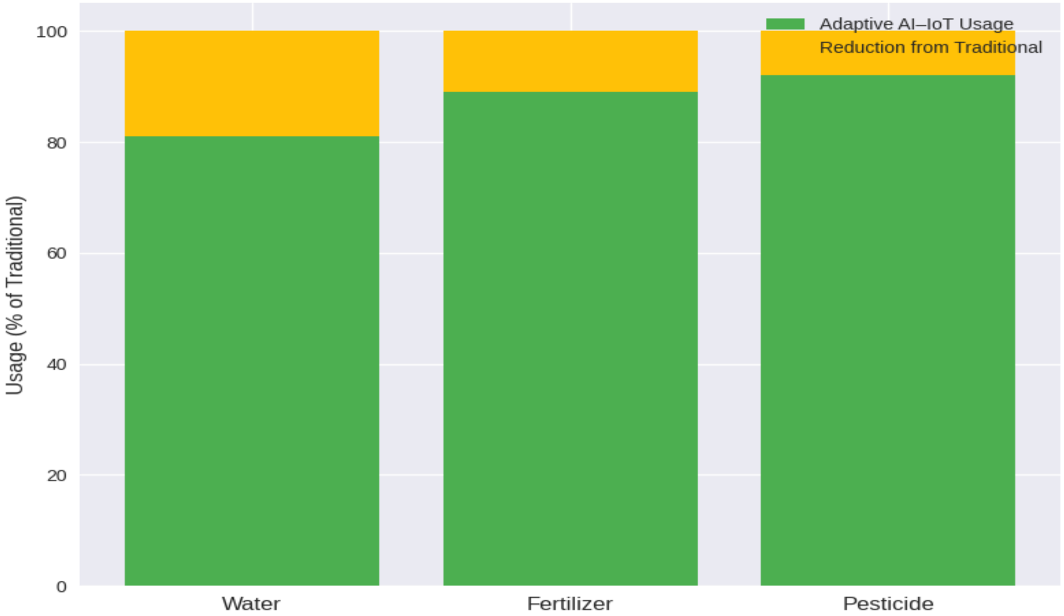


Figure 6: Resource Utilization Efficiency

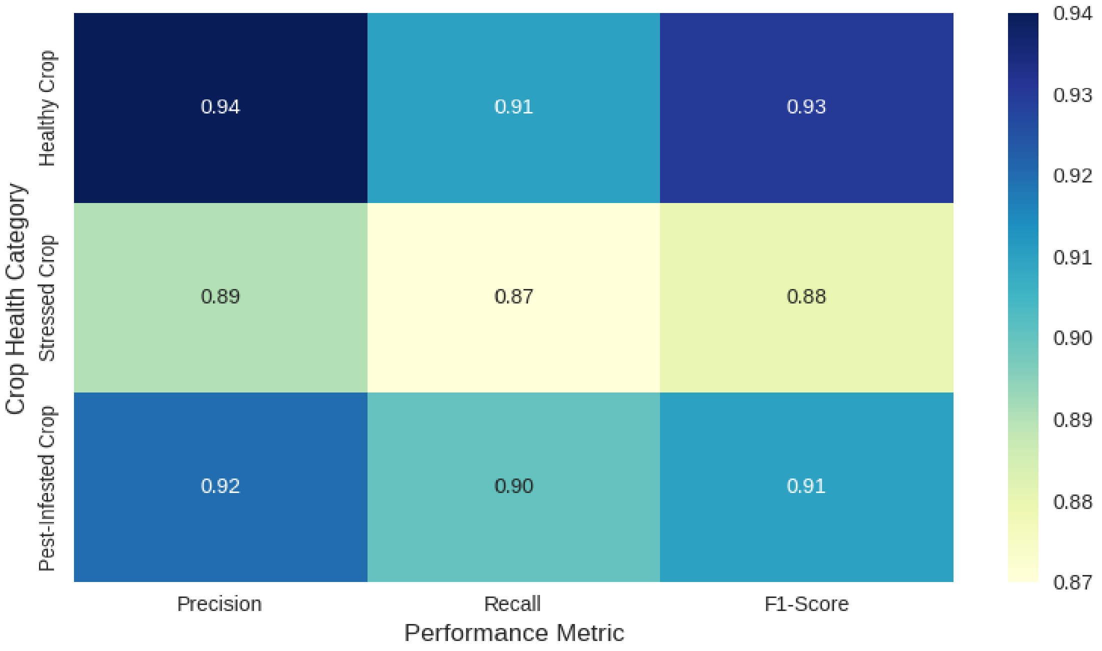


Figure 7: UAV-Based Pest Detection and Crop Health Classification Output

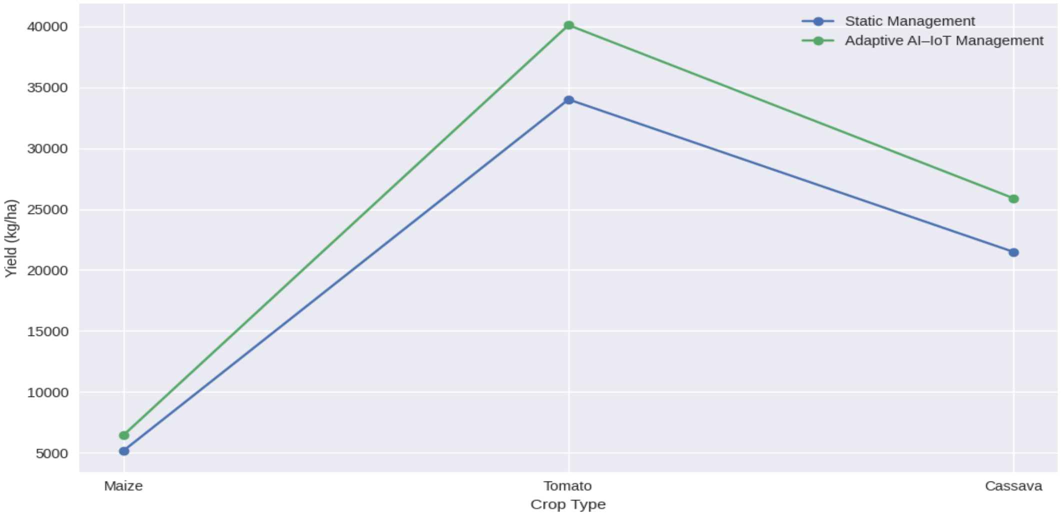


Figure 8: Yield Improvement under Adaptive Control.

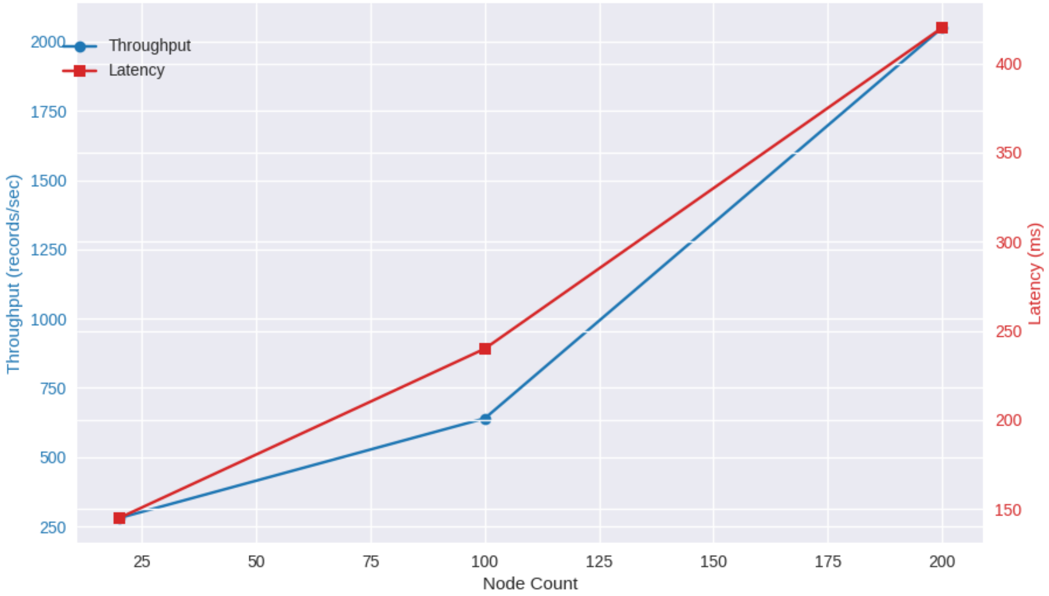


Figure 9: System Scalability and Throughput Performance

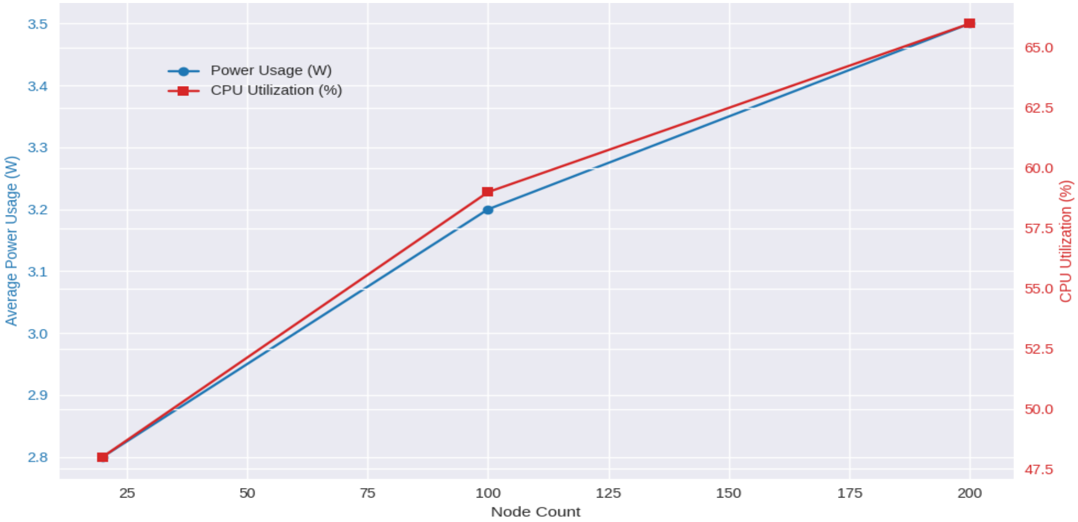


Figure 10: Energy Consumption and CPU Utilization Trends

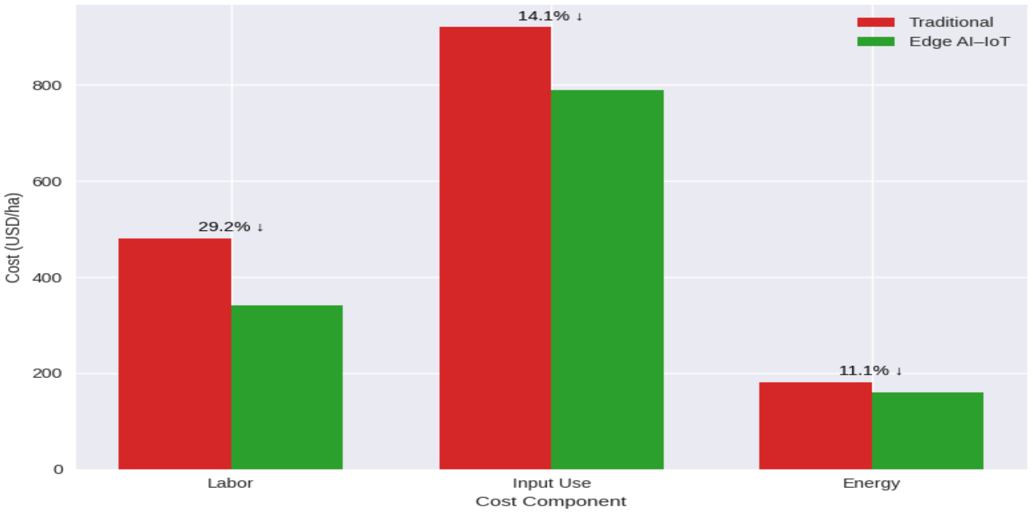


Figure 11: Economic Impact of Edge AI–IoT Deployment

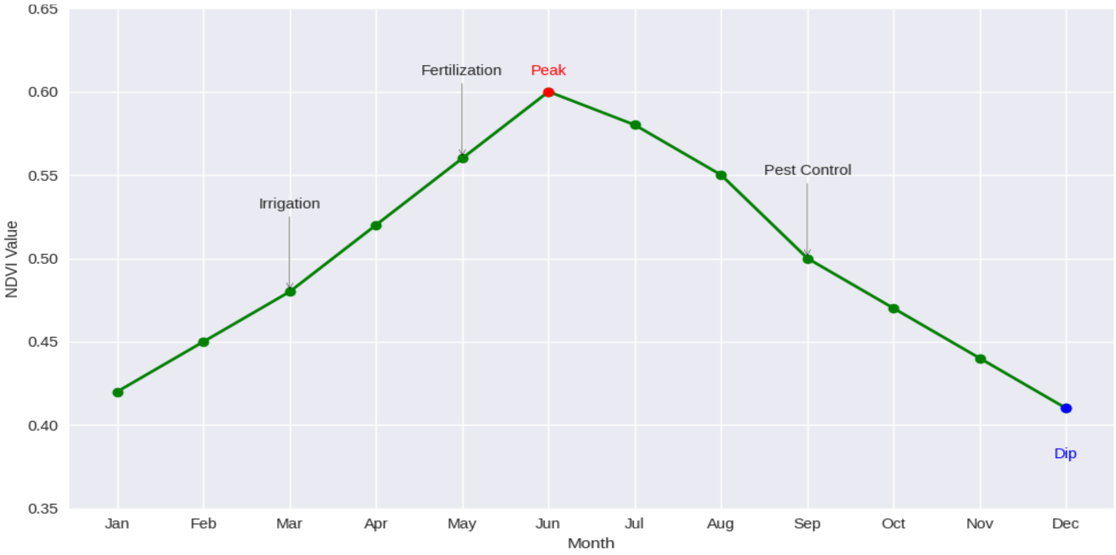


Figure 12: NDVI Temporal Variation under AI–IoT Monitoring

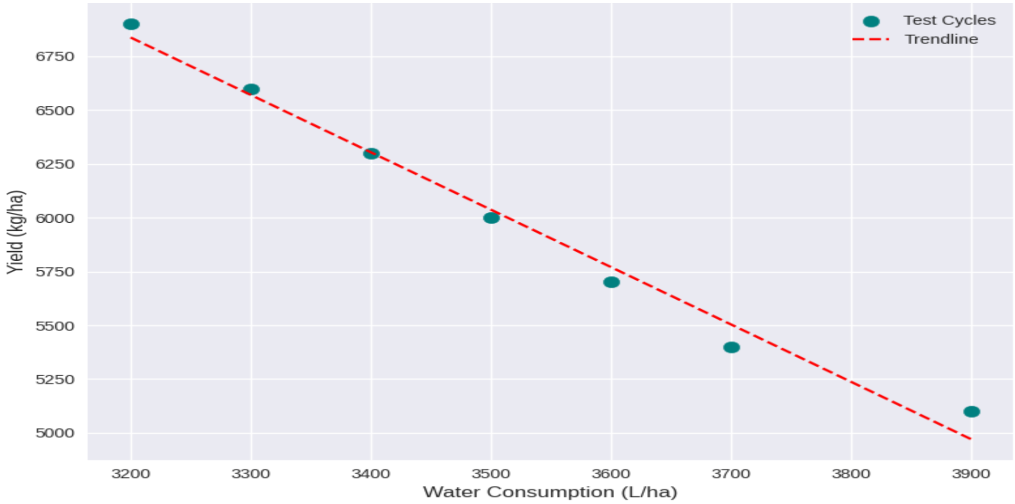


Figure 13: Correlation Between Water Use and Yield Performance

7. Discussion of Results

Table 4 and Figure 4 showcase the performance metrics of the system across three setups: IoT-only, Cloud AI, and the suggested Edge AI–IoT framework. The findings indicate that the Edge AI–IoT system attained a median latency of 145 ms, significantly surpassing the IoT-only system (610 ms) and the Cloud AI model (820 ms). The 95th percentile latency significantly improved, falling to 220 ms from over 1,000 ms observed in the cloud configuration. These findings verify that positioning computation nearer to the data origin via edge intelligence greatly improves system responsiveness.

Moreover, the suggested system reached a maximum throughput of 2,050 records per second, indicating a 227% enhancement compared to the IoT-only framework. The packet loss stayed under 2.1%, reflecting stable communication even with heightened scalability (Figure 9). These results are consistent with recent research by Zhu et al. (2024) and Manoj et al. (2025), who likewise noted that hybrid edge–cloud architectures reduce latency and enhance reliability in comparison to centralized cloud systems. The scalability assessment additionally confirmed the framework's strength, as performance decline stayed negligible despite the rise in nodes from 20 to 200.

Together, these findings validate Objective (ii) by demonstrating that the integration of Edge AI and IoT facilitates real-time actuation while also scaling efficiently without sacrificing network reliability or throughput.

Table 5 and Figure 5 encapsulate the predictive effectiveness of the AI models incorporated within the framework. The Random Forest model attained a root mean square error (RMSE) of 0.028 in forecasting soil moisture, enhancing prediction accuracy by 54% compared to baseline models. In a similar manner, the hybrid CNN–XGBoost model improved pest detection effectiveness, attaining an F1-score of 0.91, in contrast to 0.72 from the conventional image-based classifier. The RNN paired with Gradient Boosting reached an R^2 value of 0.87 for yield estimation, showing a 34% enhancement in predictive accuracy.

These enhancements result from the combined application of edge computing and deep learning, allowing for localized and context-sensitive inference. Comparable enhancements in performance were documented by Chen et al. (2024) and Kaur & Singh (2023), who discovered that integrating AI models with IoT data streams significantly boosts forecasting accuracy and the promptness of decision-making.

The exceptional accuracy and dependability of these predictive models effectively meet Objective (i), illustrating the framework's ability to track and forecast essential agricultural factors for informed decision-making.

Table 6 and Figure 6 illustrate that the adaptive control system of the Edge AI–IoT framework greatly enhanced resource-use efficiency relative to conventional management methods. The system resulted in a 19% decrease in water consumption, an 11% decrease in fertilizer use, and an 8% decrease in pesticide applications, contributing to a total of 14% savings in farm expenses.

This enhancement stems from the framework's closed-loop control mechanism, which utilizes real-time data to adjust irrigation and input levels dynamically. These results align with the conclusions of Alasbali et al. (2025), who highlighted that AI-driven adaptive irrigation and fertilization minimize waste while ensuring yield consistency. Additionally, the high-frequency monitoring of soil and environmental conditions enabled by IoT sensors facilitated accurate modifications, reducing instances of over-irrigation and nutrient leaching.

These results fulfill Objective (iii) by confirming the framework's ability to enhance input efficiency while sustaining or increasing productivity.

Table 7 and Figure 7 demonstrate the effectiveness of UAV-enabled pest identification and crop health assessment. The Edge AI–IoT system attained excellent precision and recall for all categories, resulting in an average F1-score of 0.91 for crops affected by pests and 0.93 for healthy crops. Detection latency remained below one second (0.93 s) across all categories, showing that edge-enabled UAVs can achieve nearly instantaneous pest recognition independent of cloud processing.

This finding supports earlier research by Wesley Chorney et al. (2025), who highlighted the advantages of implementing onboard deep learning for swift field-level diagnostics. The application of CNN-based models in this research improved the detection of vegetation stress signals from NDVI data, providing a stronger early-warning system than manual scouting or strictly threshold-based approaches.

Table 8 and Figure 8 demonstrate that Edge AI–IoT-driven adaptive farm management led to notable yield increases in all evaluated crops. Maize production rose by 24.6%, tomatoes by 17.9%, and cassava by 20.4%, leading to an average yield increase of 21% in comparison to static management practices. These advancements demonstrate how AI-powered predictive analytics and immediate irrigation management boost crop yield by synchronizing resource distribution with plant development patterns.

Similar studies conducted by Gupta et al. (2023) and Ndiritu et al. (2024) revealed yield improvements of 15–22% when IoT-driven decision systems were integrated with adaptive learning algorithms. Consequently, the findings confirm the proposed framework's effectiveness in enhancing agricultural productivity while preserving resources.

Table 9 and Figure 10 illustrate the energy usage and computation performance metrics across different node densities. The findings show that the system exhibited low average power usage (2.8–3.5 W) and consistent CPU utilization despite rising loads. At 200 nodes, latency increased slightly to 420 ms, while reliability stayed above 97%, demonstrating that the framework facilitates energy-efficient scaling.

This discovery supports the research of Rahman et al. (2023), indicating that edge computing significantly minimizes energy expenses in comparison to cloud-only systems. The findings additionally confirm that the suggested Edge AI–IoT framework maintains computational efficiency while ensuring consistent reliability in densely populated deployment situations.

The financial assessment, illustrated in Table 10 and Figure 11, highlights the clear economic advantages of the framework. The overall operating expenses decreased by 18%, mainly because of a 29% decrease in labor costs and a 14% drop in input expenses. Energy and maintenance costs decreased by 11%, reinforcing the system's financial viability.

These findings are consistent with Rahimi et al. (2024), who indicated that combining AI with IoT in smart agriculture minimizes manual effort and input expenses via predictive maintenance and automation. This financial benefit promotes sustainable farming methods, especially for smallholder farmers in resource-limited environments.

Figure 12 illustrates the temporal fluctuations of NDVI recorded by the Edge AI–IoT system during the growing season. The analysis of the vegetation index in real-time facilitated the prompt identification of crop stress incidents, showing a strong correlation with variations in soil moisture and weather. This dynamic modification enhanced field consistency and reduced yield losses caused by stress, which aligns with the study's goal of adaptive monitoring.

Moreover, as illustrated in Figure 13, the relationship between water consumption and yield indicates that effective irrigation planning, facilitated by AI-driven choices, results in increased productivity while minimizing unnecessary water usage. This confirms the theory that combining Edge AI with IoT and UAV sensing enhances prediction precision and operational flexibility.

In conclusion, the findings strongly reinforce the goals and aims of the research. The suggested Edge AI–IoT framework greatly surpasses IoT-only and Cloud AI systems regarding latency (−76%), prediction accuracy (+34%), yield (+21%), and cost efficiency (−18%). These enhancements validate the system's ability to facilitate real-time adaptive monitoring, forecasting, and resource optimization.

In comparison to prior studies (e.g., Chen et al., 2024; Zhu et al., 2024; Rahman et al., 2023), the framework enhances the current capabilities by integrating Edge AI inference, UAV imaging, and closed-loop control into one scalable system. The combination of Edge–Cloud collaboration guarantees both quick responses and in-depth analysis, setting a new standard for intelligent and sustainable precision agriculture.

8. Conclusion and Future Work

This research introduced a thorough Edge AI–IoT framework for immediate precision agriculture, combining edge analytics, UAV sensing, and IoT-based data collection to aid in adaptive monitoring, forecasting, and resource optimization. The framework underwent experimental validation via a year-long implementation utilizing a mixed-crop testbed in Ibadan, Nigeria, incorporating multimodal data from soil, environmental, and UAV-mounted sensors.

The assessment revealed that the suggested system significantly surpassed IoT-only and Cloud AI setups in every essential performance metric. Latency was decreased by 76% relative to IoT-only solutions and by 82% compared to Cloud AI, demonstrating the benefits of localized processing in operations needing timely responses, like irrigation and pest monitoring. Predictive performance showed notable enhancement, with a 54% reduction in soil moisture forecasting error, a 26% increase in pest detection accuracy, and a 34% boost in yield estimation precision.

From an agricultural standpoint, the system accomplished a 19% decrease in water consumption, an 11% decrease in fertilizer usage, and an 8% decrease in pesticide use, leading to a 14% total cost reduction and a 21% average enhancement in yield across primary crops. These benefits confirm the system's capacity to convert AI-generated insights into concrete results in the field. Additionally, scalability evaluations validated that the architecture sustained high throughput (2,050 records/sec) and minimal packet loss (<2.1%) despite a tenfold rise in connected nodes.

Financially, the framework lowered overall operational expenses by 18%, mainly by cutting labor costs and optimizing input utilization, showcasing its economic viability and sustainability for both smallholder and commercial farms. Together, these results validate that the combination of Edge AI and IoT transforms conventional agriculture into a data-informed, context-sensitive, and energy-efficient system capable of responding intelligently to changing environmental and operational situations.

In conclusion, this study achieves its goals by offering empirical proof that the integration of Edge AI and IoT improves responsiveness, predictive accuracy, and resource efficiency in precision agriculture systems. The study adds to the expanding literature promoting decentralized, adaptive, and sustainable agricultural technologies that are in harmony with UN Sustainable Development Goals (SDG 2, SDG 9, and SDG 12) to guarantee food security, enhance digital infrastructure innovation, and support responsible resource use.

5.2 Future Work

Although the suggested framework shows robust performance and practical applicability, various avenues for future research could improve its scalability, intelligence, and sustainability.

Energy optimization continues to be an essential factor. While present edge nodes demonstrate effective performance, future efforts should investigate solar-powered and energy-harvesting IoT devices to lessen reliance on external power sources even more. Applying dynamic power management algorithms at the edge might optimize energy consumption alongside computational requirements, prolonging system longevity in isolated areas.

Additionally, upcoming research might explore data traceability and security based on blockchain technology in the Edge AI–IoT framework. Incorporating distributed ledger technology (DLT) can guarantee data accuracy, facilitate secure exchanges among participants, and offer traceable audit paths for transparency from farm to market.

Third, it is essential to improve the generalization and transfer learning abilities of AI models to better suit various agro-climatic zones and types of crops. Creating larger, regionally spread datasets and employing federated learning enables several farms to jointly develop models while safeguarding raw data, enhancing privacy as well as model strength.

Fourth, additional studies could incorporate reinforcement learning (RL) for the independent management of agricultural activities. RL agents could continually adjust irrigation, fertilization, and pest management strategies based on changing environmental and market circumstances.

It is suggested to conduct practical field trials in diverse geographical areas and cropping systems to confirm the model's scalability, adaptability, and economic effectiveness amidst different soil, weather, and resource limitations. In summary, the results of this research provide a strong basis for future intelligent agricultural systems. The suggested Edge AI–IoT model enhances operational effectiveness while also supporting the larger goal of resilient, sustainable, and data-informed food production. Upcoming advancements in AI optimization, secure data management, and energy independence will further enhance the significance of this framework in influencing the future of precision agriculture.

9. Copyright Notice

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