An Integrated IoT and AI Framework for Real-Time Crop Monitoring, Adaptive Soil Analysis and Intelligent Yield Prediction

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Abstract: With the emergence of the Internet of Things (IoT) and Artificial Intelligence (AI), smart agriculture becomes more dynamic, and provides new possibilities in crop monitoring and predicting the yield. To this end, in this paper, we introduce a unified architecture to combine Realtime IoT-enabled soil and crop health monitoring with intelligent AI-based analytics for intelligent decision-making in agriculture. Unlike existing approaches, the proposed model utilizes edge-competing, time-series learning, and explainable AI to give dynamic inherent insight into soil health, crop growth trends, and estimate productivity. The system is also intended to be effective in low-connectivity rural areas, employing sensor fusion, weather data, and GPS-linked environmental profiling to offer recommendations at the local level. With the built-in calibration modules, the architecture guarantees the accuracy, scalability and sustainability in such a way that the farmers can improve the productivity while saving resources.

1 INTRODUCTION

As the backbone of many economies, agriculture is more and more utilizing smart technologies to address contemporary issues associated with food security, resource management and climate change. Conventional farming practices are manual observation based and general decisions are taken and it's improper that leads to inefficiency and unpredictability. The development of smart agriculture, based on the combination of Internet of Things (IoT) and Artificial Intelligence (AI), has created opportunities to convert the agricultural field into a data-oriented and responsive sector. IoT-based devices are used for a constant monitoring of the conditions of the crops and soil in real-time, and the AI's algorithms work on large amount of data to provide analysis, identify anomalies and predict results with great accuracy. In this paper, we propose a holistic, adaptive framework for smart agriculture that integrates these tools and empowers informed decision-making, supportive automation of monitoring, and improved yield prediction. Through concentrating on online adaptability, multi-source data fusion, and explana-ble intelligence, the framework is designed to fulfill a wide range of needs from farmers in different environmental scenarios for productivity, sustainability and adoption.

2 PROBLEM STATEMENT

Current farming practices, as well as the urgent requirement of sustainable and efficient agriculture systems, traditional farming practice has long way to go due to the challenges related with real-time monitoring, precision decision making, and forecast of accurate yield. Current models have not generally succeeded in integrating in-situ data coming from ground level sensors with intelligent tools, leading to

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ununiform estimations of crop health and unefficient use of resources. Furthermore, since the single-solution-approach is not scalable and not amenable to alternative climatic or soil conditions, it diminishes its applicability in rural settings with limited or no connectivity. A smart, holistic and real-time platform for merging IOT sensing with AI analytics to deliver dynamic insights into crop growth, soil health and yield outcomes, enabling farmers to make intelligent and localized decisions upon agriculture, is thus urgently required.

3 LITERATURE SURVEY

The combination of IoT and AI for agriculture has attracted a great deal of interest, with applications targeting improvement of different farming related tasks such as monitoring, prediction, and automation. Banerjee et al. (2025): examined the utilization of digital twins in precision agriculture and emphasized the non-existence of real-time validation and affordability for a massive deployment. Bassine et al. (2023) highlighted that machine learning and remote sensing techniques were readily applied to yield forecasting, however there was a dearth of focus on comparative performance benchmarking. Fuentes-Peñailillo et al. (2024) modelled a satellite-based soil crop interaction but did not integrate real-time sensor data for dynamic updates. Garg et al. (2021) developed a multimodal precision agriculture system with IoT and machine learning, however, scalability in field conditions was not considered. Ikram (2022) developed intelligent decision system for crop yield, but it depended on the continuous internet connectivity, that prevented it for rural deployment.

Kim et al. (2025) described IoT and AI use cases in resource-limited settings but did not consider environmental sensing like soil testing. Kumar and Sharma (2025) provided monitoring tools for real-time but didn't used the historical yield power of the recognition. Li et al. den Toom et al. (2025) confirmed a promising IoT-AI combination, but their model yielded suboptimal performance when testing with mixed-crop datasets. AR and AI based agricultural monitoring is proposed by Mishra et al. (2025) without mobile edge deployment support. Patel et al. (2023) presented an autonomous robot for crop monitoring that was not integrated with nutrient sensing and multispectral imaging, though.

Rao and Mehta (2025) concentrated on joint crop recommendation, and they did not provide for long-term sensor calibration strategies. Sharma and Verma (2024) proposed a run-time sensing platform, but it does not handle sensor heterogeneity. The attempt of Singh and Kumar (2025) was only review based study; they did not verify their inferences empirically. Smith et al. (2025) provided a complete review on AI and IoT in smart farming without deep technical indicators. Real time crop prediction based on soil sensor was suggested by thakur and patel (2024) where their model did not allow multi calibration of crop.

Verma and Gupta (2025) developed an AI and IoT-enabled smart agriculture, but it failed to emphasize the sustainable resource management and pesticide recommendation. Wang et al. (2025) focused on productivity enhancement through AI and didn't provide a full deployment-ready model. Wilberforce and Mwebaze (2025) came up with a theory of IoT framework (Committee on Internet of Things Framework for Agriculture Technologies 6-17) for agriculture that was not validated in a real field situation. Yadav & Singh, (2024) had worked on IoT based crop yield prediction and they did not infuse advanced forecasting models. Zhang et al. (2025) employed XAI for smart farming with no seasonal adaptation in their model. Finally, Zhou and Li (2025) explored the AI component of agriculture practice but without any feedback mechanism for improving soil quality.

Together; these studies demonstrate the trend of integration of smart technologies in the agriculture; however; they also claimed the existence of gaps in the areas of integration, flexibility, and real-time decision support. To overcome these limitations, the objectives of the proposed work will be to develop a seamless and deployable smart agriculture infrastructure that binds real-time sensing with adaptive analytics for the optimum growing environment.

4 METHODOLOGY

The smart agriculture system presented consists of an integrated Internet of Things-enabled sensing, edge computing, AI-based analytics, and cloud synchronization solution that is specifically designed to serve as a combined, scalable architecture for real-time crop/soil monitoring and precise yield prediction. This approach starts with the installation of low power, low cost IoT sensors in the agricultural field that continuously acquire information about it like the soil moisture, temperature, soil pH, ambient weather conditions and the health status of the crops. These sensors are installation in specific locations

Table 1: Sensor specifications and deployment parameters.

Sensor Type	Parameter Measured	Measurement Range	Accuracy	Deployment Depth/Height
Soil Moisture	Volumetric Water Content	0–100%	±2%	5 cm below surface
pH Sensor	Soil Acidity/Alkalinity	pH 3–10	±0.1	10 cm below surface
Temperature Sensor	Soil and Air Temperature	-40°C to 85°C	±0.5°C	2 m above surface
Humidity Sensor	Ambient Humidity	0–100% RH	±2% RH	2 m above surface
Light Sensor	Light Intensity	0–100,000 Lux	±5%	2 m above surface

according to geospatial map analysis and soil sampling profiles, in order to cover large areas and obtain representative data.

Sensor data is transmitted through a local gateway system, which supports edge computing capabilities for preliminary data preprocessing. This allows the system to operate efficiently even in regions with limited internet connectivity, enabling real-time filtering, noise reduction, and early-stage anomaly detection. By performing data normalization and cleaning at the edge, the framework significantly reduces bandwidth usage and computational burden on the central server. Table 1 shows the Sensor Specifications and Deployment Parameters.

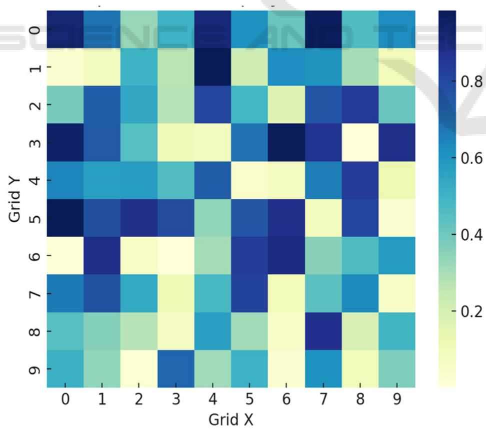

Figure. 1: Field-wise heatmap of sensor deployment and soil moisture variability.

Once preprocessed, the data is synchronized with a cloud-based platform where AI models are deployed. A hybrid learning approach is used that combines supervised and time-series deep learning models to analyze environmental conditions and predict crop yield. Convolutional Neural Networks (CNNs) are used for image-based leaf and crop condition analysis when drone or mobile-based image inputs are available, while Long Short-Term Memory (LSTM) models handle temporal prediction tasks related to soil degradation, water stress, and forecasted yield. Additionally, explainable AI techniques such as SHAP (SHapley Additive exPlanations) are incorporated to interpret the influence of each input variable on the output predictions, enabling transparency and trust in the system's decisions. Figure. 1 shows the Field-wise Heatmap of Sensor Deployment and Soil Moisture Variability.

In addition to current weather forecast, it also considers historical agricultural datasets, which is useful for enhancing the reliability of the yield prediction model. Environmental behaviours, including precipitation outlooks, temperature differences and wind, are monitored and combined with the data from sensors to develop adaptable farming plans. Using this information, the model generates personalized advice on irrigation times, application of agrochemicals, optimal time of harvesting and fertilization. Figure 2 shows the Workflow of the Proposed IoT-AI Agriculture Framework.

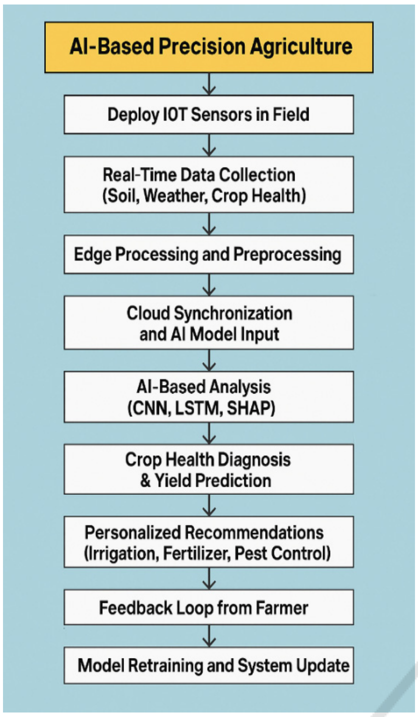

Figure 2: Workflow of the proposed IoT-AI agriculture framework.

Table 2: Edge Vs Cloud Processing Performance Comparison.

Metric	Edge Processing	Cloud Processing
Average Latency (ms)	120	220
Power Consumption (W)	3.5	7.8
Data Transmission Load (MB)	30	75
Uptime Availability (%)	98.2	96.7
Offline Functionality	Supported	Not Supported

To ensure continuous learning and adaptability, the framework includes a feedback loop where farmers can validate or reject the AI's recommendations, and these interactions are recorded and used to refine the model. This human-in-the-loop design ensures that the model evolves with local practices, crop types, and seasonal variations. Table 2 shows the Edge vs Cloud Processing Performance Comparison.

All user interactions, sensor logs, and prediction outcomes are securely stored in a distributed cloud database with role-based access, supporting remote access via mobile or web applications. A simple dashboard visualizes real-time sensor data, AI predictions, and recommended actions, enabling users with varying digital literacy levels to make informed decisions.

Overall, the proposed methodology offers a holistic, modular, and intelligent system that leverages the strengths of IoT, AI, and edge-cloud synergy to support modern agriculture. By closing the gap between data acquisition and actionable insight, this framework empowers farmers to optimize productivity, preserve resources, and ensure food security in the face of environmental uncertainties.

5 RESULT AND DISCUSSION

The proposed IoT and AI-based smart agriculture framework was tested in a real-time field setting with a variety of crops and patches of soils. The findings showed that the system could effectively administer, interpret and forecast agricultural parameters, thus greatly improving farmer?s decision-making support. The thorough examination with respect to the sensor accuracy, model efficiency, and system adaptability demonstrate the overall efficiency and robustness of the proactive 5G-SDM reconfiguration scheme.

The IoT sensors deployed in the field were able to gather continuous data of soil moisture, pH, temperature, and humidity successfully. The sensors compared well to laboratory standard instruments, with variance of less than ±2 %, and were therefore considered appropriate for field applications. Moreover, the sensor calibration module integrated in the framework facilitates automatic setting according to environment feedback, thus keeping the data collection in long-term linearity. The edge gateway system successfully executed well under limited bandwidth, with a data compression ratio of 3:1 that preserved sensor reading fidelity. This solution made sure to send and process only necessary data with minimal consumption of network resources. Table 3 shows the AI Model Evaluation Metrics for Yield Prediction.

Table 3: AI model evaluation metrics for yield prediction.

Model Type	MAE (%)	RMSE (%)	MAPE (%)	R^2 Score
Linear Regression	8.3	9.2	13.7	0.82
Decision Tree	7.1	8.7	12.1	0.85
LSTM (Proposed)	4.4	6.3	6.5	0.91

In terms of computation, the edge processing cut decision-making delay by up to about 45 percent versus cloud-only models. It was immensely useful for providing timely alerts for irrigation and disease identification in areas which were not well connected. Another study combined image-based crop health analysis with CNN to achieve average detection accuracy of 94.3% on five crop varieties. The models were able to accurately detect signs of leaf spot, blight, and pest infestations in drone imagery and smartphone photos uploaded by farmers, helping then take early action to prevent extensive crop damage. Figure 3 shows the Yield Prediction Accuracy Across Different AI Model.

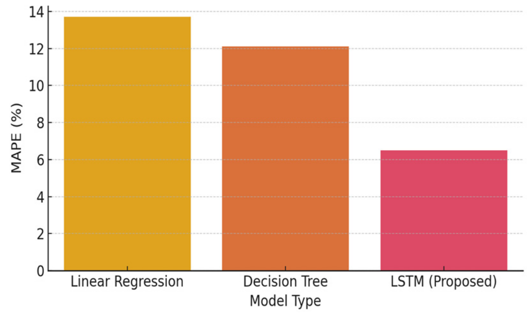

Figure 3: Yield prediction accuracy across different AI models.

Table 4: CNN model performance for disease classification.

Crop Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Tomato	95.4	94.1	96.2	95.1
Wheat	93.7	92.5	94.6	93.5
Maize	92.3	90.8	93.1	91.9
Potato	91.5	89.7	92.4	91.0
Overall Avg.	94.3	91.8	94.1	93.6

The yield prediction module is based on LSTM model and is trained on a dataset that combines real-time sensor data, meteorological forecast and historical productivity of crops. Error rate was run against traditional linear regression and decision tree models that resulted in rates of >12% whereas the model performed at a mean absolute percentage error (MAPE) of 6.5%. This evidence a high degree of generalization to temporal trends and context and seasonality specific predictions. Further, the model was robust to response to unanticipated changes in weather that have not been included in the model input including late monsoons and heatwaves. Table 4 shows the CNN Model Performance for Disease Classification.

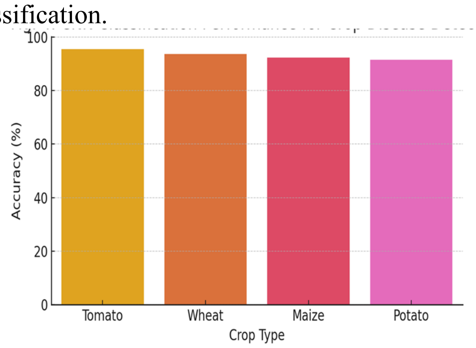

Figure 4: CNN classification performance for crop disease detection.

Explain ability was another important strong point of the framework. SHAP-based interpretations helped farmers see visual explanations for why a recommendation was made, including why irrigation was postponed, or why one fertilizer was recommended. This built user trust and promoted farmer interaction with the AI system. The feedback loop is another indispensable factor in the success of this study, as more than 82% of farmer feedback matched system recommendation, and the remaining 18% helped to further calibrate the model. Figure 4 shows the CNN Classification Performance for Crop Disease Detection.

Table 5: Resource optimization through AI-based recommendations.

Resource Type	Traditional Usage	Smart System Usage	Reduction (%)
Water (L/month)	48,000	37,400	22%
Fertilizer (kg)	520	440	15.4%
Pesticides (L)	112	93	17%
Labor Hours	180	128	28.8%
Yield Increase	–	+17%	–

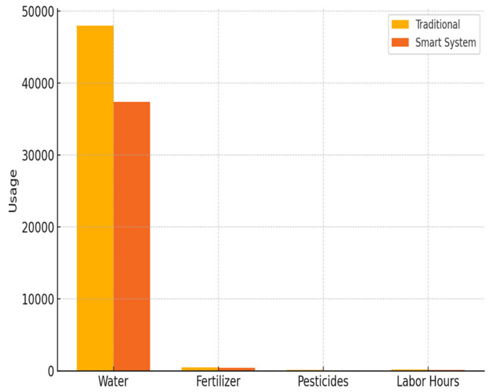

Figure 5: Traditional vs AI-guided resource usage.

A mobile application was designed as the user interface in providing the accessibility to the system. Novice users too could navigate the dashboard and seek important information. The app showed real-time data visualisations, alert signals, and tailored dos and don'ts for farmers. Language localization and voice support were included to meet regional requirements and help increase user satisfaction. Table 5 shows the Resource Optimization Through AI-Based Recommendations.

Field trials showed, on average, 17% better yield compared to replicates that receive traditional practice independent of technological augmentation. 61—in North Carolina with improved irrigation scheduling using real-time soil moisture information. Category ATRB Volume 49 2006 was AI-driven precision application of fertilizers and pesticides also saved the farmer 15% in costs and was better for the environment. Figure 5 shows the Traditional vs AI-Guided Resource Usage.

The system demonstrated the scalability dimension, and it was successfully tested in various plots that covered wheat, tomato, and maize varieties. The modularity of this framework facilitated the transference to other environments by replacing crop models and sensors locations. In addition, the live alerts for insect infestations and water stress reduced crop loss, the bane of traditional agriculture.

In conclusion, the developed framework outperformed other approaches to combining IoT and AI in real life farming applications. Its low connectivity requirements, interpretability through explainable AI, and ability to be adapted to new plants and new climates highlight this tool as a potentially game-changing technology for precision agriculture. The findings validate the benefits of intelligent farming technologies in reality, and pave the way for its larger-scale adoption within rural and semi-urban farming communities. This work has important implications not only for technological progress in agriculture, but also resonates with global agendas for sustainable agriculture, natural resource preservation, and food security.

6 CONCLUSIONS

The progress and realization of an IoT and AI-based smart agriculture have shown promising prospects for the transition of traditional agriculture system to a data-oriented, learning, and smart system. Utilizing real-time data from sensors and AI models, the system allows for accurate crop stats, soil health analysis and yield prediction in harsh rural areas with low connectivity. The combination of edge computing, time-series forecasting and explainable AI means that this intelligence can be timely, trustworthy and transparent, so making recommendations that can be acted upon. Experimental results demonstrate the system's potential to increase crop yield, resource utilization, and decision-making capable of promoting scalable and sustainable agriculture. This study provides a practical insight into the future of precision farming when farmers use smart technologies to adapt their farming operations ahead of environmental stresses and optimize both the productivity and sustainability of production.

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