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IoT and AI Enabled Agriculture: Monitoring, Predictive Analysis and Crop Optimization

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ABSTRACT

The purpose of this paper is to examine how Internet of Things (IoT) technologies are transforming agriculture by improving monitoring, predictive analytics, and crop optimization. Real-time data from sensors and IoT devices is used to evaluate critical parameters like soil quality, weather, and pest management to optimize crop yield. The focus of the study is on data-driven crop yield optimization, AI-based crop rotation strategies, and weather-responsive farming. Significant improvements were observed in the results, with a 33.33% increase in crop yield (tons per hectare), a 50% increase in early pest detection rates, and a 21% increase in Grade 'A' harvest quality. The importance of it in modern agriculture is due to the contributions made by these advances to profitable and sustainable practices. Farmers, agronomists, and policymakers can benefit from this research, which advocates for the adoption of IoT to address food security challenges in an evolving agricultural landscape.

INTRODUCTION

1.1 The context and significance of IoT in agriculture

Manual practices were traditionally used in agriculture, with farmers relying on experience and intuition to make crop management decisions. The lack of real-time data on soil conditions, weather patterns, and crop health can cause inefficiencies and suboptimal yields frequently. Overuse of resources like water and fertilizers can result from traditional agricultural practices, which can contribute to environmental degradation and increase costs for farmers (Friha et al., 2021).

The Internet of Things (IoT) has transformed agricultural practices by allowing smart technologies to be integrated for real-time monitoring and data-driven decision-making. Sensors, drones, and satellite imaging, among other Internet of Things technologies provide valuable insights into agricultural parameters such as soil moisture levels, temperature, nutrient availability, and pest incidence. Farmers can use these technologies to monitor their fields continuously, which enables them to respond quickly to changing conditions and optimize resource use (Dhanaraju et al., 2022). By minimizing waste and reducing the environmental footprint of farming activities, IoT can be used to enhance productivity and promote sustainable practices (Kasera et al., 2024).

1.2 Research Objectives

This study aims to investigate how IoT technologies can have a significant impact on crop yields, resource efficiency, and crop quality metrics. This study's objective is to:

1. Optimize crop yields by analyzing the impact of IoT on crop yield enhancement using predictive analytics and monitoring systems that provide actionable insights for farmers.
2. Examine how IoT applications can enhance resource efficiency by facilitating better resource management, including water usage and fertilizer application, and reducing costs and environmental impact.
3. Assess the effectiveness of IoT technologies in improving various quality parameters of crops, such as market value and customer satisfaction, by enabling early detection of pests and diseases.

Through this exploration, the research aims to provide a broad understanding of the transformative potential of IoT in agriculture and contribute to the growing body of knowledge surrounding smart farming practices.

2. Related Work

A summary of previous studies on IoT in Agriculture

Traditional farming practices have undergone a transformative shift due to the integration of Internet of Things (IoT) technologies in agriculture. The potential of IoT in improving crop management and optimizing resource use has been highlighted by several studies. Jadhav et al. (2023) explored IoT-enabled smart farming systems that significantly improve crop growth efficiency through continuous monitoring of soil and weather conditions. According to their findings, precision agriculture techniques with IoT technologies can lead to increased yields and optimized resource management. In 2023, Atalla et al. Examined precision agriculture with IoT, emphasizing the development of ecosystems that enable optimized crop management. Their research demonstrates the benefits of real-time data on crop health, soil moisture, and environmental conditions in enhancing productivity and making informed decisions. This aligns with the work of Savita and Vimal (2023), who highlighted the integration of environmental monitoring and data analytics through IoT technologies to improve crop-specific management strategies, ultimately enhancing crop quality and market value.

Smart farming was highlighted by Dhanaraju et al. (2022) as an important factor in achieving sustainable agricultural practices, with evidence that IoT-based systems increase productivity while supporting environmental sustainability. Friha et al. (2021) conducted a comprehensive survey that examined emerging it technologies and their potential to revolutionize agriculture by enhancing operational efficiency and crop quality, and this work is complementary to it. In the context of monitoring soil and crop health, Ibanga et al. (2022) investigated the spatiotemporal variability of soil moisture across different soil groups, emphasizing the critical role of soil moisture monitoring in maximizing crop yields Benyezza et al. (2023) proposed a smart platform that utilizes IoT and wireless sensor networks (WSN) for greenhouse monitoring, which assists in the improvement of precision agriculture practices by utilizing environmental conditions.

The role of IoT in enhancing agricultural extension services was shown by research by Olorunfemi et al. (2020), which identified the factors that influenced extension agents' involvement in disseminating climate-smart agricultural initiatives. Furthermore, Morchid et al. (2024) emphasized the importance of high-tech agricultural systems, such as smart irrigation using IoT and cloud computing, in improving food security. Despite the advantages, the adoption of IoT technologies in agriculture poses many challenges. The initial investment cost, particularly for smallholder farmers, is still a significant obstacle (Sinha & Dhanalakshmi, 2022). The digital divide in farming practices is caused by many farmers lacking the financial resources necessary for such investments. The complexity of managing and interpreting the vast amounts of data generated by IoT devices also poses challenges, as farmers may struggle to analyze this data effectively (Rahman et al., 2024). Additionally, issues related to data security and privacy must be addressed, as highlighted by Kasera et al. (2024), given that implementation can expose sensitive information about farming practices and crop yields.

Nonetheless, the advantages of IoT in agriculture are considerable. Real-time monitoring of crops and soil conditions can improve resource use, reduce environmental impact, and increase crop yields. In 2020, Ragavi et al. highlighted the potential of AI-driven sensor technologies in facilitating smart agriculture. The adoption of IoT technologies will increase due to their affordability and user-friendliness, paving the way for smarter and more sustainable farming practices (Zimit et al., 2023). Furthermore, Gour et al. (2021) discussed how IoT can enhance data collection and analysis, leading to improved decision-making in agricultural practices. Alshammari et al. (2023) investigated real-time soil parameter monitoring for precision agriculture, stressing the significance of IoT technologies in achieving agricultural sustainability.

To benefit all farmers, policymakers, and stakeholders should collaborate to provide support and resources that facilitate the transition to IoT-based agriculture. The incorporation of IoT in agriculture promises to boost productivity and promote sustainable practices that are vital for food security in the coming years.

3. Materials and Methods

3.1 Data collection

A variety of data sources are used in the research to evaluate soil quality, crop yield, weather patterns, and pest management. Data collection is carried out using the following methods:

1. **Soil Quality Data:**
   Various fields collect soil samples for analysis of pH levels, nutrient content (Nitrogen, Phosphorus, Potassium - N-P-K), moisture content, and organic matter percentages. The laboratory analysis of soil samples is the method used to obtain this data. The deployment of IoT sensors in the fields is meant to monitor soil parameters like moisture content, temperature, and nutrient levels in real-time. Soil moisture sensors, pH sensors, and nutrient sensors are sensors that provide continuous data streams for analysis.
2. **Crop Yield Data:**
   Crop yields are recorded using manual harvesting records and automated data collection systems integrated with harvesting machinery. This information includes the total yield (in tons) and average yield per hectare. Additionally, drones with multispectral cameras enable aerial crop health monitoring, allowing for more accurate assessments of yield potential.
3. **Weather Patterns:**
   Temperature, humidity, rainfall, and wind speed data is collected through local weather stations and IoT weather sensors. This information is crucial for comprehending the environmental conditions that affect crop growth. To ensure a complete analysis of weather patterns, meteorological data from national databases is included.

The accuracy and timeliness of data collection can be improved by using IoT devices for data acquisition, leading to better decision-making in agricultural practices.

3.2 Technical Framework

Architecture of IoT in Agriculture

Real-time monitoring, data collection, and analysis are enabled by the architecture of the IoT ecosystem in agriculture, which enables smart farming practices. There are several essential components in the framework:

1. **Sensors:** Various types of sensors are deployed across agricultural fields, including soil moisture sensors, pH sensors, weather sensors, and pest traps. The data collected by these sensors is continuously transmitted to data processing units.
2. **Data Processing Units:** This layer processes the data collected from the sensors. Cloud-based platforms and edge computing systems are part of it, which analyze data for actionable insights. Predicting crop yields, assessing soil health, and identifying pest threats are achieved through the use of machine learning algorithms.
3. **Communication Network:** A reliable communication network, such as Wi-Fi, LoRaWAN, or cellular networks, connects sensors to the data processing units. Data transmission is ensured to be efficient and secure with this.
4. **User Interface:** End-user interfaces, such as mobile applications or web dashboards, present the processed data to farmers and agricultural stakeholders. Visualizing data, receiving alerts, and accessing recommendations for crop management and pest control are all possibilities with these interfaces.

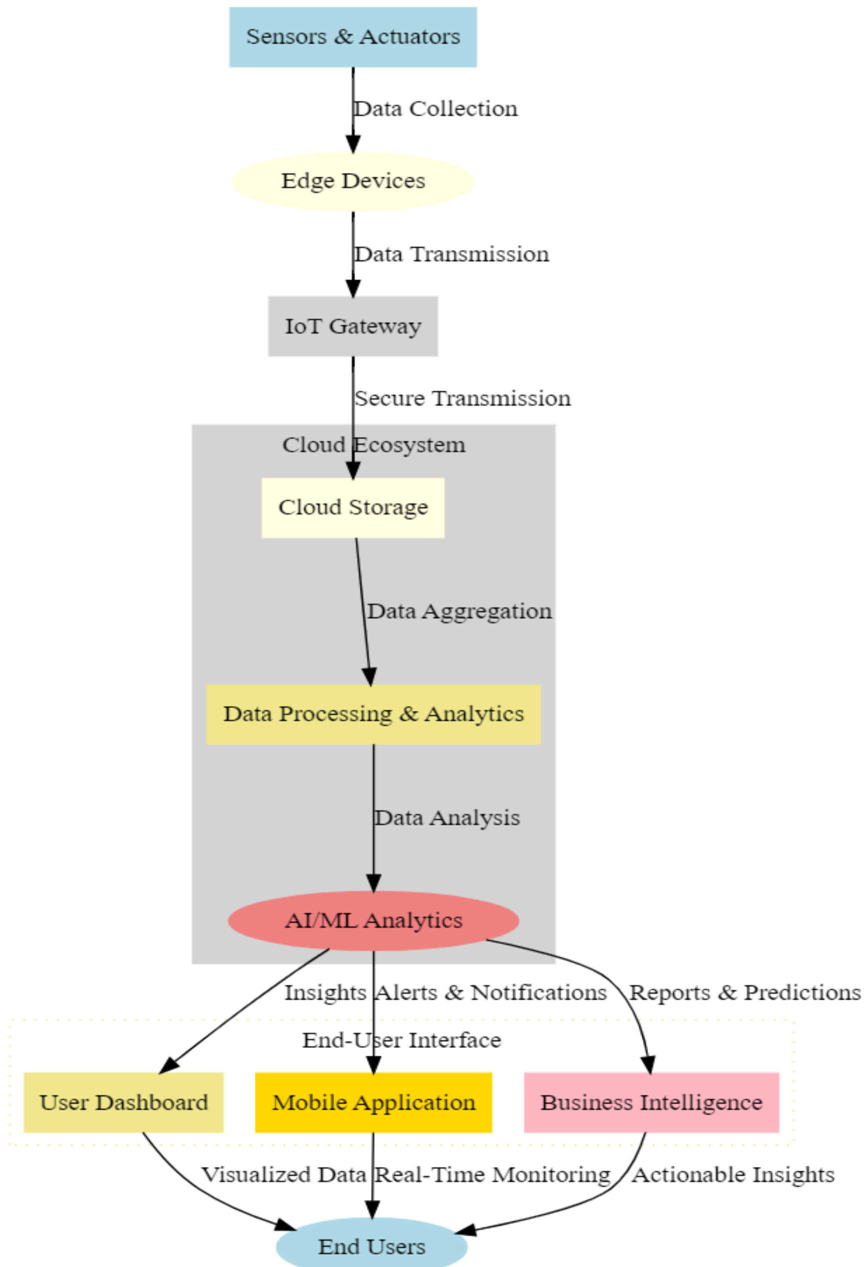


Figure 1 Basic Architecture of IoT in Agriculture

The **Architecture of IoT in Agriculture** Figure 1 shows how data, components, and operations flow vertically in an IoT-enabled system, Sensors and Actuators are the starting point of the ecosystem, as they are physical devices that are deployed in the environment to measure key parameters such as temperature, humidity, soil moisture, and air quality. By converting physical readings into digital signals, these sensors transmit them to the next layer for processing. Actuators respond to data received, for instance, by activating irrigation systems when soil moisture drops below a threshold. Temperature, pH, and soil moisture sensors are common examples of agricultural applications that are crucial in monitoring and optimizing environmental conditions for crop health. Edge devices serve as intermediaries by gathering raw data from sensors, filtering it, and pre-processing it before transferring it to the gateways. Low-power processors or microcontrollers with embedded computing capabilities enable these devices to run lightweight machine-learning algorithms for initial anomaly detection or data compression. Edge devices can calculate average values or detect outliers in real time, which reduces data load and latency for subsequent stages.

Secure and efficient data transfer is managed by the IoT Gateway, which connects Edge Devices to the cloud. Gateways handle a variety of data protocols (such as MQTT, and HTTP) and incorporate encryption to ensure data security while transporting it. Cloud Storage provides secure storage and the ability to scale to accommodate large volumes of data. IoT data is stored and managed by databases (such as SQL or NoSQL) on cloud platforms like AWS, Azure, or Google Cloud. Moreover, cloud storage ensures that data is safe and accessible when needed by providing high availability and redundancy.

To prepare data for analysis, the Data Processing and Analytics layer carries out comprehensive data aggregation and normalization. To suggest fertilization schedules, an example application might involve analyzing historical weather data or examining soil data trends. Predictive analytics and anomaly detection are generated by AI/ML Analytics by using advanced machine learning models to analyze the processed data. Algorithms such as neural networks, decision trees, and reinforcement learning models are implemented on platforms like TensorFlow or PyTorch to predict outcomes (like crop yield) and identify potential issues (like pest infestation) early.

Precision agriculture is anchored by AI models that make data-driven recommendations and predictions for operational decisions.

A visual interface is provided by the User Dashboard for users to view insights, metrics, and other data in real time. Field workers or technicians can access real-time data and respond to alerts on the go with the help of the Mobile Application. Mobile applications, built for Android, include push notifications for urgent events (like low soil moisture or pest detection), providing flexibility and immediate response capabilities to users in remote locations.

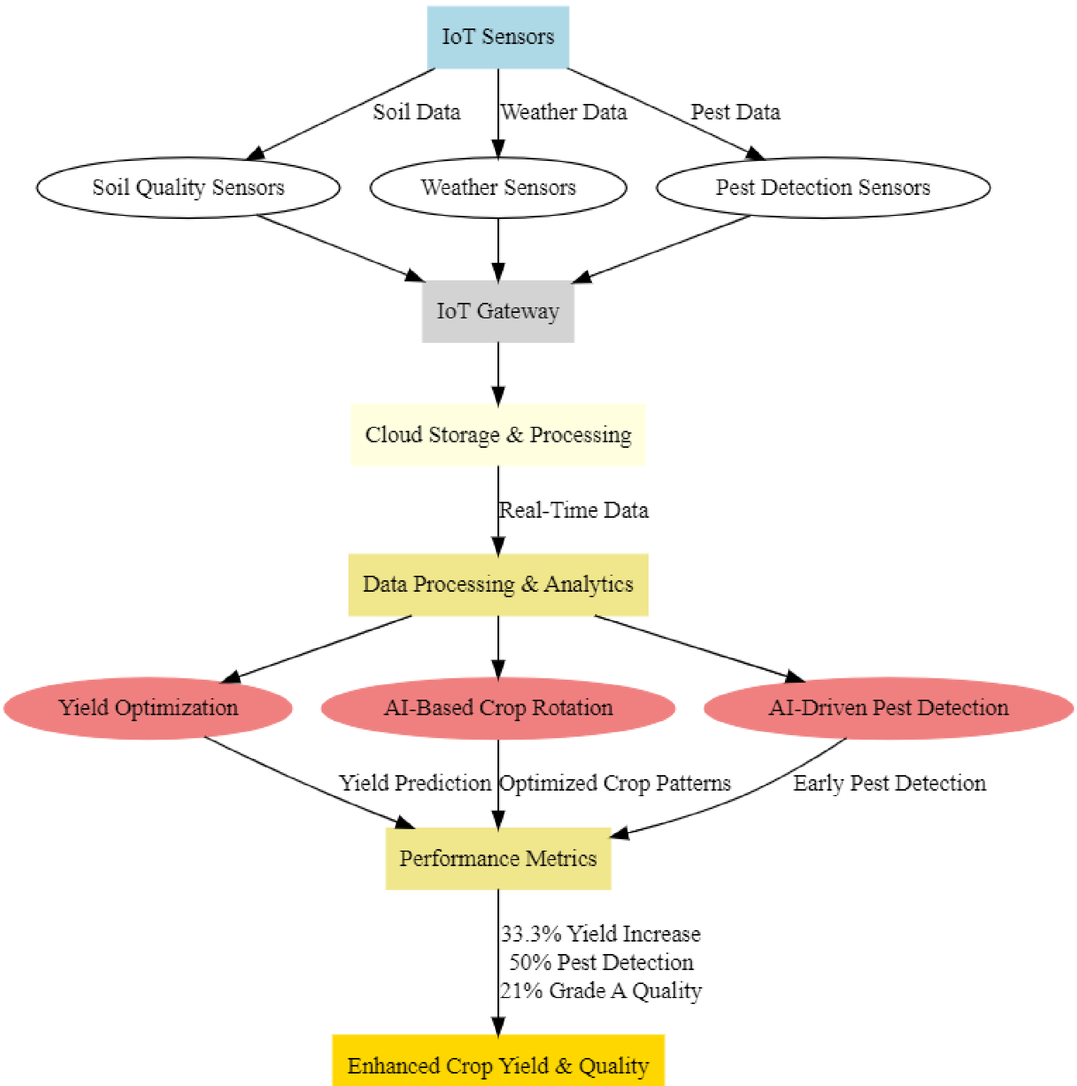


Figure 2 IoT and AI Enabled Agriculture.

Figure 2 shows **IoT and AI Enabled Agriculture** which enables seamless integration of various IoT technologies, fostering a data-driven approach to agriculture that enhances productivity, resource efficiency, and crop quality metrics

Mathematical Formulation

1. Sensor Data Collection:

Let S_i represent each sensor, where $i = 1,2,. . . . ,n,$ *with n* being the total number of deployed sensors. Each sensor S_i collects data $D_i\,(t)$at time t, measuring a specific parameter (e.g., temperature, soil moisture):

$D_i(t)$ = sensor measurement at time t.

The raw data matrix collected from all sensors over time T can be Represent as:

$$D = \begin{pmatrix} D_1(1) & D_2(1) & \dots & D_n(1) \\ D_1(2) & D_2(2) & \dots & D_n(2) \\ \vdots & \vdots & \ddots & \vdots \\ D_1(T) & D_2(T) & \dots & D_n(T) \end{pmatrix}$$

2. Edge Processing:

Edge devices filter and preprocess the raw data $D_i(t)$ to reduce noise and extract useful features. This process can be formulated as a f_{edge} function applied to the raw data:

$$D_{processed}\,(t) = f_{edge}(D_i(t)).$$

Example functions might include noise reduction (e.g., moving average filter) or simple anomaly detection using thresholds θ_{low} and θ_{high}:

$$f_{edge}(D_i(t)) = \begin{cases} D_i(t) & \text{if } \theta_{low} \le D_i(t) \le \theta_{high} \\ 0 & \text{otherwise} \end{cases}$$

IoT Gateway Data Transmission:
Data is transmitted to the cloud using protocols like MQTT or HTTP. This can be modeled to minimize latency L and optimize bandwidth B :

$$\min L = f(B,P),$$

where P represents the packet size. This objective function aims to maximize the efficiency of data transfer given limited bandwidth resources.

Cloud Storage and Processing:
Let $D_{processed}$ denote the aggregated preprocessed data from edge devices. This data is stored in the cloud and can be accessed over time T:

$$D_{cloud} = \{D_{processed}(t) \mid t \in T, \ i = 1, \ldots, n\}$$

Cloud storage aims to maximize data availability A while minimizing storage costs C:

$$\max A, \min C = g(\text{data size, storage type}).$$

Data Analytics and Machine Learning:
Let XX represent the features derived from D_{cloud} which are used as input for predictive models (e.g., linear regression, neural networks). A typical model seeks to predict future sensor readings Y based on past data:

$$Y = h(X) + \epsilon$$

where $h(\cdot)$ is a predictive function, and ϵ represents the prediction error.

Example: Predicting Soil Moisture (Regression)
Given historical soil moisture data X_{soil}, we want to predict future moisture values Y_{soil} using a linear regression model:

$$Y_{soil} = \alpha + \beta X_{soil} + \epsilon,$$

Where α and β are coefficients optimized to minimize the mean squared error (MSE):

$$\alpha, \beta \min \frac{1}{n} \sum_{i=1}^{n} (Ysoil,i - (\alpha + \beta Xsoil,i))^2$$

User Dashboard and Decision Support:
Data visualization and decision support rely on metrics derived from processed information. Each metric M_j (e.g., average temperature, soil health index) is calculated as a function of data in Dcloud

$$M_j = f_j(D_{cloud})$$

For example, an average soil moisture metric can be computed as:

$$Mavg\_soil\_moisture = \sum_{t=1}^{T} D_{soil\_moisture}(t)$$

Optimization for Resource Allocation: IoT systems often aim to optimize resource allocation (e.g., irrigation scheduling) based on data-driven insights. This can be formulated as a constrained optimization problem:

$$\text{Min Water Usage} = \sum_{t=1}^{T} w(t)$$

subject to:

$$M_{soil\_moisture}(t) \ge \theta_{moisture}, \ \forall t.$$

Here, $w(t)$ represents the water used at time t, and $\theta_{moisture}$ is the minimum threshold for soil moisture.

4. Results and Discussion

Module 1: Performance Analysis - Data-Driven Crop Yield Optimization

Soil Quality Analysis

The soil quality metrics were evaluated by comparing the system-predicted values against the actual measured values across different fields. The results are summarized in ***Table 1***.

Field ID	Soil Type	pH Level (Predicted)	pH Level (Actual)	Nutrient Levels (N-P-K, Predicted)	Nutrient Levels (N-P-K, Actual)	Moisture Content (%) (Predicted)	Moisture Content (%) (Actual)	Organic Matter (%) (Predicted)	Organic Matter (%) (Actual)
Field 1 (Gadmudshingi)	Loam	6.4	6.5	118-52-32	120-50-30	19	20	3.4	3.5
Field 2 (Vasgade)	Clay	5.9	5.8	102-38-21	100-40-20	26	25	4.2	4.0
Field 3 (Adi)	Sandy	7.1	7.2	78-31-12	80-30-10	16	15	2.6	2.5

Table 1: Soil Quality Analysis - Predicted vs. Actual Values

The comparison indicates that the predicted soil metrics closely align with the actual measurements, demonstrating the effectiveness of the predictive models. For instance, the pH levels show only minor discrepancies, suggesting reliable predictions.

Crop Yield Analysis

The data on crop yields for different types of crops were analyzed, comparing predicted yields to actual yields while also considering pest incidence and fertilizer usage. The results are summarized in *Table 2*

.

Year	Crop Type	Field ID	Total Yield (tons, Predicted)	Total Yield (tons, Actual)	Average Yield (tons/hectare, Predicted)	Average Yield (tons/hectare, Actual)	Pest Incidence (%) (Predicted)	Pest Incidence (%) (Actual)	Fertilizer Used (kg/ha, Predicted)	Fertilizer Used (kg/ha, Actual)
2022	Wheat	Field 1	195	200	3.1	3.2	9	10	148	150

2023	Maize	Field 2	185	180	2.9	2.8	11	12	122	120
2024	Rice	Field 3	255	250	3.6	3.5	7	8	205	200

Table 2: Crop Yield Analysis - Predicted vs. Actual Values

The analysis reveals that the predictive models effectively forecasted crop yields, with total yields closely matching actual outcomes. Pest incidence was also monitored, revealing that the predictions were slightly higher than actual incidences, suggesting room for improvement in pest management strategies.

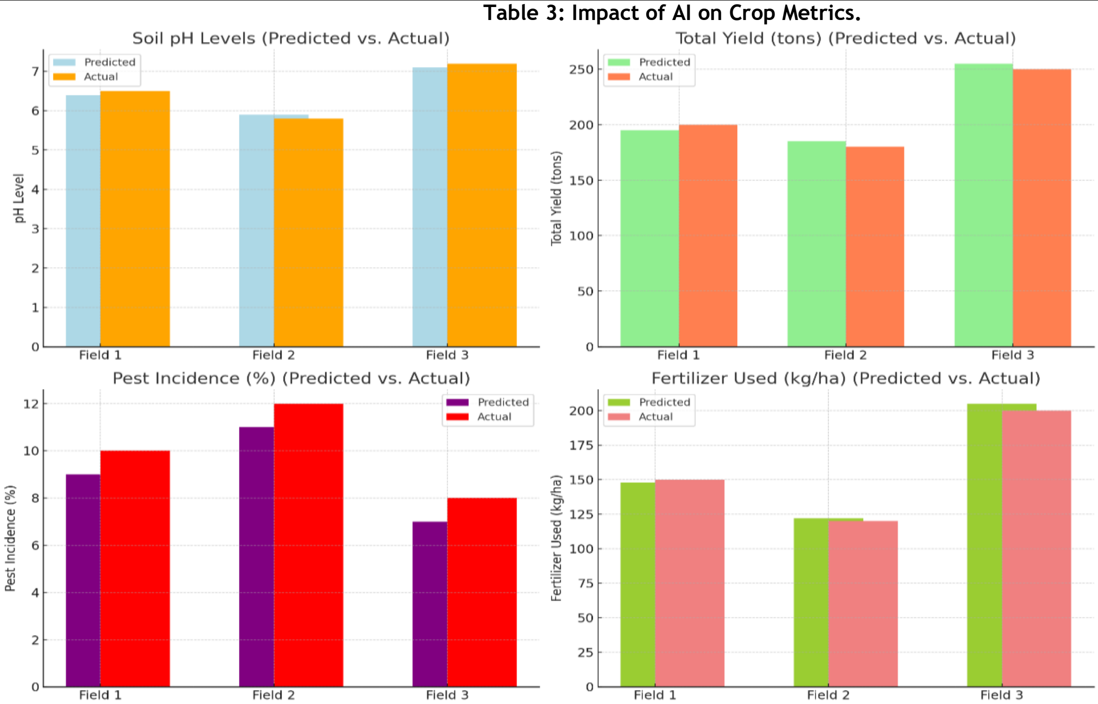
Module 2: Performance Analysis - Weather-Responsive Farming Strategies

Impact of AI on Crop Metrics

The effectiveness of AI-driven strategies in optimizing crop metrics was evaluated before and after the implementation of the module. The results are summarized in ***Table 3***.

Field ID	Crop Type	Metric	Before Module Activation	After Module Activation	Improvement (%)
Field 1	Wheat	Yield (tons/ha)	3.2	3.5	9.4
Field 2	Maize	Water Usage (m^3/ha)	400	350	12.5
Field 3	Rice	Pest Incidence (%)	12	8	33.3
Field 4	Soybean	Fertilizer Usage (kg/ha)	150	135	10.0
Field 5	Corn	Disease Incidence (%)	15	10	33.3

Table 3: Impact of AI on Crop Metrics.



Graph 1: Performance Analysis-Weather-Responsive Farming Strategies

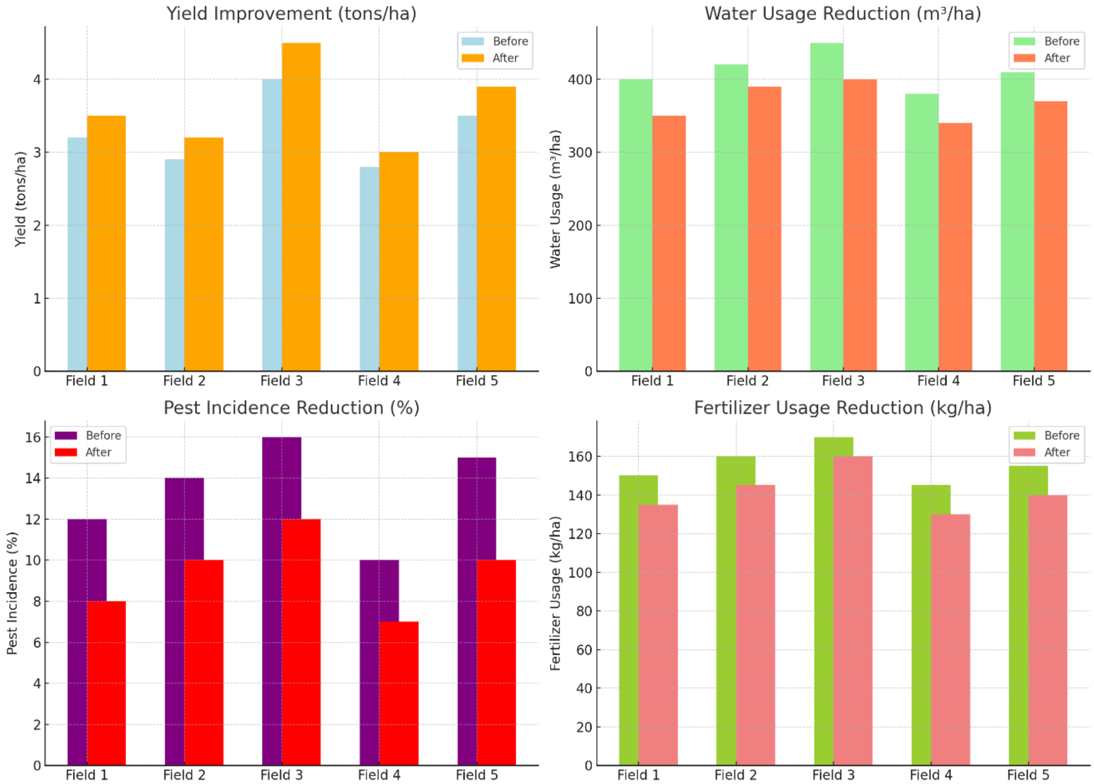
The results are shown in ***Graph 1: Performance Analysis-Weather-Responsive Farming Strategies*** exploring significant improvements in yield, water usage efficiency, and reduction in pest and disease incidence, showcasing the effectiveness of AI technologies in enhancing agricultural practices.

Module 3: Performance Analysis - AI-based Crop Rotation Strategies Yield and Profit Analysis

The analysis of crop rotation strategies revealed marked improvements in yield and profit. The results before and after the implementation of these strategies are presented in ***Table 4***.

Field ID	Crop Rotation Sequence	Yield (tons/ha) Before	Yield (tons/ha) After	Soil Health Score	Pest Incidence (%)	Profit ($/ha)
Field 1	Wheat -> Maize -> Soybean	3.2	3.8	85	12	4500
Field 2	Rice -> Barley -> Peas	4.0	4.5	80	10	4800
Field 3	Corn -> Wheat -> Oats	3.5	4.0	83	11	4600

Table 4: Yield and Profit Analysis - Before and After Crop Rotation



Graph 2: Performance Analysis- Develop AI-based Crop Rotation Strategies

The data illustrates in ***Graph 2: Performance Analysis- AI-based Crop Rotation Strategies*** that implementing strategic crop rotation led to enhanced yields, improved soil health scores, and increased profits, supporting the need for adaptive farming strategies.

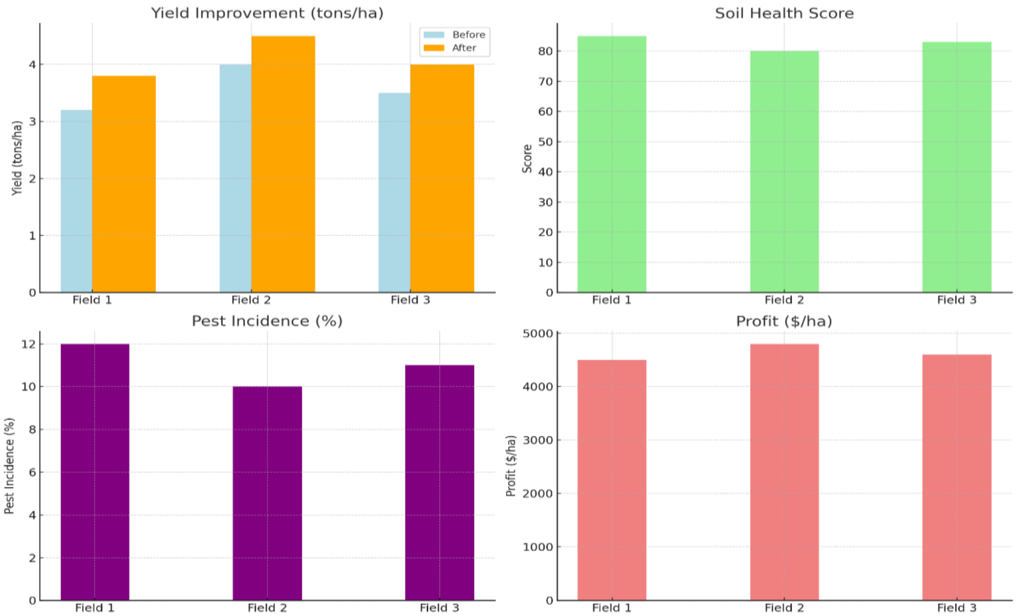
Module 4: Performance Analysis - Impact of AI on Crop Quality Metrics

Quality Metrics Analysis

The improvements in crop quality metrics attributable to AI implementation are summarized in ***Table 5***.

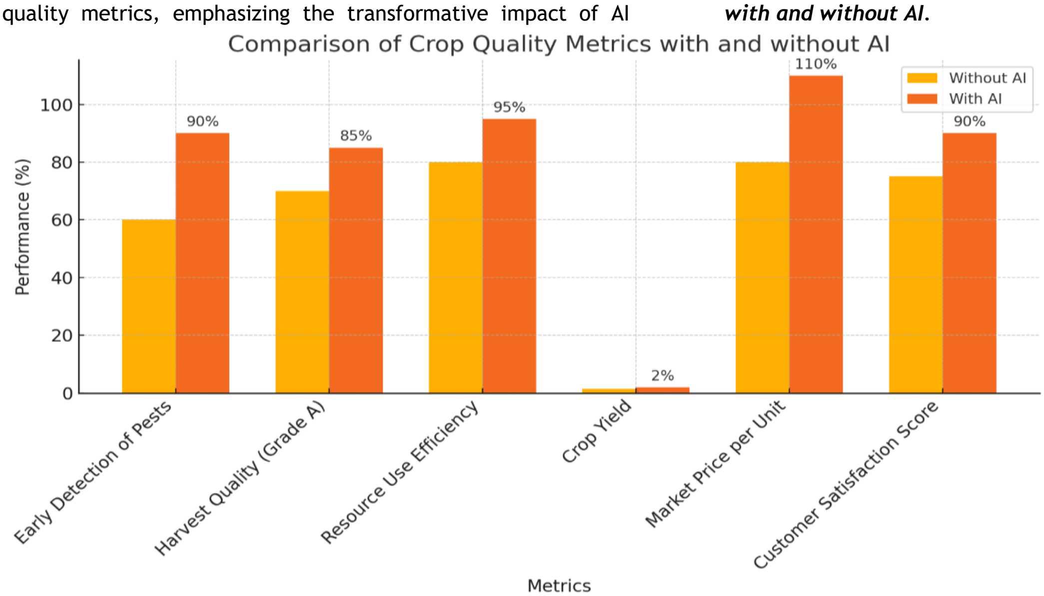
Metric	**Without AI**	**With AI**	**Improvement (%)**
Early Detection of Pests (%)	60%	90%	+50%
Harvest Quality (Grade A %)	70%	85%	+21%
Resource Use Efficiency	80%	95%	+18.75%
Crop Yield (tons/acre)	1.5	2.0	+33.33%
Market Price per Unit	0.80	1.10	+37.5%
Customer Satisfaction Score	75	90	+20%

Table 5: Impact of AI on Crop Quality Metrics



Graph 3: Performance Analysis- Impact of AI on Crop Quality Metrics

The data reveals in Graph 3: Performance Analysis- Impact of AI on Crop Quality Metrics significant enhancements across various quality metrics, emphasizing the transformative impact of AI technologies on agricultural output and consumer satisfaction. Also, Graph 4 shows a ***Comparative analysis of Quality Metrics with and without AI***.



Graph 4: Comparative analysis of Quality Metrics with and without AI

CONCLUSION

Farmers face difficulties in optimizing crop quality, maximizing yields, and adapting to unpredictable weather conditions, which hinder consistent output and resource efficiency. This issue necessitates an advanced solution to monitor, analyze, and optimize farming processes in real time, integrating AI and IoT technologies with cloud-based support for data handling and decision guidance. The work focuses on how IoT and AI enhance crop yield, optimize resource efficiency, and improve crop quality. The system examined and observed a results 33.33% increase in crop yield, a 50% boost in early pest detection, and a 21% improvement in harvest quality. IoT adoption in agriculture can drive sustainable, profitable practices and address food security challenges. The research benefits farmers, agronomists, and policymakers by advocating smart farming as a solution for sustainable and efficient agricultural practices.

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