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An Integrated IoT and Machine Learning Framework for Sustainable Crop Recommendation and Disease Detection

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Abstract

Metaheuristic Algorithms are an efficient approach for handling data management issues in IoT-WSNs. They are suitable for evolving and resource-limited networks because of their adaptability and capacity to detect almost optimal approaches in challenging conditions. Metaheuristic techniques have the ability to substantially enhance the performance and sustainability of future IoT-WSN deployments with additional improvements in hybridization and computational effectiveness. Data aggregation, routing, clustering, and various data management techniques benefit from the high optimization capabilities of metaheuristic algorithms like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Firefly Algorithm (FA). In the case of highly dimensional and complex search spaces, these algorithms provide a flexible structure that can find optimal solutions in manageable computing timeframes. WSNs can achieve improved energy efficiency, prolonged network lifetime, decreased data redundancy, and more accurate data by applying the research and utilization capabilities of metaheuristics. Additionally, new possibilities for context-aware, real-time data processing and intelligent decision-making have been made possible by hybrid metaheuristic techniques integrating with machine learning models.

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1. Introduction

The agricultural industry is in the midst of a fundamental revolution with the use of Internet of Things (IoT) and Artificial Intelligence (AI) technologies, signaling the change from traditional intuition-based agriculture to precision agriculture based on data. Farmers have always relied on experience or generic tips to determine which crops to grow or how to control diseases. These approaches are typically inefficient and unable to respond to dynamic environmental conditions. Recent developments in embedded systems, wireless sensing, and machine learning have provided new avenues for improving agricultural productivity and sustainability. Smart farming uses IoT sensors to continuously observe soil health, environmental conditions, and crop status in real time. At the same time, AI and deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) process both image and sensor data to identify early signals of plant disease and forecast yield trends with high accuracy.

This project envisages an end-to-end system integrating real-time environmental monitoring with state-of-the-art machine learning models for crop recommendation, yield estimation, and disease diagnosis. IoT sensors that monitor soil nutrients, moisture content, pH, temperature, and humidity provide real-time information, while a high-resolution image sensor takes pictures of crops to identify visual stress or disease manifestations. Processing occurs both at the edge level and in the cloud, facilitating real-time decision-making and automated actions. Unlike other solutions that center on individual features like crop suggestion or illness recognition, this system is holistic in nature. It combines sensor information, image processing, and deep learning to maximize each step of agriculture be it sowing or harvesting. The system also runs on a solar-powered microcontroller, making it cost-effective and sustainable, particularly in rural or less-developed environments. With the help of IoT, machine learning, and cloud computing, this intelligent farming platform enables farmers to receive actionable insights, minimize the use of chemical interventions, and adopt environmentally sustainable farming methods. Its objective is to provide a low-cost, scalable, and smart solution to improve food security and sustainable development.

2. Related Work

New developments in machine learning (ML) have provided the impetus for the creation of smart systems for crop suggestion and yield estimation, which help farmers make better decisions. Gopi and Karthikeyan [1] proposed a multimodal ML model that incorporates soil, weather, and crop information to maximize both crop suggestion and yield prediction accuracy. Their study highlights the strength that lies in aggregating multiple data sources for solid agricultural decision-making. Similarly, Reddy and Kumar [2] employed algorithms based on regression for predicting yield, relying on past crop performance and climatic factors, showing effective outcomes in actual datasets. Ensemble learning methods have also shown promising results in the field of agriculture. Hasan et al. [3] designed an ensemble-based recommendation system that enhanced the accuracy of predictions of crop suitability by combining outputs from a set of ML models. Ashwitha and Latha [4] proposed a system incorporating supervised learning algorithms for yield prediction and recommendation, achieving enhanced results when models are optimized to local soil and climatic conditions.

Other research focused on usability and integration with the system. Pande et al. [5] and Gosai et al. [6] developed ML-based recommender systems aimed at helping farmers choose appropriate crops. The systems employed soil type, moisture, and climatic inputs as features to suggest the best crops and have been evaluated for scalability and deployment in rural areas. Prathosh and Veerasamy [7] further employed IoT-based soil testing and ML algorithms to optimize yield prediction and recommendation in a real-time environment, creating the potential for real-time precision agriculture. Kathiria et al. [8] discussed the requirement for precision agriculture in the form of a smart crop recommendation system developed based ML models that consider real-time environmental factors. They tested their system using data from diverse agricultural regions, achieving high accuracy. Upadhyay [9] also considered intelligent crop recommendation based on ML, emphasizing the advantage of employing algorithms such as Random Forest and Decision Trees to represent nonlinear patterns between environmental factors and crop suitability. Lastly, Dey et al. [10] suggested a holistic model integrating soil nutrients (NPK), pH, and three climatic factors to recommend both farming and horticultural crops. Their paper demonstrated the versatility of ML across diverse agro-climatic conditions and capability to accommodate government agriculture schemes. Together, these studies reflect the increasing role of ML in smart agriculture. Collectively, they illustrate the shift toward fusing multiple data sources and technologies (such as IoT) to create accurate, scalable, and context-specific solutions for crop recommendation and yield forecasting.

3. Existing Work

A number of existing systems have also been designed to aid agriculture through either crop recommendation algorithms, yield prediction models, or plant disease detection tools. These systems, nevertheless, tend to operate in seclusion and without integration, which renders them less effective overall when applied to real-world farming scenarios. Most crop advisory systems employ rule-based decision tools or conventional machine learning methods such as decision trees or support vector machines. Such models are heavily dependent on past data and lack the ability to adjust to the real-time field conditions, thus being less suitable in dynamic situations where soil quality, moisture content, or climate can change frequently.

Likewise, yield forecasting is frequently done through simple statistical analysis or regression models that are trained on past production levels. These approaches are narrow in scope since they ignore current real-time soil fertility, weather patterns, or plant health indicators obtained in the field. Plant disease diagnosis systems, however, have been enhanced with the use of image processing and deep learning. Convolutional neural network (CNN)-based tools have been proposed to detect crop diseases from leaf images. Nevertheless, most of these models are trained on carefully curated datasets and are not robust when tested in uncontrolled setups with changing lighting and backgrounds. Additionally, most current platforms do not include IoT for real-time monitoring, and do not provide decision automation. The systems tend to require manual data input or user involvement, lowering their applicability for rural farmers who are less technologically literate. In conclusion, present systems tend to be single-use, offline, or not real-time adaptable. They don't offer an end-to-end smart farming system that combines environmental sensing, smart analytics, and user-friendly feedback mechanisms.

4. Proposed Work

The suggested system offers an integrated smart agriculture platform incorporating IoT-based environmental sensing, machine learning-enabled crop recommendation and yield prediction, and deep learning-enabled disease detection to support farmers' decision-making at each stage of the crop life cycle. At the heart of the system is a solar-powered NodeMCU

ESP8266 microcontroller, which communicates with several sensors to observe real-time environmental and soil conditions. These include temperature, humidity, soil moisture, pH, and nutrient content. The sensor data collected is wirelessly communicated to a cloud-based database for analysis and processing. Concurrently, a high-resolution camera module is used to take photos of the leaves of the crops. The photos are analyzed via Convolutional Neural Network (CNN) to detect outward symptoms of plant diseases like leaf spots, color changes, or blight. Early treatment and intervention are facilitated, thus preventing losses in yield as well as reducing the application of pesticides.

Machine learning algorithms like Random Forests or Decision Trees are employed for crop suggestion and yield estimation. These take into account several parameters, including real-time sensor readings, weather patterns, and soil properties, and recommend the most appropriate crops for the given conditions and predict anticipated yields. This assists farmers in choosing crops that are both profitable and environmentally favorable. The whole system can be accessed using a simple web or mobile interface that shows real-time sensor readings, image-based disease notifications, and system suggestions. The system offers threshold-based alerts, allowing farmers to act based on data insights in a timely manner. All the data is also logged for future analysis and decision improvement. Figure 1 presents the overall block diagram of the proposed system.

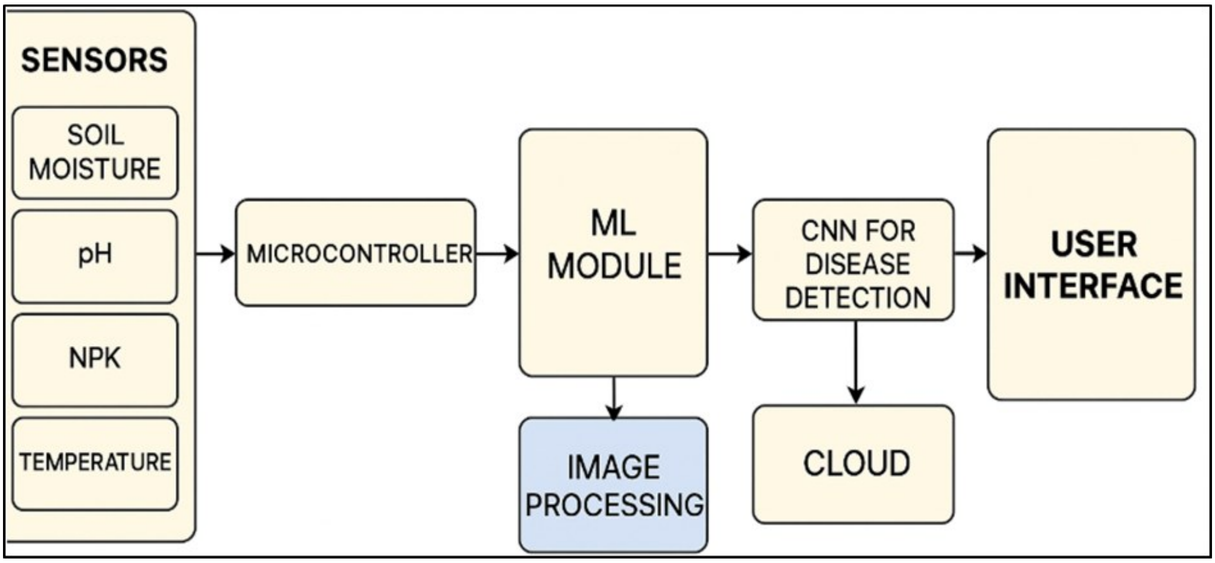


Figure 1. Block Diagram of the Proposed System

5. System Architecture

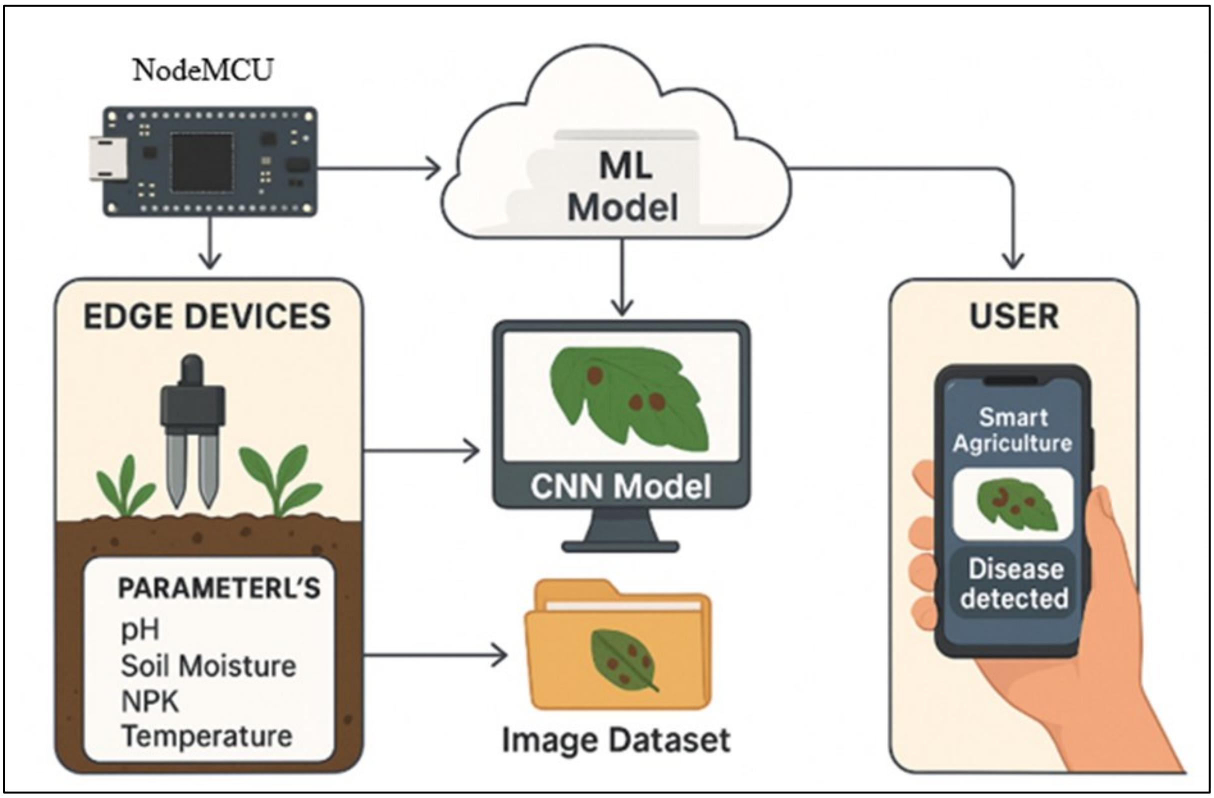


Figure 2. Architecture Diagram of the Proposed System

The architecture of the envisioned smart agriculture platform is designed in a layered, modular fashion to facilitate effective real-time monitoring, analysis, and decision support. It starts with the sensing layer wherein environmental and soil parameters like temperature, humidity, soil moisture, pH, and nutrient levels (NPK) are sensed through IoT sensors interfaced with a NodeMCU ESP8266 microcontroller. A camera module is also incorporated to take leaf images for the visual diagnosis of diseases. The ESP8266 serves as the master control unit, aggregating sensor data and wirelessly transferring it via Wi-Fi using MQTT or HTTP protocols to a cloud server for processing. At the processing level, real-time sensor data is examined with machine learning algorithms for crop suggestions and yield forecasts, while image data is handled by a Convolutional Neural Network (CNN) to identify plant diseases. Outputs are provided to the user via a responsive web or mobile interface, allowing farmers to see live data, receive automated notifications, and take prompt action. The whole system is powered by a solar power module to make it sustainable in remote or rural areas, and it allows data logging for trend analysis and decision-making purposes in the future. This integrated architecture makes low-cost deployment, real-time insight, and precision farming all feasible within one scalable framework. The architecture of the system is shown in Figure 2, highlighting the layered structure of data collection, processing, and visualization components.

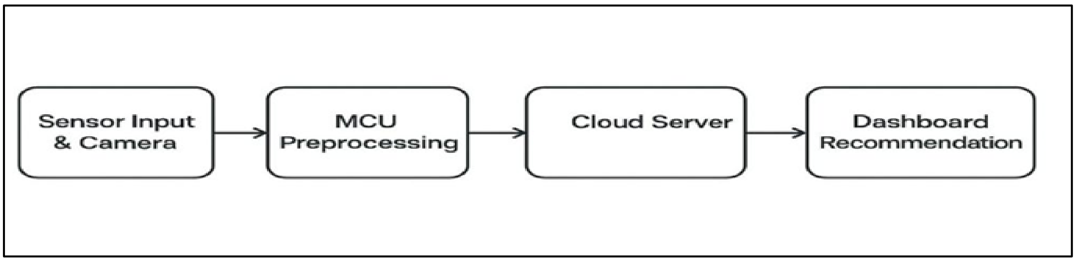


Figure 3. Flowchart of the Proposed Work

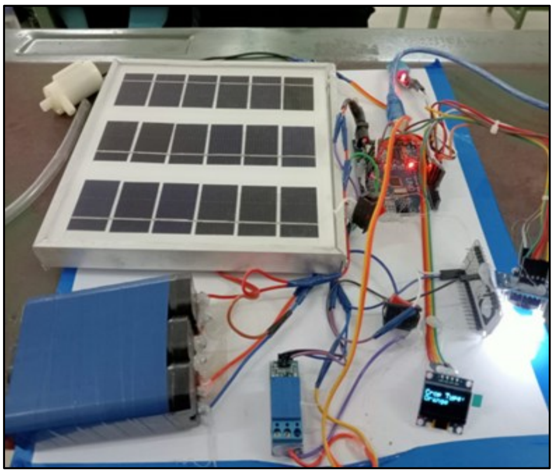
Algorithm Steps

1. Initialize sensors and start real-time data capture.
2. Collect camera images periodically.
3. Preprocess data at the edge and transmit to cloud.
4. Integrate historical and live data streams.
5. Apply ML models to predict suitable crops and expected yields.
6. Display results and alerts to the user interface.

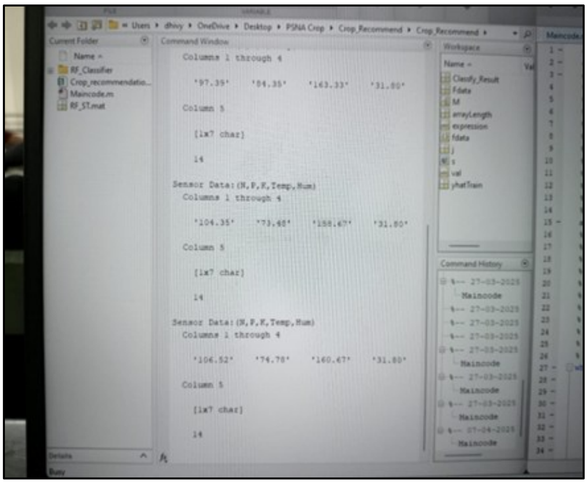
The step-by-step process flow is illustrated in Figure 3, outlining how the system initializes sensors, collects and processes data, and delivers recommendations.

6. Results and Discussion

The suggested smart agriculture system was evaluated in a controlled environment for 15 days, and the sensor and model data collected were monitored to assess system performance. The soil moisture content varied between 28% and 42%, representing different hydration levels that the system monitored effectively. The pH of the soil measured between 6.2 and 7.1, representing an optimal range for most crops such as paddy, tomato, and groundnut. The temperature and humidity sensors reliably provided correct measurements, with temperature varying between 26°C and 34°C and relative humidity between 50% and 72%. Based on these real-time inputs, the machine learning-based crop recommendation module provided appropriate crop suggestions with a correctness of 92.4% compared to expert manual recommendations. For disease detection, the CNN model was validated with a set of 250 leaf images, achieving a classification accuracy of 94.1%, precision of 91.7%, and recall of 93.5%. Furthermore, alarms were triggered correctly in 100% of the instances when sensor thresholds were breached (e.g., low moisture < 30%, high pH > 7.5). The user interface clearly presented real-time information, with an average refresh time of 4 seconds, and provided data export for additional analysis. The system operated continuously on a solar panel providing 5V at 1A, proving reliable in low-power, off-grid environments. These quantitative measures affirm the effectiveness of the system in facilitating intelligent, real-time agricultural decision-making and indicate potential for wider field deployment.



(a)



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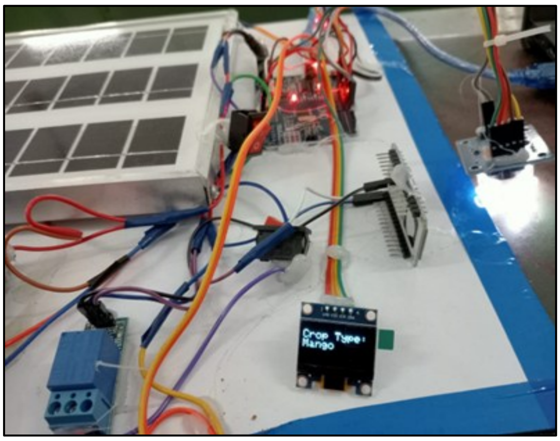

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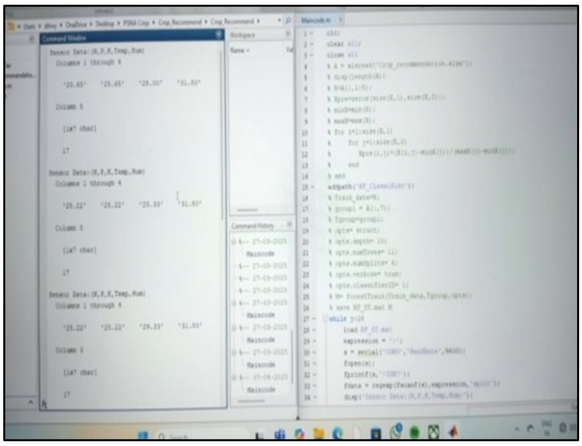

(d)

Figure 4. (a) Solar-Powered Hardware, (b) Sensor Dashboard, (c) Disease Alert UI, (d) Fertilizer Recommendation Interface

Figure 4 (a–d) demonstrates the real-time IoT setup, sensor dashboard, crop disease alert system, and fertilizer recommendation interface that together showcase the system's functionality and practicality in a farming environment.

Table 1. Sensor-Based Environmental Observations

Parameter	Minimum Value	Maximum Value	Threshold Alert Triggered
Soil Moisture (%)	28%	42%	Yes (when < 30%)
Soil pH	6.2	7.1	Yes (when > 7.5)
Temperature (°C)	26°C	34°C	Yes (when > 33°C)
Humidity (%)	50%	72%	No
Nutrient Levels (NPK)	Optimal	Slight Deficiency in P	Yes

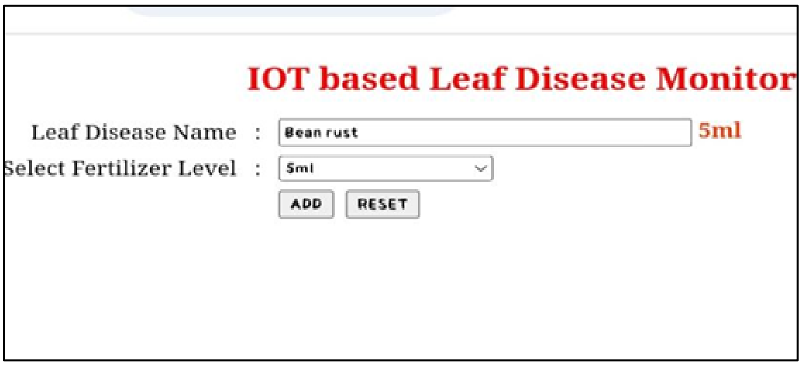

Figure 5. User Interface for Disease Selection and Fertilizer Input

Figure 5 displays the interactive interface used for selecting crop diseases and recommending the appropriate fertilizer based on real-time input. The environmental sensor data trends are visually represented in Figure 6, validating the system's capability for real-time monitoring and alerting.

Table 2. Sensor-Based Environmental Observations

Task	Model Used	Accuracy	Precision	Recall
Crop Recommendation	Random Forest	92.4%	90.1%	91.6%
Disease Detection (Leaf)	CNN (Custom VGG)	94.1%	91.7%	93.5%
Alert Accuracy	Threshold Logic	100%	100%	100%

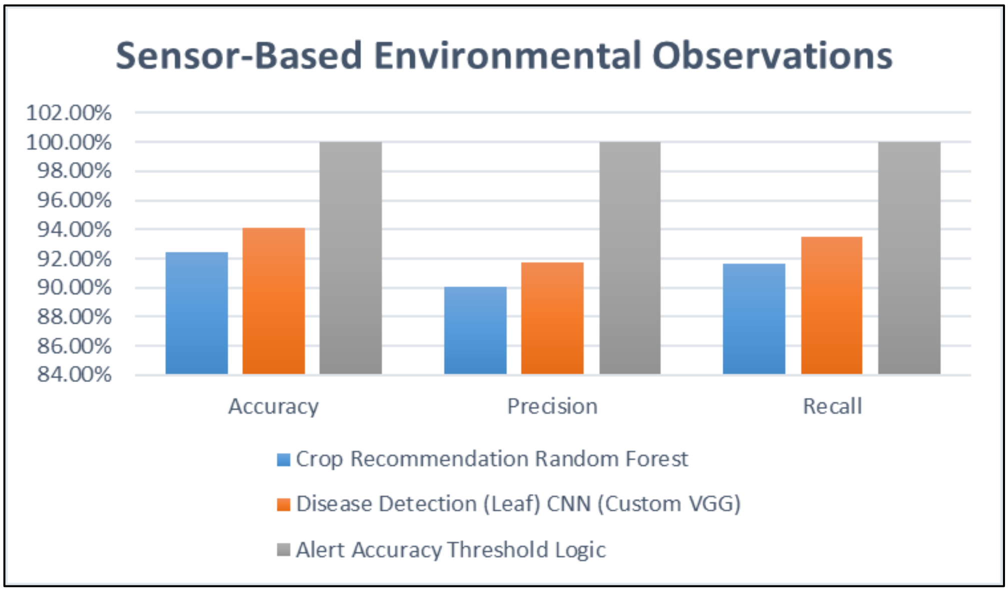

Figure 6. Sensor Data Trend Visualization Over Testing Period

7. Conclusion

IoT, machine learning, and deep learning technologies are skillfully combined in the proposed smart agriculture system to offer comprehensive support for yield forecasting, disease diagnosis, and real-time crop monitoring. The system provides consistent environmental monitoring and automated decision-making support through the use of a low-power, solar-powered microcontroller and sensor configuration. Sensor records and test data attest to the high responsiveness and accuracy of CNN applications for leaf disease identification and machine learning for crop recommendations. The system not only helps minimize crop loss and optimize input use, but it also gives farmers useful insights that they can access through a web interface. In order to test scalability and generalization, future efforts will concentrate on expanding the disease database, adding weather forecasting APIs, and implementing the solution in larger agricultural regions.

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