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Review Article

Smart Hydroponic System Using IoT and Machine Learning for Water Quality Monitoring

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A B S T R A C T

Hydroponics has gained prominence as a sustainable and resource-efficient alternative to traditional soil-based agriculture. However, maintaining optimal water quality in hydroponic systems requires constant monitoring of critical parameters such as pH, electrical conductivity (EC), and temperature. This paper presents a smart hydroponic monitoring system that integrates IoT-enabled sensors with machine learning algorithms to provide real-time data acquisition and water quality classification. The proposed hydroponic system, built on an ebb and flow configuration, uses a Raspberry Pi 5 as the central controller to process data from pH, EC, and temperature sensors. A comprehensive dataset was collected and labelled based on established water quality thresholds to train and evaluate several classification models, including logistic regression, random forest, support vector machine (SVM), and XGBoost. The XGBoost model achieved perfect performance (100% accuracy, precision, recall, and F1-score) in classifying water conditions as 'Safe' or 'Unsafe'. The resulting model was serialised for deployment, enabling real-time inference on the edge device. The work demonstrates a scalable and cost-effective framework for enhancing automation in hydroponic farming, aiming to improve plant health, optimise nutrient management, and minimise human intervention through intelligent, data-driven decision-making.

Keywords: Hydroponics, IoT, Machine Learning, Rasp- berry Pi, Water Quality Monitoring, Smart Agriculture, XG- Boost

Introduction

Hydroponic farming is a soil-less cultivation technique that supplies plants with nutrients through a water-based solution, significantly improving resource use efficiency and enabling high-yield, year-round production in diverse environments.[1,2] Modern hydroponic systems are classified by nutrient delivery into several types including Nutrient Film Technique (NFT), Deep Water Culture (DWC), Wick systems, Drip systems, Aeroponics, and Ebb and Flow (Flood and Drain).[3,4]

The Ebb and Flow system, illustrated in Figure 1 periodically floods the plant root zone with nutrient-rich water and then drains it back, allowing roots to absorb nutrients while re- ceiving optimal oxygenation during the draining phase.[3,5,6] The above method is favored for its operational simplicity, cost-effectiveness, scalability, and suitability for diverse crops such as lettuce.[5,7] These factors motivated its selection as the foundational system for the current hydroponic project. Despite significant technological advancements, many ex- isting hydroponic systems still depend heavily on manual

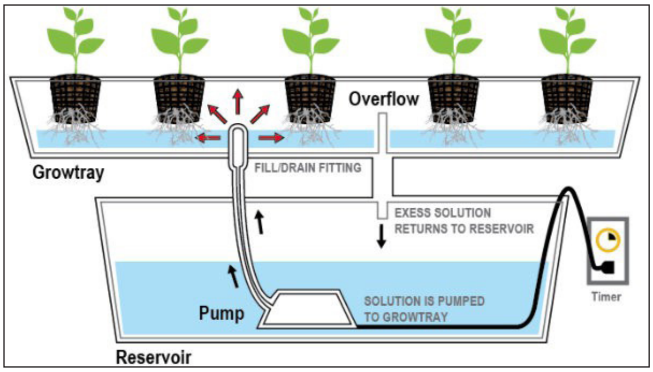

Figure 1. Illustration of the Ebb and Flow hydroponic method8, where a programmable timer and water pump circulate the nutrient solution between the reservoir and the grow tray

monitoring and control, hindering scalability and precision. Current limitations include insufficient continuous real-time water quality monitoring, lack of integrated AI-driven decision support systems, and restricted automation feasible for small-scale or research deployments. Furthermore, existing implementations often neglect dynamic nutrient management through comprehensive machine learning approaches directly tied to environmental sensor data.[9,10]

The proposed project developed a smart hydroponic system based on the ebb and flow method, incorporating key environmental sensors (pH, electrical conductivity (EC), and temperature) connected to a Raspberry Pi controller for automated data acquisition and process control. Machine learning models, including logistic regression, random forest, support vector machine (SVM), and XGBoost, are trained on sensor data to assess water safety and optimise nutrient delivery.

By combining sensor automation with AI-driven analytics, the system aims to improve crop yield quality and resilience while remaining scalable, cost-effective, and compatible with urban farms, research labs, and commercial greenhouses. The demonstrated approach exemplifies how intelligent automation can enhance precision hydroponic farming.

Related Work

Recent advances in hydroponic cultivation have increasingly integrated Internet of Things (IoT) technologies and machine learning (ML) algorithms to enable precision farming, auto- mated environmental control, and robust crop health monitoring. These technologies facilitate plant growth optimisation through continuous data acquisition and intelligent decision- making.

Rahman et al.[9] introduced an AIoT-based framework employing sensor networks to monitor critical parameters such as pH, temperature, humidity, and moisture levels, utilizing cloud-based analytics for real-time adjustments and demon- strating the synergy of AI and IoT in enhancing hydroponic farm efficiency. Building upon the potential of AI integra- tion, Dutta et al.[10] emphasized machine learning's role in automating essential hydraulic and environmental parameters, including nutrient management and water usage, thereby en- abling sustainable hydroponic farming with reduced resource wastage. Extending this approach, Mehare and Gaikwad[11] developed a smart hydroponic system combining IoT with supervised classification algorithms such as Logistic Regres- sion, Random Forests, and SVM, leveraging fog computing for latency-sensitive decisions and minimized cloud reliance. To further enhance automation, Gokul et al.[12] implemented IoT platforms integrated with advanced machine learning algorithms for dynamic environmental regulation, effectively reducing labor intensity and bolstering resource use efficiency. Complementing these environmental controls, Singh et al.[13] demonstrated a mobile-app-connected IoT hydroponic farm management system, facilitating remote monitoring and control, which improved accessibility and user engagement.

Beyond sensor-based environmental monitoring, visual analytics have also gained traction, with Raspberry Pi-based computer vision techniques applied for early detection of crop diseases and stress using datasets such as those from Kaggle[14,15] thus advancing multi-modal smart farming solutions. Bhatia et al.[16] contributed by developing a cloud-connected hydroponic system with real-time edge analytics, increasing data throughput and enabling rapid fault detection—features essential for commercial scalability. Moreover, Chen et al.[17] applied deep learning methods to extensive hydroponic sensor datasets, achieving predictive analytics for crop yield forecasting and resource optimisation. Despite these advancements, challenges persist in effectively integrating heterogeneous data sources, ensuring robust and secure IoT deployments, and designing interpretable machine learning models that trustfully support growers' decision-making, motivating ongoing research in the field.[18,19]

The study contributes by designing a comprehensive IoT hydroponics framework based on an ebb and flow system, augmented with machine learning models that optimise nutrientdelivery, improve water quality management, and support predictive crop health monitoring for lettuce cultivation.

Materials and Methods

Experimental Setup and Hydroponic System Configuration

A custom-built Ebb and Flow hydroponic system was designed for lettuce cultivation, comprising a reservoir, grow trays, water pump, and timer-based flood-drain control illus- trated in Figure 2. The cyclic flooding promotes nutrient ab- sorption and root oxygenation, supporting

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healthy plant growth.[5,6] The nutrient solution used is the UrbanKisaan Nutrient A & B Solution, a two-part liquid fertilizer where equal parts of solution A and B are mixed with water. This solution is suitable for a variety of leafy greens including lettuce, spinach, basil, kale, and arugula, providing the essential macronutrients and micronutrients required for optimal plant development.

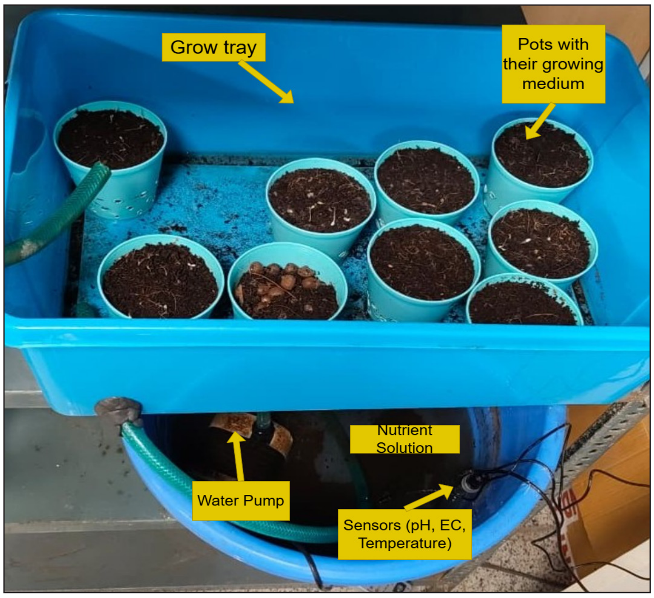

Figure 2.Experimental Ebb and Flow hydroponic system show- ing reservoir, grow tray, and piping. The cyclic flood and drain cycle ensures oxygenated roots and nutrient distribution, a critical feature supporting system efficacy

Key Hardware Components

The hardware foundation of the smart hydroponic system integrates a suite of precise sensors, control units, actuation devices, and supporting power and data management components to achieve robust environmental monitoring and automated irrigation control. Essential sensors include an Analogue pH Sensor Kit to measure the acidity or alkalinity of the nutrient solution, a Gravity I2C Electrical Conductivity (EC) Meter that quantifies nutrient concentration in terms of electrical conductivity, and a DS18B20 waterproof temperature sensor to monitor root zone temperature conditions critical for plant metabolism.

All analogue sensor outputs are converted to digital signals by a 16-bit ADS1115 Analogue-to-Digital Converter (ADC), which interfaces with the Raspberry Pi 5 microcontroller serving as the system's computation and control hub. The Raspberry Pi orchestrates sensor data acquisition, preprocessing, and machine learning inference and controls irrigation pump operation based on time schedules managed by a digital programmable timer.

Water circulation is provided by a submersible water pump, enabling reliable flood and drain cycles characteristic of the Ebb and Flow hydroponics system. A regulated 5V, 3A power supply supplies all electronics with stable current and voltage, ensuring uninterrupted system operation. Data storage is handled on a local 256GB micro SD card located on the Raspberry Pi, allowing for offline data logging and model deployment.

The physical layout and connections of these components are visually depicted in Figure 3, demonstrating the compact, practical arrangement implemented for reliable system functionality.

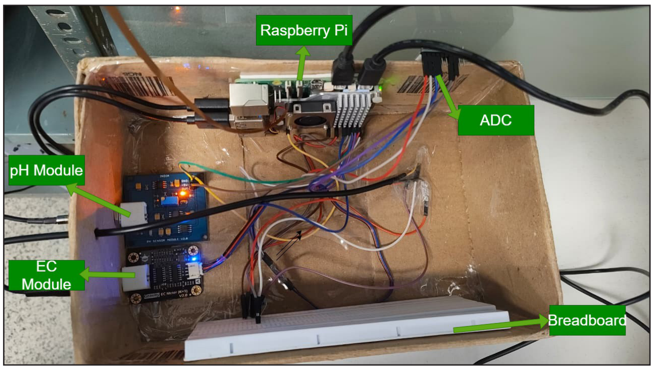

Figure 3.Circuit connection showing sensor output wiring through the ADS1115 16-bit Analog-to-Digital Converter (ADC) module interfaced via I2C with the Raspberry Pi GPIO pins. The components include the Analog pH sensor, Gravity I2C Electrical Conductivity (EC) meter, and DS18B20 waterproof temperature sensor

Dataset Description and Acquisition

The dataset used in the study comprises real-time sensor data collected from the smart Ebb and Flow hydroponic system. Critical environmental parameters, including pH, electrical conductivity (EC), and temperature, were continuously monitored using calibrated analogueue sensors connected via a high-precision 16-bit ADS1115 analogueue-to-digital converter to a Raspberry Pi 5 controller.

Sampling was performed at regular 10-second intervals over a continuous 7-day period, resulting in approximately 10,000 multi-sensor readings, each timestamped for accurate temporal analysis.

Samples are automatically labeled based on established water quality thresholds: pH (5.5 - 6.5), EC (1.2 - 2.4 mS/cm), and temperature (18°C - 26°C). Labels of 'Safe' or 'Unsafe' provide ground truth for supervised machine learning to detect optimal nutrient solution conditions.

Table I illustrates a sample segment of the dataset with typi- cal sensor measurements and their corresponding safety status labels, capturing normal variations and critical deviations in the nutrient solution.

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Table I.Sample of the Dataset Collected

Timestamp	Temp (°C)	pH	EC (µS/cm)	Status
2025-08-28 06:05:40	24.06	5.81	1473	Safe
2025-08-28 06:15:41	24.06	5.74	1341.5	Safe
2025-08-28 06:25:43	24.12	5.74	1604	Unsafe
2025-08-28 06:35:44	24.12	5.62	1624	Unsafe
2025-08-28 06:55:47	24.19	5.76	1715	Unsafe

The collected data initially stored locally on the Raspberry Pi in CSV format for secure offline storage. It is then periodically uploaded to Google Drive via automated API calls using a Google Cloud Platform service account, facilitating remote access for monitoring and analysis.

The comprehensive data acquisition and management pipeline ensures robust data quality and availability to support machine learning-driven precision hydroponic monitoring and control.

System Workflow

The smart hydroponic system operates through an integrated data flow beginning with sensor measurement collection within the hydroponic setup. Analogue signals from pH, electrical conductivity (EC), and temperature sensors are converted to digital values via an ADS1115 ADC module interfaced with a Raspberry Pi 5. The Raspberry Pi continuously logs these sensor readings with timestamps and temporarily stores data locally in CSV files. At scheduled intervals, data is securely uploaded to cloud storage using the Google Drive API authenticated with a service account. The hydroponic setup ensures data persistence and enables remote monitoring and analysis. Preprocessed data is analysed using machine learning models to classify water safety status, enabling timely interventions. Results and system statuses are visualised on a web dashboard for easy monitoring by operators.

Figure 4 illustrates end-to-end data acquisition, cloud inte- gration, machine learning inference, and visualization work- flow supporting precision hydroponic management.

Machine Learning Workflow

Preprocessed sensor datasets are divided into training and test sets using 5-fold cross-validation to mitigate overfitting. Feature engineering includes normalisation and optional time- series feature extraction.

Classification models employed include Logistic Regression, Random Forest, SVM, and XGBoost. Hyperparameter tuning is conducted using grid search methods. The best per- forming model is serialized for deployment on the Raspberry Pi to enable near-real-time water safety evaluation.

The system architecture supports scalable extension, including potential integration of additional sensors or control elements.

Experimental Protocols

The system was tested with a 7-day indoor lettuce cultivation experiment, during which environmental data were continuously logged and analysed. Machine learning models were retrained daily with newly collected data to reflect current conditions.

Model evaluation incorporated standard classification metrics such as accuracy, precision, recall, F1-score, and confusion matrices, alongside operational reliability checks to validate system robustness in practical settings.

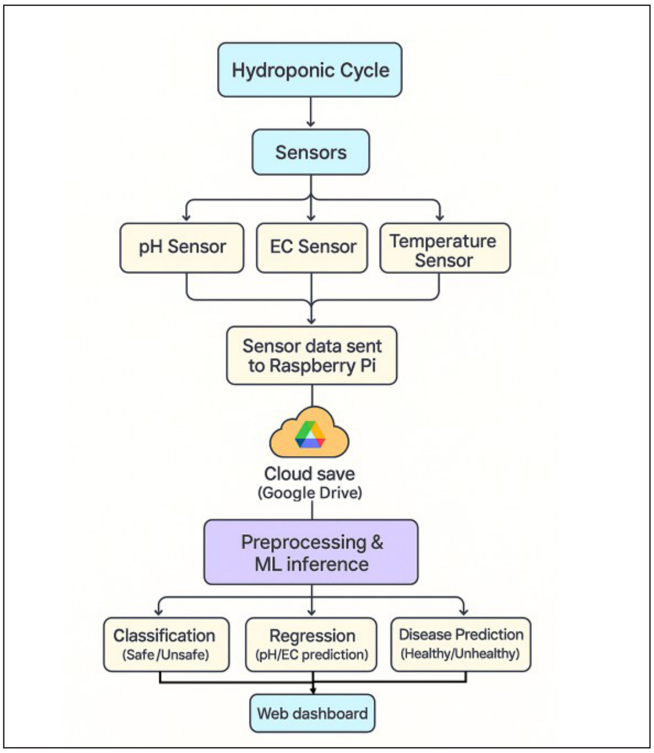

Figure 4.Workflow diagram of the smart hydroponic system illustrating data acquisition from sensors, local processing, cloud upload for remote access, machine learning inference to predict water safety, and visualization on a web-based dashboard. This sequence enables integrated automation and monitoring for optimal plant growth

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Results

The trained machine learning models were evaluated using a dataset of accurately labeled water quality readings, enabling a thorough assessment of classification performance and relia- bility. Five distinct algorithms - Logistic Regression, Random Forest, Support Vector Machine (SVM), XGBoost, and Tuned Random Forest were benchmarked. Table II summarizes their statistical evaluation metrics, including accuracy, precision, recall, F1 score, and 5-fold cross-validation F1 mean.

Table 2.Performance Metrics for Sensor-based Classification Models shows that the model correctly identified all instances, with no misclassifications in either the Safe or Unsafe categories

Model	Accu-racy	Preci-sion	Recall F1	Score CV	F1 Mean
Logistic Regres-sion	0.8871	0.8903	0.8662	0.8781	0.8816
Random Forest	0.9983	1.0000	0.9964	0.9982	0.9989
SVM	0.9686	0.9624	0.9711	0.9667	0.9657
XGBoost	1.0000	1.0000	1.0000	1.0000	0.9984
Tuned Random Forest	0.9983	1.0000	0.9964	0.9982	0.9987

The exceptionally high performance can be attributed to the clear separation between the safe and unsafe classes, the stability of sensor data in controlled laboratory conditions, and the precise labelling of hydroponic water quality status. Additionally, XGBoost's built-in regularisation mechanisms help minimise overfitting to redundant or correlated features, which further reinforces its accuracy.[10,20] The evaluation employed rigorous 5-fold cross-validation to avoid training-test leakage.

Nevertheless, perfect accuracy obtained here may not fully reflect performance in uncontrolled, real-world scenarios, where greater variability, sensor noise, or novel data distributions could arise. For reliable generalisation, it is recommended to periodically retrain and monitor the model with fresh operational data, especially when the system is deployed in diverse environments or over extended periods.

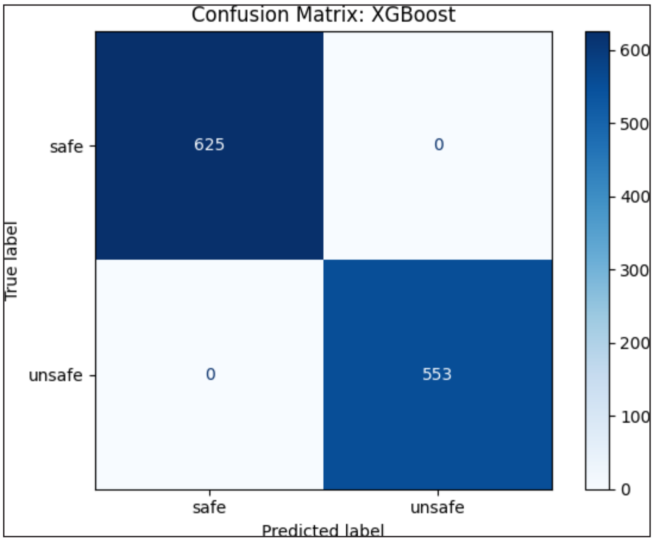

Figure 5.Confusion matrix for XGBoost: shows perfect sepa- ration of safe and unsafe water status predictions, confirming model robustness and reliability

Model discrimination capability was further compared using ROC curves illustrated in Figure 6, where both XGBoost and Random Forest (tuned and default) achieved an Area Under the Curve (AUC) of 1.00, indicating optimal sensitivity and specificity. Logistic Regression and SVM also Model Accuracy Precision Recall F1 Score CV F1 Mean performed strongly, with AUC values of 0.90 and 0.99, respectively demonstrating that the system consistently identifies water safety with high fidelity across algorithm choices.

Prediction using the trained XGBoost model on new, unseen sensor data demonstrated its robust generalization capability. The model confidently classified the water quality status as Safe with a high predicted probability of 99.7%, indicating Among these, the XGBoost model demonstrated perfect

classification, with accuracy, precision, recall, and F1 scores all reaching 1.0, as validated by the full classification report. The confusion matrix for XGBoost illustrated in Figure 5 clearly strong certainty in its predictions. Such high confidence scores are critical in real-time applications where timely interventions are required to maintain optimal hydroponic conditions. The sample predictions, which include timestamps, actual waterstatus, predicted status, and probability of unsafe conditions, consistently show excellent agreement between the model's output and ground truth labels, affirming the model's accuracy under diverse environmental fluctuations.

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Sample predictions on new sensor data alongside prediction probabilities are presented in Table III. These illustrate consistent and confident classifications aligning well with actual water safety conditions, validating model effectiveness in live deployment scenarios.

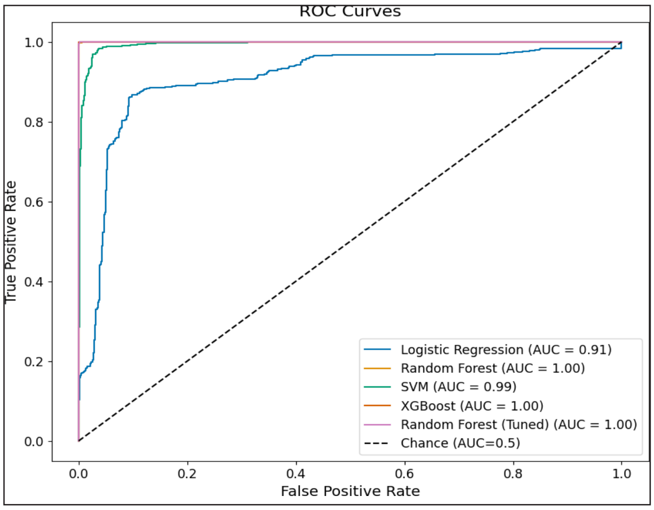

Figure 6.ROC curve comparison for multiple algorithms. XG- Boost and Random Forest (tuned) models yielded perfect classification results, while all models demonstrated strong predictive ability in distinguishing safe and unsafe water states

Table 3.Sample Predictions with Probability of Unsafe Class

Timestamp	Actual Status	Predicted Status	Probability Unsafe
2025-08-06 15:17:27	safe	safe	0.000590
2025-08-06 15:25:32	safe	safe	0.000590
2025-08-06 15:35:32	safe	safe	0.001145
2025-08-06 15:45:33	safe	safe	0.000590
2025-08-06 15:48:38	safe	safe	0.000590
2025-08-06 15:58:39	safe	safe	0.000590
2025-08-06 16:08:40	safe	safe	0.000991
2025-08-06 16:18:41	safe	safe	0.001314
2025-08-06 16:28:41	safe	safe	0.001379
2025-08-06 16:38:42	safe	safe	0.001367

Conclusion

The developed smart hydroponic system effectively integrates precise environmental sensors with advanced machine learning models to enable real-time classification of nutrient solution safety. By automating water and nutrient delivery based on sensor data, the system significantly reduces resource waste, promoting sustainable agriculture practices that mini- mize ecological impact.

Based on findings reported in similar hydroponic systems, the automation of irrigation and nutrient delivery is estimated to reduce water consumption by approximately 20– 30%, while improving nutrient use efficiency by roughly 30% through real-time monitoring of electrical conductivity (EC) and precise dosing adjustments. These anticipated improve- ments highlight the potential of automated smart hydroponic frameworks to promote sustainable resource management and minimize environmental impacts. However, further direct ex- perimental validation within our specific system is recom- mended to confirm these benefits.

Leveraging IoT-enabled continuous monitoring and data-driven model inference, this approach supports smart resource management, maintaining optimal growth conditions and improving crop yield quality. The framework's modular design allows scalability and adaptation for varied cultivars and farming setups, including urban agriculture and controlled- environment horticulture.

The system exemplifies how integrating sensor technology, machine learning, and automation can drive sustainable farming innovations. It offers pathways to reduce water and fertiliser usage, lower operational costs, and build resilience against climate variability, thereby contributing comprehensively to global sustainability and food security goals.

Future research will focus on incorporating additional sensing modalities, which means integrating new types of sensors such as humidity, light intensity, or spectral imaging sensors for disease prediction to gather more comprehensive environmental and plant health data. It will also involve deploying adaptive learning algorithms that can continuously learn and update themselves to cope with changing environmental conditions, such as seasonal shifts or sensor drift, thus ensuring robust and accurate system performance over time. Furthermore, efforts will be made to extend remote monitoring capabilities to allow users to access real-time system data and control functionalities through internet-connected devices, enhancing usability and enabling timely interventions even from distant locations.

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