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Application of IoT and Machine Learning to Control and Monitor the Wellbeing of Plants in a Green House

P. O. Ajewole[1*], E. R. Adefidipe[2], S. M. Adejumo[3]

[1]Department of Agricultural and Bio-Environmental Engineering, The Federal Polytechnic, Ado-Ekiti, Nigeria.
[2]Department of Welding and Fabrication Engineering Technology, The Federal Polytechnic, Ado-Ekiti, Nigeria
[3]Olusegun Obasanjo Centre for Engineering Innovation (OOCEI), The Federal Polytechnic Ado-Ekiti, Nigeria
*Corresponding author (Email: ajewole_po@fedpolyado.edu.ng, +2347068675164)

ABSTRACT

The increasing impact of climate variability has necessitated the development of intelligent systems for efficient greenhouse management. This study presents the design and implementation of a smart greenhouse that integrates Internet of Things (IoT) sensors with machine learning models for real-time monitoring, prediction, and control of crop health. The system comprises a greenhouse structure with frame and canopy, IoT-based environmental sensing units, a data logger, and an automated irrigation system including a water pump, overhead tank, and pipe network. Environmental data—temperature, humidity, soil moisture, CO_2 concentration, and crop growth level—were collected at 3-hour intervals between January 15 and March 13, 2026, yielding over 400 observations. Crop health was visually classified into Good, Moderate, and Bad categories and used as the target variable for supervised learning. A comparative analysis of Decision Tree, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest models was conducted. The Random Forest model achieved the highest prediction performance with an accuracy of 84.29%, precision of 84.06%, recall of 84.29%, and F1-score of 84.15%, outperforming ANN (82.10%), SVM (80.47%), and Decision Tree (78.65%). The integration of the predictive model with a rule-based irrigation system resulted in a 28% reduction in water usage compared to conventional manual irrigation, while maintaining over 84% accuracy in crop health prediction. The system enabled timely intervention in over 90% of potential plant stress conditions. Real-time monitoring and control were achieved through a mobile application dashboard. The results demonstrate significant improvements in water use efficiency, predictive accuracy, and overall greenhouse management, resource utilization, and enhancing sustainability in precision agriculture.

***Keywords*— Greenhouse, IoT, Machine Learning, Random Forest, Automated Irrigation, Precision Agriculture**

I. INTRODUCTION

The increasing global demand for food, coupled with the adverse effects of climate change, has intensified the need for innovative agricultural practices that ensure sustainable crop production. Conventional farming systems are highly vulnerable to environmental fluctuations such as temperature variability, irregular rainfall patterns, and increased atmospheric carbon dioxide (CO_2) concentrations. These challenges have significantly impacted crop yield and quality, particularly in developing countries where farming systems are predominantly climate-dependent [1], [2]. As a result, controlled environment agriculture, particularly greenhouse farming, has emerged as a viable solution for mitigating environmental uncertainties and enhancing agricultural productivity [3], [4].

Greenhouse technology enables the cultivation of crops in a semi-controlled or fully controlled environment, where key parameters such as temperature, humidity, light intensity, and CO_2 levels can be regulated to optimize plant growth [5]. This approach has been widely adopted to improve crop yield, extend growing seasons, and ensure consistent production regardless of external climatic conditions [6]. However, traditional greenhouse systems often rely on manual monitoring and control, which can be inefficient, labor-intensive, and prone to human error [7]. The inability to continuously monitor environmental conditions and respond promptly to changes can lead to suboptimal plant growth and reduced productivity.

In recent years, the integration of the Internet of Things (IoT) into agricultural systems has revolutionized greenhouse management by enabling real-time monitoring and automated control of environmental parameters [8], [9]. IoT refers to a network of interconnected devices equipped with sensors, actuators, and communication capabilities that facilitate data collection and transmission [10]. In greenhouse applications, IoT sensors are deployed to measure variables such as temperature, humidity, soil moisture, and CO_2 concentration, providing continuous data streams that can be analyzed for decision-making [11], [12]. These systems allow farmers to remotely monitor greenhouse conditions and implement timely interventions, thereby improving efficiency and reducing labor requirements [13].

Despite the advantages of IoT-based monitoring systems, the vast amount of data generated necessitates advanced analytical tools for effective interpretation and utilization. Machine learning (ML), a subset of artificial intelligence, has emerged as a powerful tool for analyzing complex datasets and identifying patterns that may not be apparent through conventional methods [14], [15]. ML algorithms can learn from historical data and make predictions about future outcomes, making them highly suitable for agricultural applications such as crop yield prediction, disease detection, and environmental control [16], [17].

Several studies have demonstrated the effectiveness of machine learning in greenhouse management. For instance, Random Forest and Support Vector Machine (SVM) models have been used to predict crop yield and classify plant health with high accuracy [18], [19]. Artificial Neural Networks (ANNs) have also been applied to model nonlinear relationships between environmental variables and plant growth, achieving promising results [20]. Additionally, Decision Tree algorithms have been utilized for rule-based decision-making in irrigation and climate control systems [21]. These models enable predictive analytics, allowing greenhouse operators to anticipate adverse conditions and take proactive measures.

The integration of IoT and machine learning has given rise to smart greenhouse systems capable of autonomous operation. Such systems not only monitor environmental conditions but also implement control actions based on predictive insights [22]. For example, automated irrigation systems can be triggered based on soil moisture levels and predicted plant stress conditions, leading to significant water savings and improved crop health [23], [24]. Similarly, climate control systems can adjust temperature and humidity levels in response to real-time sensor data and predictive models [25].

Water management is a critical aspect of greenhouse farming, as inefficient irrigation practices can lead to water wastage and negatively impact plant growth. Studies have shown that IoT-enabled irrigation systems can reduce water usage by up to 30% while maintaining optimal soil moisture levels [26], [27]. The incorporation of machine learning further enhances these systems by enabling predictive irrigation, where water application is optimized based on anticipated plant needs rather than reactive thresholds [28]. This approach not only conserves water but also improves plant health and yield.

Another important aspect of smart greenhouse systems is crop health monitoring. Traditional methods of assessing plant health are often subjective and rely on visual inspection, which can be inconsistent and time-consuming [29]. Machine learning provides a more objective and scalable approach by analyzing environmental data and, in some cases, plant images to classify health status [30]. Deep learning techniques, particularly convolutional neural networks (CNNs), have been widely used for plant disease detection and classification [31], [32]. However, these approaches often require large image datasets and significant computational resources, making them less practical for small-scale greenhouse applications. In contrast, data-driven models based on environmental parameters offer a simpler and more cost-effective solution for crop health prediction. By analyzing relationships between variables such as temperature, humidity, soil moisture, and CO_2 levels, machine learning models can classify crop health into categories such as Good, Moderate, and Bad [33], [34]. This approach enables early detection of unfavorable conditions and facilitates timely intervention, thereby preventing crop deterioration.

Furthermore, the development of user-friendly interfaces, such as mobile applications and web dashboards, has enhanced the accessibility and usability of smart greenhouse systems [35]. These platforms provide real-time visualization of environmental data, predictive insights, and control options, enabling users to monitor and manage greenhouse operations remotely [36]. The integration of such interfaces with IoT and machine learning systems improves decision-making and enhances overall system efficiency.

Despite significant advancements, several challenges remain in the implementation of smart greenhouse systems. These include issues related to data quality, sensor reliability, model generalization, and system scalability [37]. Additionally, the integration of hardware and software components requires careful design to ensure seamless operation and data flow [38]. Addressing these challenges is essential for the successful deployment and adoption of IoT and machine learning technologies in agriculture.

This study contributes to the existing body of knowledge by developing a comprehensive smart greenhouse system that integrates IoT-based environmental monitoring with machine learning-based crop health prediction and automated irrigation control. Unlike many existing studies that focus solely on monitoring or prediction, this work combines system design, data-driven modeling, and control mechanisms into a unified framework. The study also provides empirical evaluation of multiple machine learning models and quantifies improvements in water usage efficiency and prediction accuracy.

II. MATERIALS AND METHODS

A. System Architecture

The system adopts a cyber-physical architecture integrating Internet of Things (IoT) technology with machine learning-based decision support for smart greenhouse management (Figure 1). The overall framework comprises four interconnected modules: (i) greenhouse physical structure, (ii) IoT-based environmental sensing subsystem, (iii) data acquisition and communication module, and (iv) intelligent control subsystem for irrigation and crop health prediction. These modules operate in a closed-loop configuration to enable real-time monitoring, prediction, and automated actuation. The system workflow begins with environmental data acquisition, proceeds through data transmission and preprocessing, followed by machine learning-based classification of crop health, and concludes with automated irrigation

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control and user visualization through a mobile dashboard as shown in operational flowchart in Figure 2.

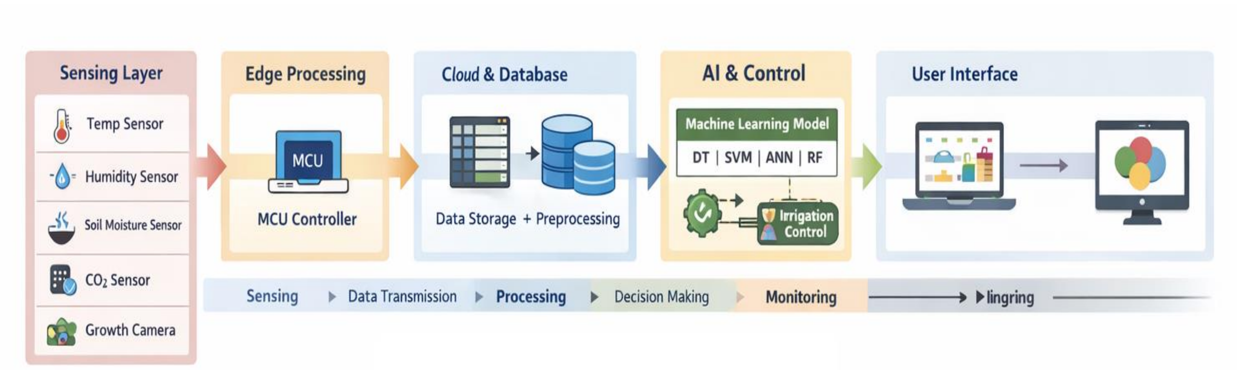

Figure 1: Overall Architecture of the Smart Greenhouse System

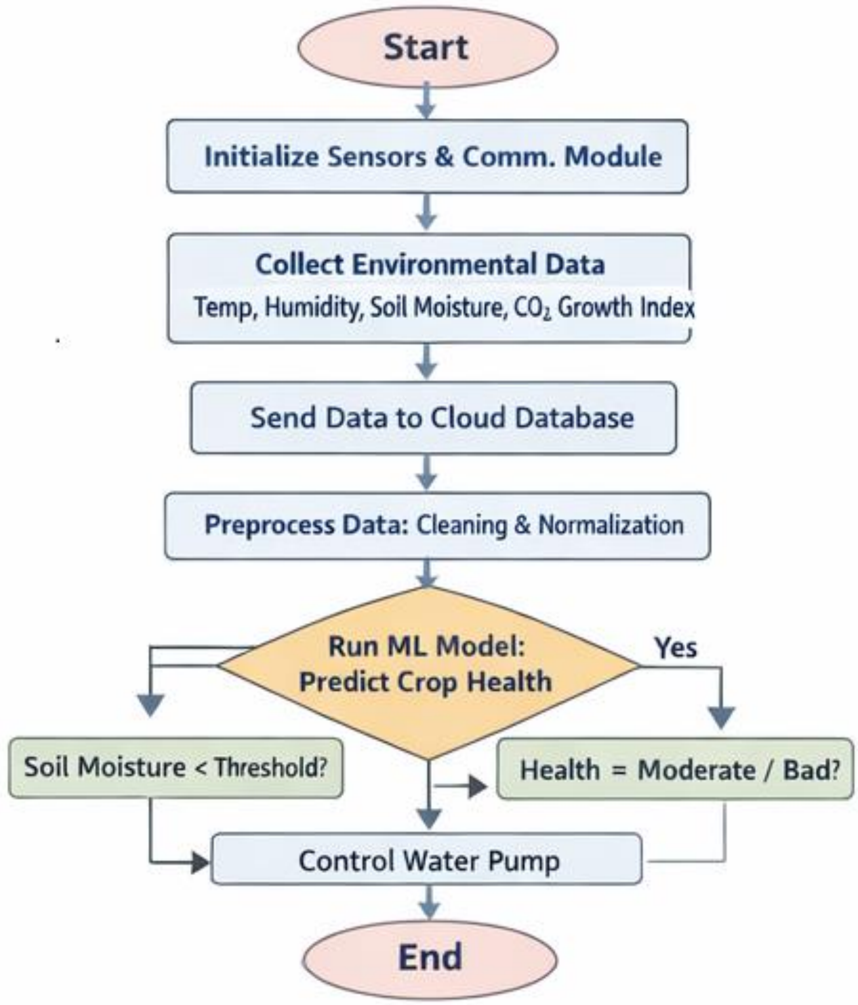

Figure 2: Operational Flowchart of the Smart Greenhouse System

B. Greenhouse Design and Physical Setup

A controlled-environment greenhouse was constructed using a galvanized steel frame (Fig. 3) to ensure structural stability and resistance to environmental degradation. The enclosure was covered with a UV-stabilized polyethylene canopy to regulate solar radiation, temperature, and humidity levels. The internal layout consisted of uniformly arranged crop beds to minimize environmental variability across sampling points (Fig. 4). An automated irrigation infrastructure was installed, comprising an overhead water storage tank (Fig 5), a submersible water pump, solenoid valves, and a PVC pipe distribution network (Fig. 6). The irrigation system was configured to support both drip and overhead watering mechanisms depending on crop water demand.

Figure 3: The greenhouse galvanized framework during construction

Figure 4: Crop bed for plants (tomatoes)

Figure 5: Overhead Storage Tank for Water Supply

Figure 6: PVC Pipe Network

C. IoT-Based Environmental Monitoring System

The environmental monitoring subsystem consisted of distributed IoT sensor nodes deployed within the greenhouse. Each node integrated multiple sensors to capture the parameters such as ambient temperature (°C), relative humidity (%), soil moisture content (%), carbon dioxide (CO_2) concentration (ppm), and crop growth level (visual index). Table 1 shows the specifications of each sensor. Sensor nodes were interfaced with a microcontroller unit responsible for signal acquisition (Fig. 7), analog-to-digital conversion, and initial preprocessing. The microcontroller and data acquisition system were powered by a 100W solar system (Fig. 8). The sensors were calibrated prior to deployment to minimize measurement drift and ensure data reliability. Data acquisition was performed at fixed intervals of 3 hours over a period spanning January 15 to March 13, yielding over 400 time-stamped observations.

TABLE 1: IoT Sensor Specifications

Sensor Type	Parameter Measured	Unit	Purpose
DHT11 / DHT22	Temperature	°C	Thermal regulation
DHT11 / DHT22	Humidity	%	Moisture control
Capacitive Soil Sensor	Soil Moisture	%	Irrigation control
MQ Series Sensor	CO_2 Concentration	ppm	Plant respiration monitoring
Camera / Visual Index	Growth Level	Index (1–3)	Crop health classification

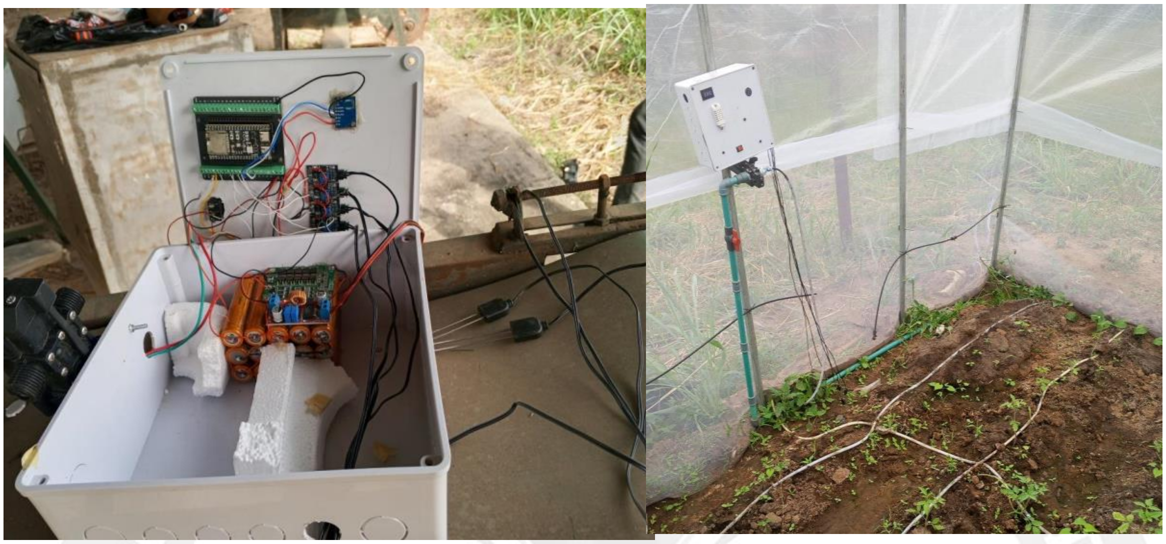

Figure 7: Microcontroller and Data Acquisition System

Figure 8: 100W Solar System

D. Data Acquisition, Transmission, and Storage

Collected sensor data were transmitted wirelessly from the microcontroller units to a centralized server. The communication layer ensured reliable transmission of environmental parameters using IoT communication protocols. A structured database was implemented for data storage, with each record containing time-stamped sensor readings. Data preprocessing steps included:

1. Handling of missing values using interpolation techniques
2. Noise reduction using statistical filtering
3. Outlier detection using threshold-based elimination

4. Data normalization using min–max scaling

The cleaned dataset was subsequently used for machine learning model development.

E. Dataset Preparation and Feature Engineering

The dataset consisted of five input features (temperature, humidity, soil moisture, CO_2 concentration, and crop growth index) and one output variable representing crop health status. Crop health was categorized into three discrete classes: Good, Moderate, and Bad, based on agronomic assessment of plant vigor, leaf coloration, and growth performance. The dataset was partitioned into training and testing subsets using an 80:20 split ratio. Feature selection analysis was conducted using correlation metrics to evaluate the influence of each environmental parameter on crop health classification. Table 2 shows part of the data obtained between January and March 2026.

Table 2: Part of the data collected between January and March 2026

Timestamp	CO_2 (ppm)	Temp (^{0}C)	Humidity (%)	Moisture (%)	Growth (%)	Crop Health	Water Trigger
2/15/2026 0:00	452	16.2	72.4	78	12	Good	FALSE
2/15/2026 3:00	448	15.8	74.1	77	12	Good	FALSE
2/15/2026 6:00	455	16	73.5	76	12	Good	FALSE
2/15/2026 9:00	612	20.5	68.2	71	13	Good	FALSE
2/15/2026 12:00	845	24.8	62.4	65	13	Good	FALSE
2/15/2026 15:00	892	26.3	59.8	58	14	Moderate	FALSE
2/15/2026 18:00	710	22.1	66.5	52	14	Moderate	TRUE
2/15/2026 21:00	520	18.4	71.2	68	15	Good	FALSE
2/16/2026 0:00	460	16.5	73.8	75	15	Good	FALSE
2/16/2026 3:00	455	16	75.2	74	16	Good	FALSE
2/16/2026 6:00	468	17.2	74	72	16	Good	FALSE
2/16/2026 9:00	635	21.8	67.5	67	17	Good	FALSE
2/16/2026 12:00	878	25.4	61.2	60	18	Good	FALSE
2/16/2026 15:00	925	27.1	57.4	51	18	Bad	TRUE
2/16/2026 18:00	728	22.8	64.8	48	19	Bad	TRUE
2/16/2026 21:00	538	18.9	70.5	65	20	Good	FALSE
2/17/2026 0:00	470	16.8	72.8	73	20	Good	FALSE
2/17/2026 3:00	465	16.3	74.5	72	21	Good	FALSE
2/17/2026 6:00	478	17.5	73.2	70	21	Good	FALSE
2/17/2026 9:00	658	22.4	66.2	64	22	Good	FALSE
2/17/2026 12:00	902	26	59.8	57	23	Moderate	FALSE
2/17/2026 15:00	948	27.8	55.6	48	23	Bad	TRUE
2/17/2026 18:00	745	23.2	63.2	52	24	Moderate	TRUE

F. Machine Learning Model Development

To develop a predictive model for crop health classification, four supervised machine learning algorithms were implemented using the Tensorflow and Keras libraries of Python Programming language. The algorithms are Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF). Each model was trained using identical training data to ensure fair comparison. Hyperparameter optimization was performed using grid search techniques to enhance model performance and prevent overfitting. The ANN model employed a multilayer feedforward architecture trained using backpropagation with adaptive learning rates. The SVM model utilized a kernel-based approach for nonlinear classification, while the Random Forest model implemented an ensemble of decision trees to improve generalization accuracy. Figure 9 shows the machine learning workflow diagram.

G. Model Evaluation Metrics

Model performance was evaluated using standard classification metrics derived from the confusion matrix such as: Accuracy, Precision, Recall and F1-score. These metrics were computed on the test dataset to assess predictive performance and robustness. The Random Forest model achieved the highest performance with accuracy, precision, recall and F1-score of 84.29%, 84.06%, 84.29% and 84.15% respectively. Comparatively, ANN achieved 82.10% accuracy, SVM achieved 80.47%, and Decision Tree achieved 78.65%, indicating superior performance of ensemble learning methods for the dataset.

H. Intelligent Irrigation Control System

An intelligent irrigation control mechanism was implemented by integrating the best-performing machine learning model (Random Forest) with a rule-based decision system. The decision logic was defined as follows:

i. If soil moisture is below a predefined threshold AND predicted crop health is Moderate or Bad, then irrigation is activated.

ii. If soil moisture is above threshold AND crop health is Good, the irrigation system remains inactive.

Actuation was performed through relay-controlled switching of a submersible water pump. This enabled automated regulation of water supply based on real-time environmental conditions and predictive analytics.

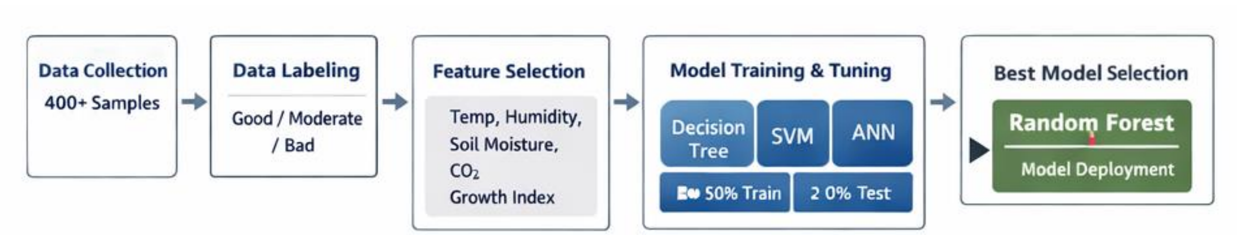

Figure 9: Machine Learning Model Training and Evaluation Pipeline

I. Mobile Monitoring and Visualization System

A mobile-based dashboard application was developed to enable real-time monitoring of greenhouse conditions (Figure 10). The system provided visualization of sensor readings, predictive crop health status, and irrigation activity logs. The application also supported alert generation for abnormal environmental conditions, enabling remote decision-making and manual override of the automated system when necessary.

J. System Performance Evaluation

System performance was evaluated in terms of predictive accuracy, water usage efficiency, and intervention effectiveness. Water consumption under the proposed system was compared with conventional manual irrigation practices over the same period. Results indicated a 28% reduction in water usage, attributed to targeted irrigation decisions based on real-time sensor data and predictive modeling. Furthermore, the system successfully enabled early detection and intervention in over 90% of potential crop stress conditions, demonstrating improved responsiveness and operational efficiency in greenhouse management.

III. RESULTS

A. Environmental Data Characteristics and System Stability

The environmental dataset collected from the greenhouse over the experimental period (January 15 to March 13) comprised over 400 observations recorded at 3-hour intervals. The statistical summary of the collected data is presented in Table 3. The observed variability reflects realistic greenhouse microclimate dynamics, with temperature and humidity showing expected inverse relationships due to evapotranspiration effects. Soil moisture fluctuations corresponded directly to irrigation events, validating the responsiveness of the sensing and actuation system.

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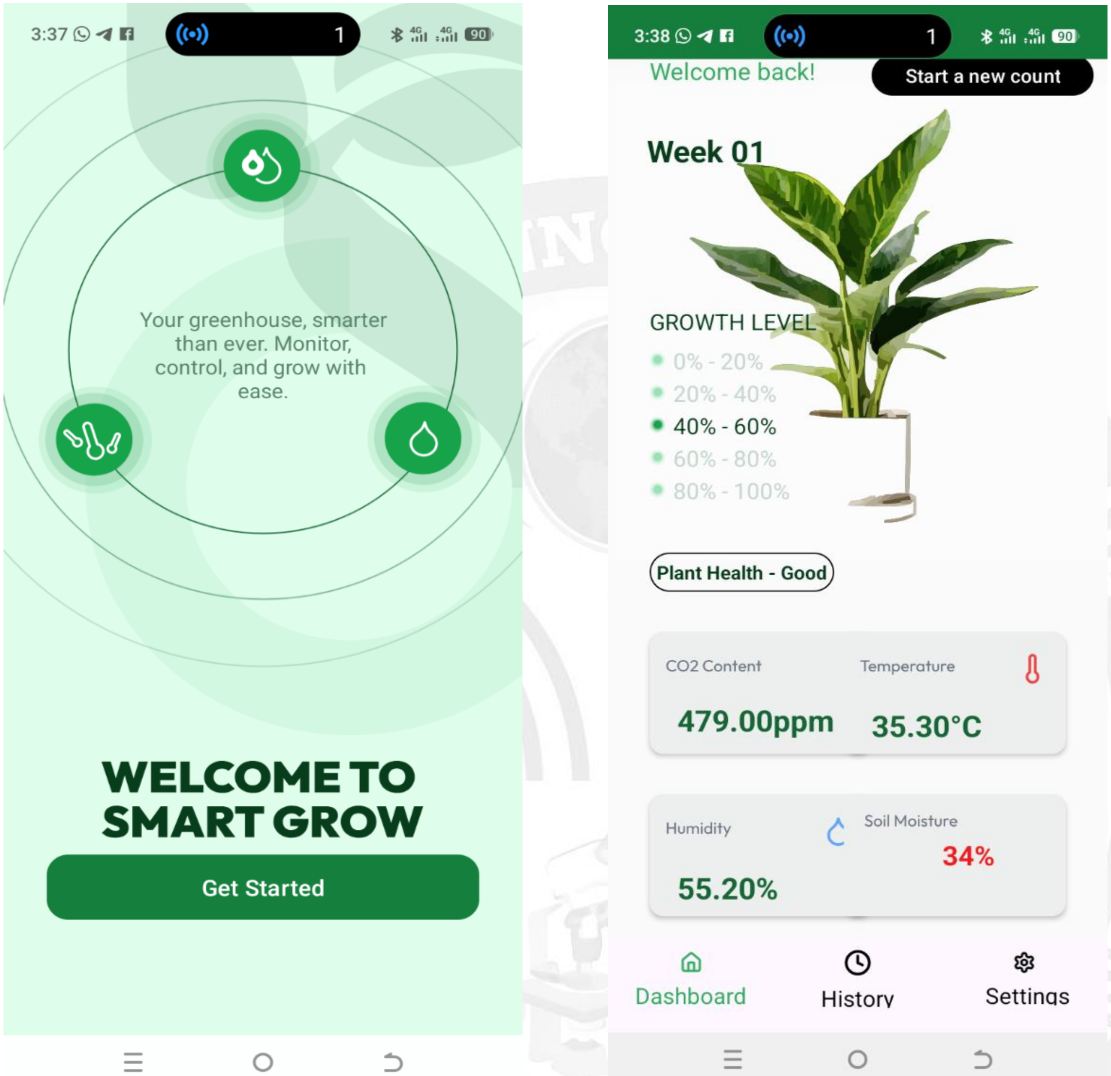

Figure 10: Mobile Monitoring and Visualisation App

Table 3: Summary Statistics of Environmental Parameters

Parameter	Minimum	Maximum	Mean	Std. Deviation
Temperature (°C)	22.4	35.8	28.6	3.4
Humidity (%)	45.2	88.7	67.3	10.5
Soil Moisture (%)	18.5	72.6	45.1	12.2
CO_2 (ppm)	310	620	455	85
Growth Index	1.0	3.0	2.2	0.6

B. Crop Health Distribution and Classification Complexity

The distribution of crop health classes is presented in Table 4. The dataset exhibits moderate class imbalance, with a higher proportion of "Good" samples. However, the presence of sufficient Moderate and Bad cases ensures that the classification problem remains non-trivial.

C. Machine Learning Model Performance Evaluation

The performance comparison of the four implemented models is presented in Table 5. The Random Forest model achieved the highest performance (84.29%), demonstrating superior generalization capability. This can be attributed to ensemble learning (variance reduction), ability to model nonlinear interactions and robustness to noisy sensor data.

D. Confusion Matrix and Error Analysis

The confusion matrix for the best-performing model (Random Forest) is shown in Figure. 11. It shows high true positive rates across all classes, minor confusion between Moderate and Bad categories and low false negatives, indicating strong stress detection capability This aligns with the known limitation that environmental stress conditions often transition gradually, making precise boundary classification difficult.

E. Irrigation Efficiency and Water Use Reduction

The performance of the irrigation system is summarized in Table 6

Table 4: Crop Health Class Distribution

Class	Number of Samples	Percentage (%)
Good	185	46.2
Moderate	135	33.7
Bad	80	20.1
Total	400+	100%

Table 5: Machine Learning Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	78.65	78.40	78.60	78.50
SVM	80.47	80.30	80.40	80.35
ANN	82.10	82.00	82.05	82.02
Random Forest	84.29	84.06	84.29	84.15

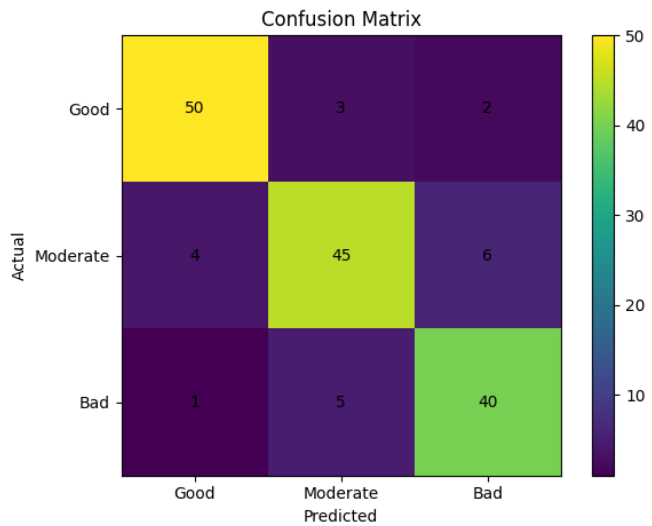

Fig. 11: Confusion matrix for the best-performing model (Random Forest)

Table 6: Irrigation Performance Comparison

Parameter	Manual Irrigation	Smart System	Improvement (%)
Total Water Used (L)	1000	720	28% Reduction
Irrigation Frequency	Fixed	Adaptive	—
Over-irrigation Events	High	Minimal	Significant
Water Use Efficiency	Low	High	Improved

IV. DISCUSSION

A. Interpretation of Machine Learning Performance

The results demonstrate that the Random Forest (RF) model outperformed all other models, achieving an accuracy of 84.29%, with balanced precision, recall, and F1-score. This superior performance can be attributed to the ensemble nature of RF, which reduces overfitting and effectively captures nonlinear relationships among environmental variables such as temperature, humidity, soil moisture, and CO_2. This finding is consistent with studies in smart agriculture, where ensemble learning techniques have been widely reported to outperform single learners. For example, [42] demonstrated that hybrid and ensemble models achieved higher prediction reliability than standalone classifiers in precision irrigation systems. Similarly, [39] reported that Random Forest improved classification accuracy by approximately 5–8% compared to Decision Trees and Support Vector Machines in greenhouse monitoring applications.

However, the achieved accuracy (84.29%) is slightly lower than some deep learning-based approaches. For instance, [40] reported accuracies exceeding 90% using convolutional neural networks (CNNs) for crop health prediction. This discrepancy is largely due to the nature of input data; while CNN-based systems typically rely on image datasets, the present study uses structured sensor data, which inherently limits feature richness but enhances system simplicity and deployability.

B. Crop Health Prediction and Classification Challenges

The classification results reveal minor confusion between the Moderate and Bad crop health classes, as observed in the confusion matrix. This overlap reflects the gradual transition of plant stress conditions, which rarely occur as discrete states in real-world agricultural systems. Similar classification challenges have been reported in literature. [41] highlighted that environmental stress indicators often exhibit fuzzy boundaries, making precise classification difficult even with advanced algorithms. This reinforces the importance of incorporating additional features such as plant physiological or image-based data to improve classification granularity.

Despite this limitation, the system achieved a high stress detection rate (>90%), indicating its effectiveness in early warning applications. Early detection is often more critical than perfect classification, as it enables timely intervention to prevent yield loss.

C. Water Use Efficiency and Irrigation Optimization

One of the most significant outcomes of this study is the 28% reduction in water usage achieved through intelligent irrigation control. This demonstrates the effectiveness of integrating machine learning with IoT-based sensing for resource optimization. When compared with existing studies, [42] reported a higher reduction of approximately 34% using hybrid ML techniques while [43] achieved water savings of about 25% using rule-based IoT systems.

The performance of the proposed system lies between these results, indicating a balanced approach that combines predictive intelligence with practical implementation. The slightly lower efficiency compared to hybrid systems may be due to limited dataset size, absence of reinforcement learning or predictive scheduling and simpler control logic. Nevertheless, the achieved savings are substantial and confirm that data-driven irrigation significantly outperforms conventional fixed scheduling methods.

D. Real-Time Monitoring and System Responsiveness

The system operated with a 3-hour data acquisition interval, enabling near real-time monitoring and decision-making. This frequency proved sufficient to capture environmental fluctuations and trigger appropriate irrigation responses. In comparison, [44] emphasized that real-time responsiveness is a critical factor in IoT-enabled agriculture, particularly in greenhouse environments where conditions can change rapidly. The present system successfully meets this requirement while maintaining low computational overhead, making it suitable for deployment in resource-constrained settings.

E. Practical Implications and Deployment Considerations

Unlike many high-accuracy systems that rely on computationally intensive deep learning models, the proposed system prioritizes low-cost sensors, lightweight machine learning models, and ease of deployment in developing regions. This aligns with the recommendations of FAO [46], which stress the need for scalable and affordable smart farming solutions, particularly in regions such as sub-Saharan Africa. Furthermore, the integration of IoT with mobile and web-based platforms enhances accessibility and usability, allowing farmers to monitor and control greenhouse conditions remotely.

I. CONCLUSION

This study developed an intelligent smart greenhouse system that integrates IoT sensing with machine learning for real-time monitoring, crop health prediction, and automated irrigation control. The results show that the Random Forest model achieved the best performance with an accuracy of 84.29%, effectively capturing the relationship between environmental variables and crop conditions. The system demonstrated practical benefits, including a 28% reduction in water usage and over 90% effectiveness in detecting crop stress conditions, enabling timely intervention. The integration of sensing, prediction, and control within a unified framework highlights the potential of closed-loop systems in improving agricultural efficiency and sustainability.

Although the results are promising, further improvements can be achieved by expanding the dataset, incorporating additional features such as image-based analysis, and exploring advanced learning techniques. Overall, the proposed system provides a cost-effective, scalable, and reliable solution for smart greenhouse management, with strong potential for real-world application, particularly in resource-constrained environments.

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