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An IoT and Machine Learning-driven Advanced Greenhouse Farming System for Precision Agriculture

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Abstract: With the world population projected to reach 9.8 billion by 2050, sustainable food production has become a significant concern. Adverse climatic changes and increasing pressure on food security have led to the search for innovative and effective agricultural methods. Traditionally, farming has not kept pace with increased demand without stressing the environment. The proposed system implements transformational agriculture through real-time monitoring and control infrastructure that picks up from the very basics of a greenhouse climate monitoring system using sensors to actuators. The new greenhouse system will be powered by solar energy—with a solar tracker—for running its operations and rainwater for irrigation, coupled with the trend of modernity in the form of a user-friendly mobile application. On this Monitoring Dashboard, there is the possibility of real-time control over temperature, humidity, light intensity, and soil moisture to arrive at optimal conditions for the crops. This system will be complete with a subsystem on crop recommendation and disease detection, making it comprehensive in agriculture. Rigorous simulations were performed on the model, and the resulting accuracy in crop recommendation and crop disease detection were 97.27% and 97.50%, respectively, quickly proving the effectiveness of smart greenhouse monitoring driven by IoT and machine learning. Such a solution can be expected to realize its objective: producing enough food for the increasing population without ruining planetary health.

Keywords: Greenhouse farming, Internet of Things, Machine Learning, Deep Learning, Crop disease detection, Crop recommendation

1. INTRODUCTION

According to the Food and Agriculture Organization of the United Nations (FAO) [1], world food production has to be increased 70% by 2050. The alarming pattern has emerged due to the world's population growth, fast industrialization, and changing climatic conditions; there is a consistent global decline in agricultural land. The requirement for more agricultural yields and hygienic, clean food sources is constant and growing in the face of this difficulty [2]. Meeting this demand, however, turns out to be a complex undertaking when one considers the existing status of agriculture and the possible consequences of such a significant rise. The challenge is boosting agriculture yields while utilizing a restricted amount of land. Reducing the use of dangerous chemicals in agriculture, such as pesticides, to make agricultural products safe for human consumption is another issue [3]. Using Advanced Farming technologies, an intelligent greenhouse system may be developed to solve this issue, increasing agricultural productivity even on a small amount of land. This study explores a comprehensive solution to the urgent global challenge at hand by promoting the integration of four innovative farming methodologies: Advanced Crop Management, Vertical Farming [4], Hydroponics [5], and Horizontal Farming. Integrating these cutting-edge methods is the basis of a comprehensive plan to bring in a revolutionary period of sustainable agriculture. Also, incorporating these methodologies represents a transformative paradigm shift in agriculture, aligning with sustainability principles and responsible resource management. By merging these advanced practices, farmers can enhance productivity, mitigate the adverse effects of conventional agriculture on the environment, and contribute to the long-term preservation of natural resources. As a critical element of this integrated strategy, the paper emphasizes the inclusion of greenhouses [6] in particular. In addition to protecting crops from bad weather and allowing for year-round agriculture, greenhouses offer a regulated environment [7]. In addition to lengthening the growing seasons, this controlled environment makes it easier to use resources optimally, reduce waste, and increase crop production efficiency. The system offers unique benefits from Hydroponics vertical and horizontal farming. Because it maximizes land utilization, horizontal farming is an excellent option for areas with a shortage of arable land [8]. Vertical farming, on the other hand, uses vertical space to cultivate crops in stacked levels, thereby increasing

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production [9]. While Hydroponics promotes water efficiency and nutrient management by doing away with the requirement for soil [10]. On the other hand, this integrated farming system's sustainability factor is significantly increased by utilizing advanced crop management techniques and strengthening them with automation from sensors, crop recommendation systems, and crop disease detection technologies, this integrated farming system's sustainability factor is significantly increased. Precision farming, data-driven decision-making, and creative cultivation techniques work with automated processes in this new paradigm to enable farmers to maximize crop yields while minimizing environmental effects and optimizing resource use. The exponential rise in global population combined with the transformational effects of industrialization and observable changes in climatic patterns presents a worrisome picture: by 2050, it is predicted that the world's food consumption will have increased by an astounding 70%. This astounding estimate raises concerns about the availability of arable land in the future, which is crucial for maintaining agricultural output. It is a warning sign. These problems' ominous presence highlights the pressing need for creative answers. We must create plans that will increase agricultural yields, ensure the security of our food supplies, and strategically reduce the negative environmental effects associated with food production. As this situation develops, there is an increasing demand for innovative, sustainable solutions. This study delves into a pioneering approach amalgamating four cutting-edge agricultural methodologies: hydroponics, horizontal farming, advanced crop management, and vertical farming. This convergence signifies a significant paradigm shift in agriculture, aligning its trajectory with sustainability principles and prudent resource management. The amalgamation of these modern techniques holds the promise of manifold advantages: vertical farming optimizes space utilization by cultivating crops in stacked layers, substantially augmenting production capacity; hydroponics, by eliminating soil requirements, champions water efficiency and precise nutrient control; horizontal farming maximizes land efficiency, particularly beneficial in regions with limited arable land; advanced crop management, complemented by sensor automation and disease detection technologies, contributes to heightened sustainability and productivity. Central to this comprehensive strategy are smart greenhouse systems, serving as the linchpin. These structures act as shields against adverse weather and facilitate year-round agriculture. Resource optimization, waste reduction, and increased crop productivity thrive within these controlled environments. Moreover, the fusion of hydroponics, vertical and horizontal farming within greenhouses amplifies their benefits, augmenting land usage while extending growing seasons. Furthermore, this integrated farming approach underscores the criticality of precision farming techniques and data-driven decision-making. Automated processes, alongside innovative cultivation methods, empower farmers to maximize crop yields while minimizing environmental impact and optimizing resource utilization.

This comprehensive study advocates a fundamental shift in agricultural practices by advocating for integrating advanced farming methodologies within innovative greenhouse systems. This transformative approach addresses the imminent surge in food demand and aligns with sustainability goals, fostering the long-term preservation of natural resources and environmental well-being. The objectives of our study endeavor encompass a diverse range of innovative pursuits, aiming to redefine greenhouse farming practices through the infusion of advanced technologies and sustainable methodologies.

The paper's significant contributions are outlined below:

- We have studied existing greenhouse farming systems and formulated a robust solution to address the challenges identified in prior research.
- We developed a machine learning-based Crop Recommendation System with significant potential to transform the agricultural sector.
- We have utilized resource-constrained deep-learning models to identify potential health risks in plants. Our proposed disease detection system is specifically designed for deployment in resource-constrained IoT devices with limited computational power.
- We have measured the performance of both the crop disease detection and recommendation systems through rigorous simulations. Additionally, we provided a comprehensive performance comparison.
- We've designed and developed a user-friendly mobile application for easy access to the greenhouse system. It features a unified dashboard for monitoring the greenhouse, crop recommendations, and disease detection systems.

The study is organized in the following manner: Section 2 looks into earlier studies, laying the groundwork for our study in the larger context. In section 3, we methodically explain the materials and procedures, offering a complete review of our approaches. Section 4 highlights the enlightening findings from several detailed tests. Section 5 concludes the study by discussing the essence of the proposed study, culminating in final thoughts.

2. LITERATURE REVIEW

Integrating machine learning, convolutional neural networks (CNNs), and their applications in intelligent greenhouses and precision agriculture is a practical strategy to address existing issues and boost the production of agricultural products. This section explores ongoing research beyond IoT to cover CNNs, machine learning, and its applications to intelligent greenhouses and precision agriculture. This section thoroughly reviews the literature, evaluating and analyzing numerous studies, research papers, and technical applications. It illuminates the path of development, scope of application, and transformative impact of machine learning and IoT on contemporary farming methods. Chakraborty et al. in [11] advises leveraging IoT-enabled environmental monitoring and irrigation infrastructure to handle contemporary agricultural concerns intelligently. In the system, temperature, humidity, soil moisture, and light intensity are monitored locally and remotely by the system. A sophisticated irrigation system is also integrated to regulate water supply effectively. Real-time data monitoring and IoT connectivity are made feasible by the BLYNK application, and direct water pump control facilitates brilliant irrigation difficulties. Zhu and Shang developed an IoT and machine learning-based intelligent farm monitoring system [12]. Here, the authors highlight new prospects for agricultural management leveraging IoT and machine learning and provide a practical remote monitoring and management solution for intelligent agriculture. In their proposed solution, a solid data management system efficiently monitors greenhouse environmental elements such as temperature, carbon dioxide, and light. The FPKM algorithm used in the system offers accurate data analysis with constant iteration times through the identification and removal of outliers. The system also incorporates user monitoring, data center, and mobile phone client modules by fusing IoT with FPKM. The work proposed by Lanitha et al. in [13] involves the integration of Internet of Things technology utilizing a NodeMCU equipped with a Wi-Fi module, which interfaces with a Raspberry Pi board for various agricultural applications. These applications encompass the maintenance of soil moisture using a motor pump and moisture sensor, ensuring air quality with an exhaust fan and gas sensors (MQ2, MQ135), temperature regulation through dht11 and lm35 sensors, and adjusting crop exposure with artificial LED and LDR. To enable remote monitoring, recording, and control, the system employs Blynk, ThingSpeak, and NodeMCU. Specifically, ThingSpeak is utilized for storing sensor data, while Blynk facilitates data collection and remote management of equipment such as motors, fans, and lights. In [14], the authors introduce SAgric-IoT, a cutting-edge technology platform designed for precision agriculture, which seamlessly integrates the Internet of Things (IoT) and Convolutional Neural Networks (CNN). This innovative tool enables monitoring of physical data and early detection of plant ailments, employing advanced communication algorithms for precise data assessment and environmental control. Convolutional Neural Networks are also harnessed for accurate plant disease classification and detection. The primary objective of this research is to create a stable, low-maintenance, and cost-effective IoT platform that can effectively manage and optimize crop production. Numerous technologies used in the agricultural area use (the Internet of Things) IoT to boost productivity and address existing obstacles, which are as follows: first, increased food production is necessary to serve the expanding population and prevent the era of starving [15]. Second, the shortage of laborers due to civilization adds obstacles to the agriculture sector; therefore, overcoming these issues requires deploying agriculture systems that do not need time, effort, or human participation. Third, due to climate change and the deterioration of water resources, several technologies are being deployed to assist in managing agricultural water supplies. Fourth, it is necessary to limit the influence of chemicals on human health by spraying these chemicals (pesticides or fertilizer) based on crop requirements rather than using planned traditional ways. Fifth, energy availability and pricing remain significant challenges in the agricultural industry. Sixth, maintaining a green environment with low GHG emissions is a significant problem [16]. The paper [17] introduces an IoT-based monitoring and automated correction system designed for aquaponics within a temperature-controlled greenhouse environment. The system continuously measures real-time parameters, including light intensity, air temperature, humidity, pH levels, and water temperature. When the collected data falls outside predefined threshold ranges, the system initiates corrective actions by activating devices such as grow lights, fans, coolers, aerators, and peristaltic buffers. This setup ensures the maintenance of optimal conditions crucial for the regular operation of the aquaponics system. Furthermore, the system enables real-time wireless data transmission and reception, facilitating remote access via an Android smartphone application for seamless monitoring and control.

Bersani et al. [18] explores the utilization of the Internet of Things (IoT) in the context of intelligent greenhouses, encompassing the deployment of sensors, devices, and communication infrastructure for continuous monitoring and real-time data acquisition. This data is then processed to effectively manage indoor variables such as light, ventilation, humidity, temperature, and carbon dioxide levels. The paper provides an in-depth analysis of the latest developments in IoT-based applications tailored for smart greenhouses, emphasizing the numerous benefits and the significant potential this technology brings to the agricultural industry. The paper [19] details implementing an intelligent greenhouse system that effectively monitors and controls critical factors influencing crop yield, including temperature, humidity, CO2 levels, light intensity, and soil moisture, utilizing a combination of Raspberry Pi and Arduino. Real-time data collection and visualization are facilitated through the Internet of Things (IoT) technology, employing the ThingSpeak platform. To surpass previous models in terms of complexity and versatility, the paper presents a fully automated greenhouse incorporating hydroponics and vertical farming techniques and state-of-the-art security and monitoring technologies. Andrianto et al. [20] focuses on developing IoT-based smart greenhouses tailored for hydroponic farming. The central controller of this system is an Arduino Mega2560. Real-time data, including information about the status of actuators (such as pumps, lights, fans, sprayers, and valves), temperature, humidity, TDS (Total Dissolved Solids), pH levels, and light intensity, is stored in the Firebase database. The ESP-32 module facilitates communication between the Arduino and Firebase. Furthermore, a smartphone application enables users to monitor the greenhouse's environmental conditions and control the various actuators. In [2], by deploying IoT sensors and devices, Farooq et al. demonstrated the practicality of remotely monitoring greenhouse conditions, including parameters like CO2 levels, pH, moisture content, humidity, temperature, and irrigation, by deploying IoT sensors and devices. This comprehensive survey delves into the evolving technologies associated with IoT and provides an extensive overview of agricultural practices in greenhouses that leverage IoT. Furthermore, the study addresses contemporary and traditional production techniques, serving as a valuable resource for gardeners looking to enhance their understanding of the technological foundations of greenhouse farming.

The proposed architecture by Khan et al. [21] provides low-cost choices for smart farming by utilizing mobile and communication technologies, the Internet of Things, and cloud computing. Sensors measure the temperature, air humidity, and light intensity. An analysis platform in the cloud gets the collected data. A smartphone app or email notifications are given to the farmer, who can take any necessary preventive action. The paper [22] presented an Internet of Things (IoT)–based greenhouse environment monitoring and control system. This system uses a lightweight, rapid Blynk IoT platform for messaging and control via a mobile app, unlike existing systems that use Zigbee-based wireless networks with restrictions. Through the ThingSpeak cloud and GSM infrastructure, the system delivers real-time wireless sensor data transfer, display, and processing. According to experimental data, this strategy successfully supports sustainability and a green environment while enabling smart farming that is energy efficient in greenhouses. Two automated system components are covered by Kumkhet et al. [23]. The first part employs a BH1750 sensor to assess ambient brightness and adjusts LED lights to offer a sufficient illumination range for gerbera growth (3000–5000 lux). The second component employs a fork-shaped sensor to monitor soil moisture and initiates a water sprayer when the moisture measurement falls within or exceeds the predetermined range (70–80%). An ESP8266 microcontroller, connected to the IoT by ISM 2.4GHz wireless communication, powers the entire system. Ullah et al. in [24] offers a revolutionary technique for autonomous farming in intelligent greenhouses. The strategy incorporates learning algorithms for optimization and prediction to control the greenhouse environment successfully. The system tries to enable more effective and autonomous control of components such as temperature, humidity, light, and irrigation within the greenhouse by blending machine-learning approaches with optimization strategies.

Our proposed work fills the literature gap by proposing a new, pioneering greenhouse system with state-of-the-art, unexplored elements. The proposed system has an intelligent rainwater collection system, a solar tracking mechanism, and a mobile application containing a Monitoring Dashboard for real-time supervision corresponding to the plant. This application can bind two major subsystems—the Crop Recommendation System and the Disease Detection Subsystem—to control the greenhouse climate optimally by continuously monitoring greenhouse parameters through various sensors. The result is a new form, integral in nature, that modern agricultural practices have taken, setting this work apart in contributions toward greenhouse technology. It further substantiates the practicality of the system and the reliability of any system that is to be implemented, which would further be valuable, offering strong proof in an agricultural real-world setup—disease detection and crop recommendation through rigorous simulation-based performance tests.

3. METHODOLOGY

The proposed system comprises the following important components: i) Greenhouse System Setup and Configuration, ii) Data acquisition, transmission, and monitoring Subsystem, iii) Intelligent Crop Recommendation, iv) Disease Detection System utilizing Image Processing, v) Rainwater Harvesting and Solar Tracking Mechanism. An overview of the system's design and interactions are shown in Figure 1. Detailed explanations of the systems are described below.

A. *Greenhouse System Setup and Configuration*

The greenhouse setup requires carefully positioning precise sensors to monitor crucial environmental elements like temperature, humidity, light levels, and soil moisture. These sensors interact with the central control unit, an Arduino Mega, which analyses the data and engages actuators such as humidifiers, heaters, chillers, and water pumps as needed. In addition, we've included MQ135 and ultrasonic sensors for CO2 level monitoring and crop height estimate, enhancing our system's capabilities. The technology uses adaptive algorithms to ensure specific Horizontal, Vertical, and Hydroponics Farming Systems conditions. An integrated ESP32 module enables simple data exchange for remote monitoring using Firebase Cloud and MySQL database.

B. *Data acquisition, transmission, and monitoring Subsystem*

The greenhouse farming system has a sophisticated setup to create optimal conditions for plant growth. This system has sensors that monitor temperature, humidity, light levels, and soil moisture. These sensors feed real-time data to a control center connected to an Arduino Mega. The control center, in turn, manages various equipment such as humidifiers, heaters, chillers, and water pumps based on the data received. The Arduino employs advanced algorithms to adapt to different farming conditions, including Horizontal, Vertical, and Hydroponic setups. Additionally, CO2 levels and crop height are monitored using MQ135 and ultrasonic sensors. Furthermore, a Real-Time video Acquisition subsystem that[25] utilizes a Pi camera and Raspberry Pi for early diagnosis of crop diseases. An ESP32 module transmits data to the Cloud, enabling remote monitoring and data-driven decision-making. The paper includes Figure 2, illustrating the sequence of processes involved in this subsystem.

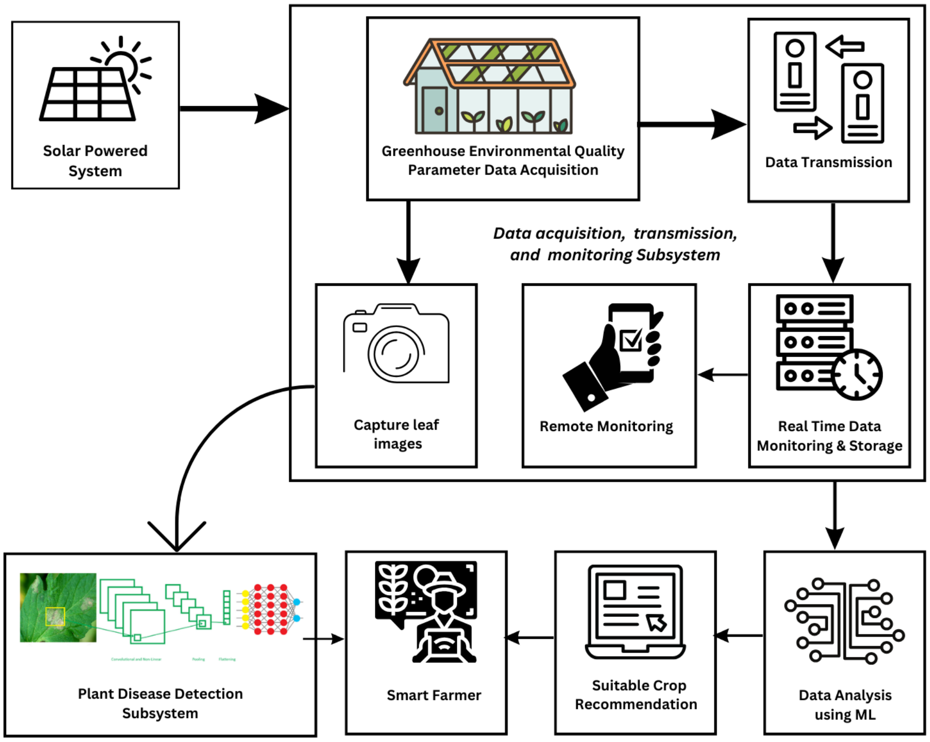

Figure 1. Block Diagram of the Proposed Greenhouse system.

C. Intelligent Crop Recommendation Subsystem

The system seamlessly integrated contemporary sensors, including pH, NPK (Nitrogen, Phosphorus, and Potassium), soil moisture, and a DHT sensor (Digital Humidity and Temperature). These sensors were meticulously chosen for their ability to capture essential information, enabling the detection of critical soil components such as nitrogen (N), phosphorus (P), and potassium (K), as well as monitoring temperature, humidity, and pH levels. Real-time data from these sensors is presented on an LCD screen, as depicted in Figure 3. This visual display functions as a dashboard, providing farmers with an immediate overview of their soil's characteristics and the surrounding environment. Moreover, The system is designed with user-friendliness in mind, allowing farmers to input vital data directly through a user-friendly application. The distinguishing feature of this subsystem is its intelligent suggestion function. It uses robust algorithms to evaluate the amalgamated data from all the sensors—pH, NPK, soil moisture, temperature, humidity, and pH. These algorithms intricately analyze the complex relationships between soil composition and environmental factors to generate crop recommendations tailored to the specific qualities of the soil. This functionality has been developed by collecting and analyzing a substantial dataset, followed by training various Machine Learning (ML) models. The conceptual process is illustrated in Figure 4.

1) Dataset collection

The dataset employed in this subsystem for crop recommendations, referenced as Crop Recommendation Dataset [26], was sourced from Kaggle. [1]. This dataset comprises 2200 samples and encompasses 7 distinct features. Among these features, the independent variables encompass the soil's nitrogen (N), phosphorus (P), potassium (K) content, along with temperature, humidity, and pH levels. In contrast, the dependent variable pertains to crop labels, comprising 22 unique crop labels as class variables.

2) Data Preprocessing

In the data preprocessing phase, a thorough assessment was conducted to ensure data cleanliness, consistency, and suitability for analysis. This process commenced by scrutinizing the dataset for any instances of missing values or duplicate entries, and no such issues were detected. We have performed a feature transformation technique and data balancing method to mitigate the bias over the target variable.

a) Feature Transformation

It is necessary to convert each feature on the same scale to reduce biases in the dataset. It makes the features of the dataset invariant to the unit. We utilized the standard scaling technique to perform feature scaling to ensure that the input features were all on the same scale. This transformation

[1]https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset

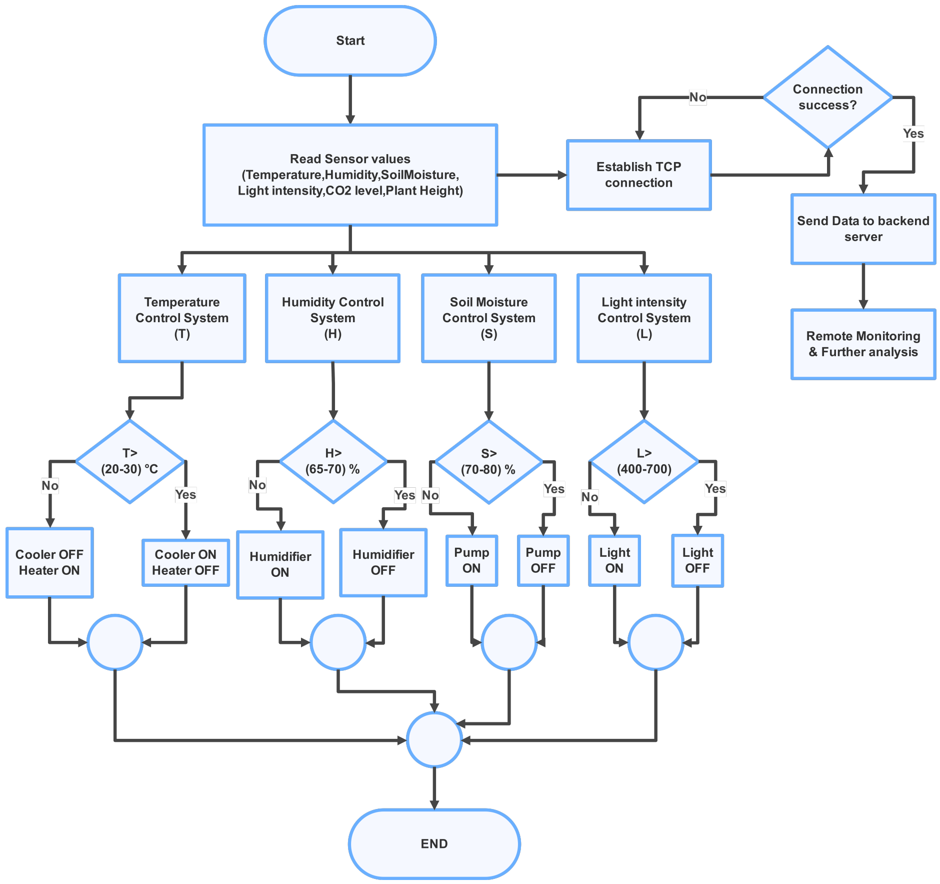

Figure 2. Flowchart of the Data Acquisition, Transmission, and Monitoring Subsystem

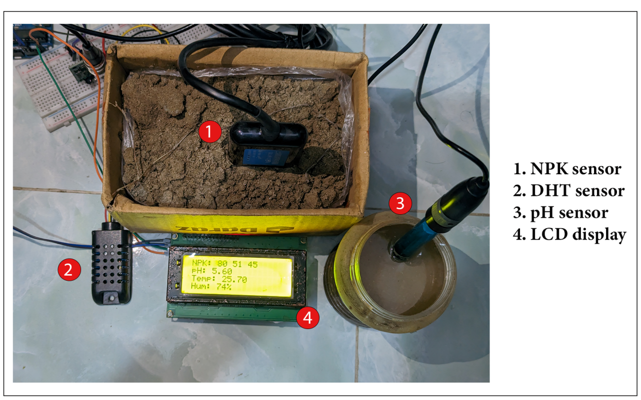

Figure 3. Prototype of the Crop Recommendation Subsystem

ensures that the input features have a mean centered at zero and approximately one standard deviation. This enables faster convergence of ML algorithms. The standard score of a sample R is derived using the formula shown in equation 1.

$$R = (S - m)/d \tag{1}$$

In the equation 1, m and d denote the mean and variance of the training samples respectively.

3) *Machine Learning Algorithm*

We have applied seven machine learning models in this part of the crop Recommendation. The models are listed below:

- Random Forest: The model [27] was constructed using 50 decision trees and 42 random states. The Classifier generates a consensus result from the decision trees.

- Support Vector Machine: The Support Vector Machine (SVM) [28] is optimized for predictive accuracy using a randomized search over kernel types, regularization strengths, and gamma values. The best-performing SVM model, identified through this process, is stored in the variable best_svm_random. This hyperparameter tuning aims to enhance the SVM's performance and generalization on the dataset.

- Decision Tree: The optimal Decision Tree model obtained through hyperparameter tuning using grid search. This fine-tuned model represents the most

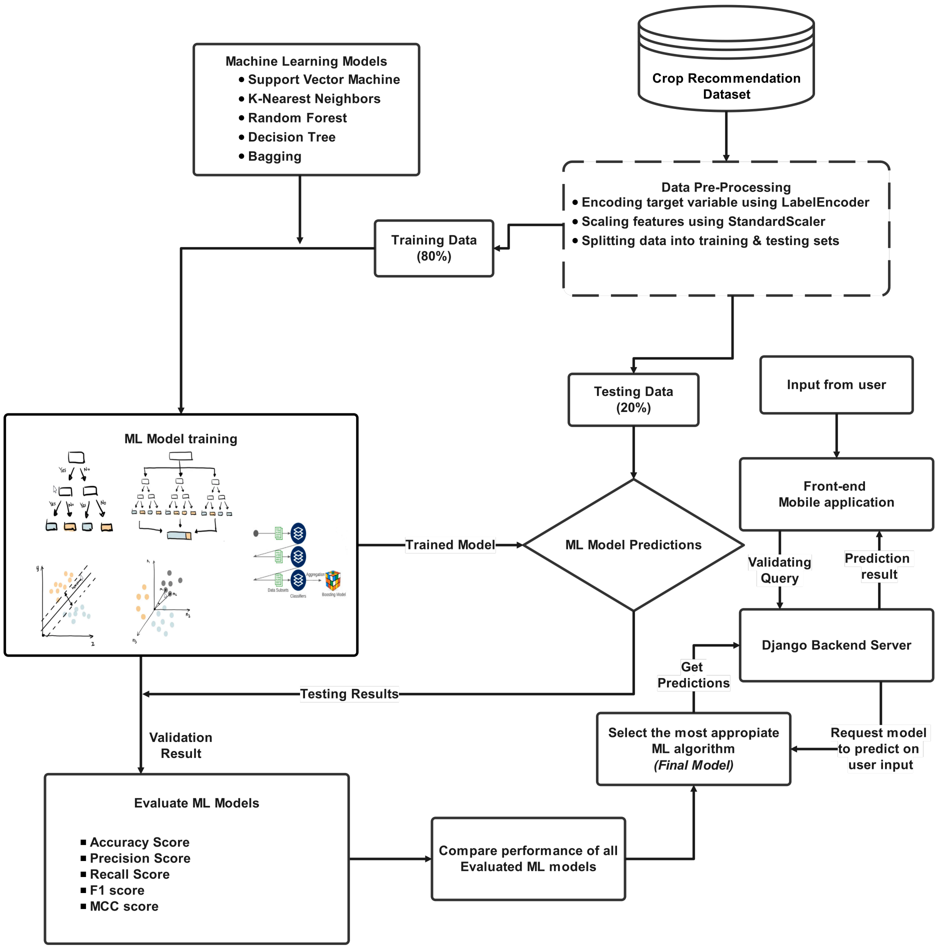

Figure 4. The conceptual diagram of the proposed Model for crop recommendation subsystem

effective configuration for predictive accuracy within the given parameter space.

- Logistic Regression: The model undergoes advanced hyperparameter tuning using GridSearchCV. The hyperparameter grid explores penalty types (L1 or L2), regularization strengths (C), intercept fitting options, solver algorithms (liblinear or saga), and maximum iteration values. Employing a cross-validated approach with 5 folds, this method systematically identifies the optimal configuration, enhancing the model's predictive accuracy and generalization on the dataset for the study.

- Bagging: The Bagging (Bootstrap Aggregating) is an ensemble learning method [29] is formed using a diverse set of base models, including RandomForest, Decision Tree, Extra Trees, and k-Nearest Neighbors, each with a maximum depth of 5. The ensemble employs 100 base models, utilizing a RandomForest as the base estimator.

- AdaBoost: The AdaBoost Classifier [30] is configured with hyperparameter tuning, utilizing a diverse set of base models: Decision Tree, Random Forest, SVM, and Gradient Boosting. The ensemble, comprising 100 base estimators with a learning rate of 0.1, aims to enhance predictive performance through model diversity. The research systematically explores AdaBoost's effectiveness for improved accuracy and generalization in predictive modeling tasks.

- Stacking: The Stacking Classifier [31] is used with diverse base models, including Random Forest, Gradient Boosting, SVM, and KNN, which are integrated to capture varied learning patterns. This ensemble is refined through hyperparameter tuning, optimizing the meta-classifier (Logistic Regression), and the stacking method.

D. Disease Detection Subsystem

This Disease Detection Subsystem uses advanced image processing techniques to identify possible plant health problems by carefully examining leaf photos. This Subsystem strategically employs lightweight Convolutional Neural Network models. The subsystem's efficiency and flexibility are improved by consciously using these lightweight models, making it the perfect choice for deployment on low-processing devices, particularly resource-constrained Internet of Things devices. Our purposeful emphasis on lightweight models guarantees our disease detection subsystem's scalability, accessibility, and smooth integration across many technological platforms, which require low computational power.

1) Dataset collection

The dataset employed in the Disease Detection Subsystem, as referenced in [32], was sourced from Kaggle[2]. This extensive dataset comprises approximately 87,000 RGB images of healthy and damaged crop leaves. These leaves are categorized into 38 different types and are affected by 26 distinct plant ailments. The dataset encompasses a variety of greenhouse crops, including but not limited to tomatoes, maize, apples, strawberries, grapes, and peppers. This dataset has 70,295 images designated for training purposes and an additional 17,572 images allocated for validation.

2) Data Preprocessing

Before feeding the images into the deep learning models, a preprocessing phase is executed to standardize their dimensions and format. This involves resizing the photographs to a consistent resolution of 256x256 pixels while maintaining RGB color format. This crucial step ensures uniformity in image size and dimensions, enabling the models to evaluate the data effectively. Data augmentation techniques are applied during training to enhance dataset variability and mitigate overfitting. These techniques encompass random rotations, flips, zooms, and color adjustments, all improving the models' adaptability to real-world environmental variations.

3) Model Selection

The Disease Detection Subsystem uses a range of deep learning models [33] to accurately detect and diagnose diseases affecting various plant species in the greenhouse environment. The models used are

- NASNetMobile: The model [34] includes two fully connected layers with dropout regularization for improved generalization and a Global Average Pooling layer to reduce spatial dimension. The sparse categorical cross-entropy loss function and Adam optimizer are used in the model's construction for multiclass classification.
- DenseNet121: The top classification layers are removed from the model based on DenseNet121 [35], and a Global Average Pooling layer is added. To avoid overfitting, two completely linked layers with dropout regularization come next. The Adam optimizer and sparse categorical cross-entropy loss function are used to train the model.
- EfficientNetB0: The model uses EfficientNetB0 [36] as its foundational architecture. Applying two completely linked layers with dropout for regularization comes after the Global Average Pooling layer. The model's construction uses the sparse categorical cross-entropy loss function and Adam optimizer.
- MobileNetV2: The top classification layers are not included when MobileNetV2 [37] is used as the basis model. Following the introduction of a Global Average Pooling layer, two completely linked layers with dropout regularization follow. The model's construction uses the sparse categorical cross-entropy loss function and Adam optimizer.
- InceptionV3: The underlying model is the InceptionV3 [38] architecture, with the top categorization layers removed. A Global Average Pooling layer and two fully linked layers with dropout are included for better performance. The model's training uses the sparse categorical cross-entropy loss function and the Adam optimizer.

The selected deep learning models offer an attractive combination of accuracy, efficacy, and flexibility for microdevice IoT applications [39]. These models have been carefully designed to combine computational complexity with predictive performance, making them suited for environments with restricted resources typically observed in IoT devices. These models may perform effectively on edge devices with low memory and processing power owing to their efficient architecture and extremely few parameters [40]. This is particularly beneficial for real-time disease classification and detection in a greenhouse farming setting, where rapid reflexes and effective treatments are necessary to avert significant crop losses.

E. Rainwater Harvesting and Solar Tracking Subsystem

This subsystem is important in our greenhouse system since it provides a two-pronged approach to increasing sustainability and operational efficiency. As shown in Figure 5, the prototype of this subsystem emphasizes its critical role in our proposed system. The solar tracker system allows solar panels to accurately follow the sunlight's direction and intensity throughout the day. By constantly adjusting the location of the solar panels, the system maximizes solar energy absorption, optimizing energy production and storage. The working flow of this tracking system is shown in figure 6. This solar-powered technique makes our proposed system more self-sufficient and cost-effective, minimizing operational expenses and decreasing the carbon footprint.

Additionally, the employment of renewable solar energy aligns with sustainable agricultural practices, adding to environmental conservation. On the other hand, Rainwater Harvesting enables water conservation and sustainable

[2] https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

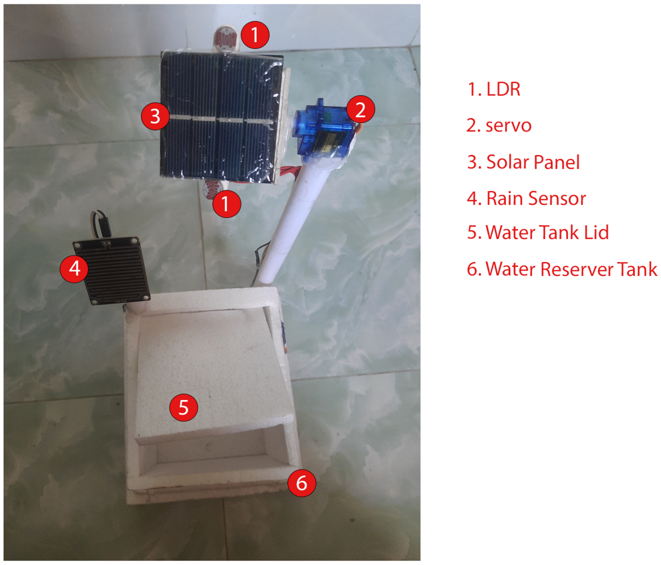

Figure 5. Prototype of the Rainwater Harvesting and Solar Tracking Subsystem

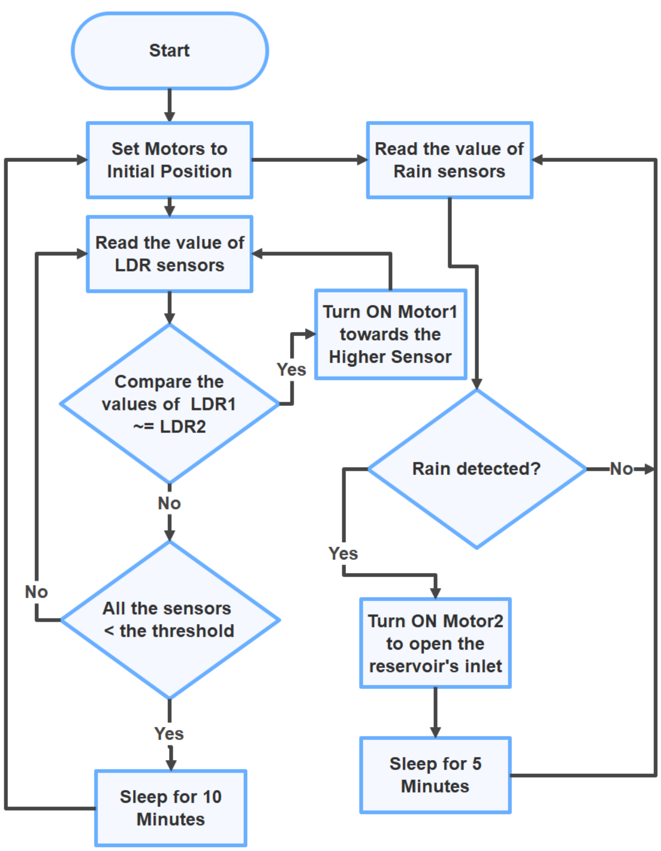

Figure 6. Flowchart of the Rainwater Harvesting and Solar Tracking Subsystem

water management approaches. This subsystem also incorporates a rain sensor to monitor rainfall events. The working flow of this system is also shown in figure 6. When the rain sensor detects rain, it prompts the subsystem to take action. Upon rain detection, a servo motor is actuated to open the water reservoir's inlet, allowing rainwater to be collected. This proactive strategy ensures that crucial rainwater is efficiently gathered and conserved for later use within the greenhouse. The proposed system dramatically lessens dependence on conventional water supplies by harnessing rainwater for irrigation and other greenhouse purposes, safeguarding vital freshwater resources. This minimizes water use, saves operational expenditures, and aids in a more environmentally friendly agriculture practice. The reservoir works as a storage facility, collecting rainwater during rains. This saved rainwater can be employed during dry seasons or droughts, providing a stable water supply for the greenhouse. This water reuse strategy increases the system's sustainability, robustness, and efficiency.

F. Mobile App Development & Design

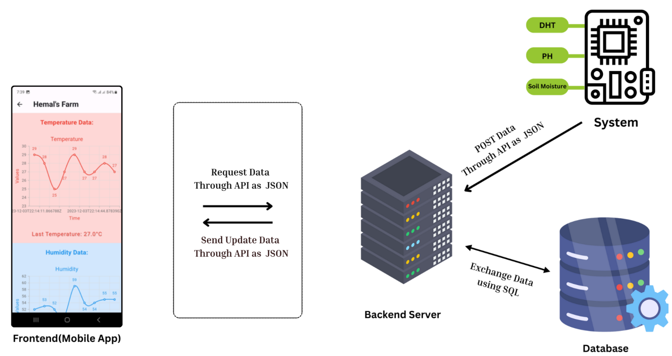

Figure 7. Mobile Application Workflow

The mobile app, built using Django for the backend and Flutter for the front end, provides a smooth and efficient user experience. A RESTful API offers dependable communication and data exchange, while a MySQL database ensures data storage reliability. The workflow of this application is visually depicted in Figure 7. The program includes a Monitoring Dashboard for real-time monitoring of crucial parameters such as temperature, humidity, light intensity, and soil moisture. The Crop Recommendation System also uses modern data analytics to deliver individualized crop recommendations, hence increasing agricultural productivity. The Disease Detection Subsystem, on the other hand, uses image processing to swiftly identify possible health hazards in plants, allowing for early action. This integrated strategy improves precision agriculture by providing farmers with a comprehensive tool for monitoring, crop management, and disease identification, resulting in more sustainable and efficient agricultural methods.

4. RESULTS AND DISCUSSIONS

In this section, we will first introduce our experimental setup and then conduct experiments to demonstrate the significance of the proposed technique. We will explain the evaluation metrics and then show the comparison results of our analysis. We also examine the efficiency of the trained student models.

A. Performance Evaluation Metrics

Several essential metrics are used to assess the performance of classification models. The confusion matrix, a table that compares model predictions to actual labels, is one such statistic that is crucial in measuring a model's performance. The four critical components of the confusion matrix are true positive (TP), false positive (FP), true negative (TN), and false negative (FN) [41]. The number of positive occurrences successfully predicted by the model is marked by TP, whereas the number of negative instances incorrectly projected as positive is denoted by FP. TN, on the other hand, represents the number of negative occurrences that were correctly anticipated as negative, and FN denotes the number of positive instances that were incorrectly classified as negative. Several metrics derived from the confusion matrix assist in assessing the model's performance. Accuracy is a statistic that measures the model's predictability by dividing the total number of occurrences by the sum of TP and TN, as indicated in Equation 2.

$$Accuracy = \frac{TP}{TP + TN + FP + FN} \tag{2}$$

Precision, a positive predictive value determined using equation 3, is concerned with the fraction of correctly predicted positive occurrences out of all cases anticipated.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

In contrast, recall, as stated in equation 4, is the proportion of correctly predicted positive occurrences relative to all positive instances. It is also known as sensitivity or true positive rate.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The F1-score gives a balanced statistic by assessing the harmonic mean of accuracy and recall. Equation 5 may be used to get the F1 score. It demonstrates the model's capacity to achieve both accuracy and recall simultaneously.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

On top of that, the Matthews Correlation Coefficient [42], a statistic, considers the confusion matrix's TP, TN, FP, and FN components. Its value ranges from -1 to 1, with 1 being an error-free classification, 0 representing an arbitrary classification, and -1 representing a completely incorrect classification. The MCC formula incorporates TP, TN, FP, and FN to provide a comprehensive measure of categorization quality, as shown in Equation 6.

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}} \tag{6}$$

The ROC AUC metric was used to compare the machine learning models. The ROC curve illustrates a binary classifier's performance at various categorization levels. At different threshold values, it shows the true positive rate (TPR) vs the false positive rate (FPR). A multiclass ROC curve is utilized in this comparison to assess how well each method performed for each class concerning the other classes. The AUC (Area Under the Curve) score gauges the algorithm's performance for each class. The boundary of AUC is (0,0 to 1,1). The highest value of AUC indicates a better classifier.

B. Experimental Design of the Proposed System

Our intelligent greenhouse system's functional prototype displays its potential to effectively monitor and adjust greenhouse conditions by seamlessly collecting and providing real-time data. Figure 8 displays the prototype of the Intelligent Greenhouse Setup, which serves as a physical indicator of our effort. We tested the system inside a home at Kaliakair near Gazipur, Bangladesh. Using our real-life application, we successfully acquired important parameter data, enabling us to adequately assess the system's performance and impact in a genuine, real-world context.

C. Comparison of several ML models for Crop recommendation subsystem

Among the machine learning models evaluated for crop recommendation, Boosting (AdaBoost) stands out as the top performer, as shown in table I and figure 9, achieving the highest accuracy, precision, recall, F1-Score, and MCC. Bagging closely follows, demonstrating strong performance across multiple metrics. Random Forest performs well but slightly lags behind Boosting and Bagging. In contrast, SVM and Decision Trees perform less than ensemble methods. The choice between Boosting and Bagging may depend on specific requirements such as interpretability and resource constraints. Boosting is the preferred choice for maximizing predictive performance in crop recommendation tasks in this scenario.

D. Crop Recommendation System Mobile Interface

In this integrated architecture, users input critical greenhouse parameters through a user-friendly form embedded in a Flutter mobile application. The input is sent via a POST request to a Django backend, which, in turn, forwards the data to a Flask server hosting a pre-trained machine-learning model for predicting optimal crops. The Flask server processes the input, returns the prediction to Django, and stores the results in a MySQL database, including the input parameters and prediction. The Django backend communicates the prediction to the Flutter app, enabling users to seamlessly receive and display personalized recommendations. This unified system harmonizes the strengths

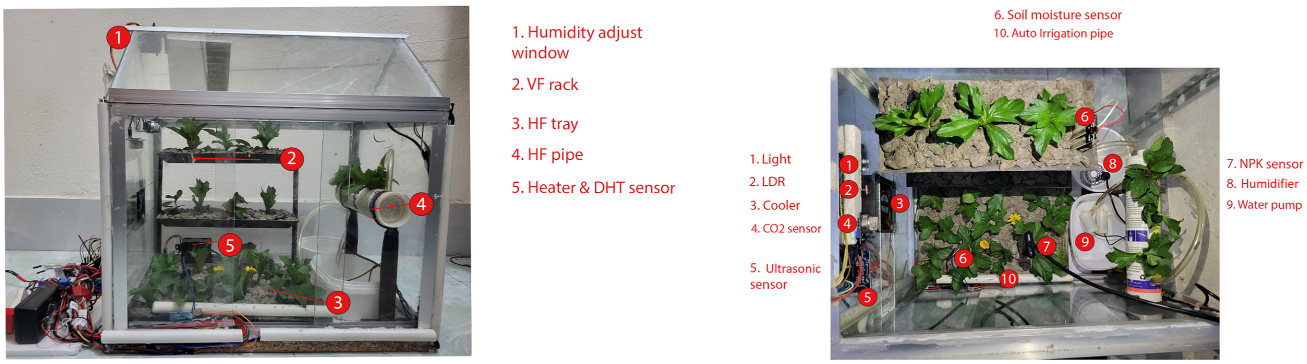

Figure 8. Prototype of the Intelligent Greenhouse Setup

TABLE I. Performance Comparison among ML Algorithms for Crop Recommendation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC (%)
Random Forest	96.36	96.84	96.36	96.43	96.20
SVM	93.41	93.65	93.41	93.38	93.10
Decision Tree	92.27	94.14	92.27	92.41	91.99
Bagging	94.55	95.67	94.55	94.58	94.33
AdaBoost	**97.27**	**97.62**	**97.27**	**97.30**	**97.15**
Stacking	92.27	93.01	92.27	92.16	91.95
Logistic Regression	86.36	87.02	86.36	86.29	85.74

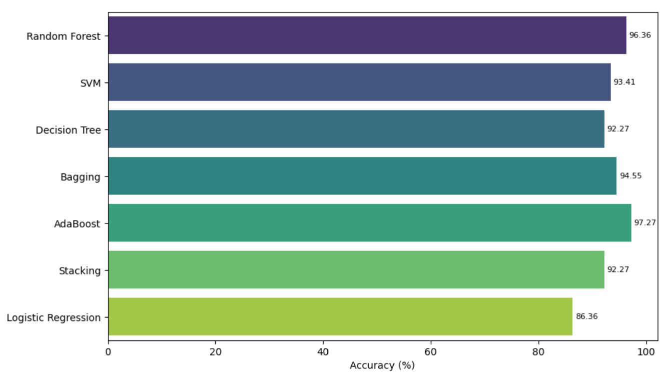

Figure 9. Accuracy Comparison among ML Algorithms for Crop Recommendation

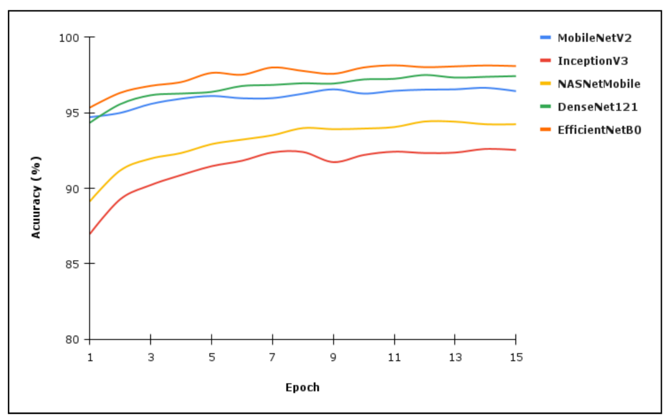

Figure 10. Accuracy Curves of Deep Learning Models for Disease Detection Subsystem

of Flutter for frontend interaction, Django for API handling and database integration, Flask for machine learning model deployment, and a MySQL database for consistent data storage, creating an efficient end-to-end greenhouse recommendation system. Figure 11 displays the interface screenshot and the prediction result.

E. Comparison of Deep Learning Models for Disease Detection Subsystem

When examining multiple deep-learning models for crop disease detection, as demonstrated in Table II and Figure 10, MobileNetV2 and EfficientNetB0 have considerably fewer parameters than InceptionV3, NASNetMobile, and Densenet121. This is critical for this proposed approach since we utilized IoT devices with limited resources. Regarding the highest accuracy, EfficientNetB0 outperforms with an accuracy of 97.50%. Precision, representing the accuracy of optimistic predictions, is also maximized by EfficientNetB0, showcasing a value of 98.82%. The model's ability to capture all relevant instances, known as recall, is best demonstrated by EfficientNetB0, boasting the highest recall score of 98.73%. The F1 score, which harmonizes precision and recall, is likewise peaked by EfficientNetB0, registering an impressive 98.77%. From these metrics, EfficientNetB0 emerges as the superior model, showcasing a balanced performance in precision and recall—crucial

TABLE II. Performance Comparison of Deep Learning Models for Crop Disease Detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2	96.06	96.43	96.43	96.43
InceptionV3	91.44	95.61	95.59	95.60
NASNetMobile	93.16	96.39	96.56	96.47
EfficientNetB0	**97.50**	**98.82**	**98.73**	**98.77**
Densenet121	96.69	98.41	98.34	98.37

aspects in classification tasks. Due to a reasonable mix of model size, computational efficiency, and accuracy, EfficientNetB0 is the most suitable solution for this proposed system with resource-constrained devices.

F. Disease Detection Subsystem Mobile Interface

The mobile app interface provides users with a user-friendly platform for plant disease detection. Users can initiate the process by clicking on the camera icon, which activates the image capture functionality. Alternatively, users can choose a pre-captured leaf image from their device's gallery. Upon image selection, the mobile application processes the chosen image using the disease detection subsystem. The system then analyzes the selected image to identify any potential plant diseases. The interface dynamically displays the results of the disease detection process, showcasing the identified disease(s) on the plant leaf. This information is presented to the user in an easily understandable format, allowing them to take necessary actions based on the diagnosis. Figure 11 illustrates a screenshot of the mobile app interface during the disease detection process, giving users a visual representation of the detected disease on the selected plant leaf.

5. CONCLUSION

Our proposed system combines technology with principles of sustainable farming, forcing a reformation in traditional agricultural production using modern sensors, automation, machine learning, and modern farming methods such as horizontal greenhouses, vertical farming, and hydroponics. Starting from rain collection to solar tracking, the stipulated subsystem rejoices in saving resources and environmental sustainability. Extensive simulations show excellent results: the highest recorded accuracy of crop recommendations was 97.27%, while crop diseases accounted for 97.50%. The results obtained from this study show that the system has potential applications in increasing crop productivity, efficient use of resources, and sustainability. Through a user-friendly mobile app, it makes monitoring easier on the greenhouse, gives recommendations on crops, and timely disease detection; hence, it remains atop in keeping up with solving challenges caused by increased populations. Although the upfront cost of installation may deter many farmers, the long-term benefits certainly outnumber these drawbacks. Future research should be oriented toward fine-tuning the system based on certain environmental parameters and increasing its adaptability to different agricultural practice conditions and crops. Then, through continuous innovation and data-driven insights, farmers will be better placed in creating a greener and more sustainable agricultural landscape: striking a perfect balance between technology and nature for a brighter future.

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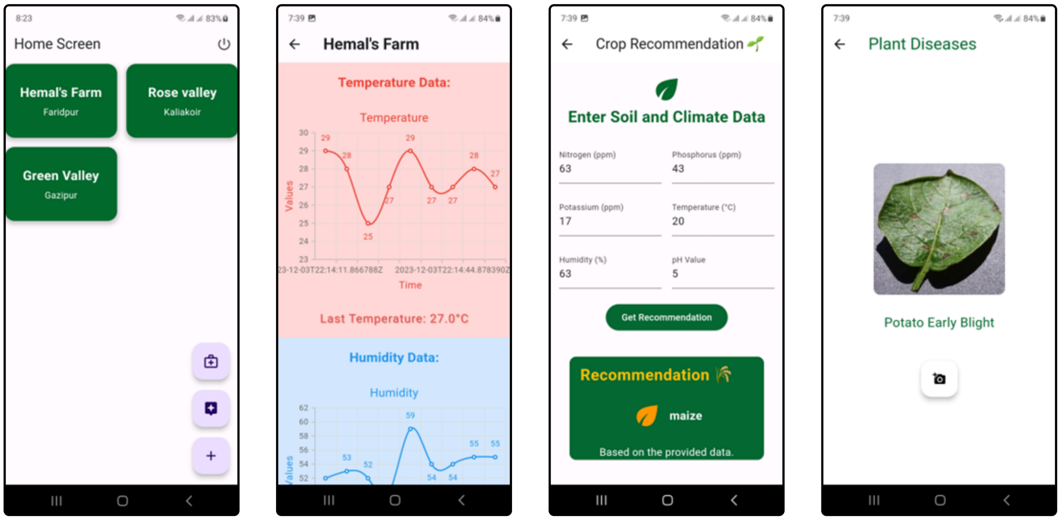

(a) (b) (c) (d)

Figure 11. (a) Homepage of Mobile application, (b) Monitoring Dashboard, (c) Crop Recommendation Subsystem, (d) Disease Detection Subsystem

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