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Automated Greenhouse For Optimal Crop Selection And Growth

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Abstract: Greenhouses provide a controlled environment that enhances plant growth by regulating temperature, humidity, and light. However, managing these environmental factors manually can be challenging and may lead to reduced crop productivity. The project presents a Greenhouse Monitoring and Control System that uses various sensors and a control unit to automate the regulation of greenhouse conditions. The system continuously monitors critical factors such as temperature, soil moisture, and light intensity, adjusting the environment by turning on fans, activating watering pumps, and controlling artificial lighting as needed.

The system incorporates machine learning algorithms to analyze sensor data and predict which crops are best suited for the current conditions. By offering crop recommendations based on real-time environmental factors, the system enables farmers to make informed decisions, optimizing crop selection for maximum yield and profitability. This project aims to reduce human error, improve farming efficiency, and increase sustainability by automating key greenhouse functions and providing data-driven insights to enhance productivity.

Index Terms – **Green House, ESP32 Microcontroller, Machine Learning, Google Colab, Crop Prediction, Sensors, IOT.**

I. INTRODUCTION

Greenhouse farming is a modern agricultural technique that involves growing crops in a controlled environment within structures made of transparent materials like glass or plastic. These greenhouses allow sunlight in while enabling control over temperature, humidity, and other factors, creating an ideal climate for plant growth. This method helps extend growing seasons, protect crops from harsh weather, and boost productivity.

Crop prediction based on environmental conditions plays a key role in modern agriculture. It helps farmers make informed decisions about crop selection, planting schedules, and resource management. Repeatedly growing the same crop in the same soil can lead to issues like soil degradation, nutrient loss, and declining yields. By analyzing factors such as temperature, humidity, soil, PH farmers can choose crops better suited to current conditions.

Using technologies like **sensors and machine learning**, real-time data can be collected and analyzed to recommend the most suitable crops. This not only improves yields but also supports sustainable farming practices by preserving soil health and minimizing resource waste. In essence, combining greenhouse farming with crop prediction tools enhances efficiency, sustainability, and resilience in agriculture.

Furthermore, integrating **automation and intelligent control systems** into greenhouse setups can drastically reduce the need for manual intervention. These systems can automatically adjust fans, irrigation pumps, and artificial lighting based on sensor inputs, ensuring optimal growing conditions around the clock. This not only reduces human error but also lowers labor costs and increases consistency in crop quality, making modern greenhouse farming a smart and scalable solution for the future of agriculture.

II. LITERATURE SURVEY

[1] This paper title as **"Design and Implementation of a Greenhouse Monitoring and Control System".** The paper explores the use of **smart technology and IoT (Internet of Things)** in agriculture, specifically for **automating greenhouse monitoring and control.** The paper was authored by Magdalena Marinca, Ellsei Liies, Szilard Bularka, and Aurel Gontean. These researchers are affiliated with technical and engineering institutions, and they specialize in areas such as embedded systems, automation, and smart technologies. The base paper focuses on developing a smart system that can monitor and control the environment inside a greenhouse automatically. It uses sensors to check important factors like temperature, humidity, light, and soil moisture. These sensor readings are sent to a microcontroller, which decides whether to turn on devices like fans, water pumps, or lights to maintain suitable conditions for plant growth. The system also sends updates to a cloud platform, allowing users to check real-time data and control the greenhouse remotely using a mobile app or website. This setup helps reduce manual work, saves energy, and improves the overall health and growth of plants in the greenhouse. While the greenhouse monitoring and control system presented in the paper is efficient and innovative, it has a few limitations. The system relies heavily on stable internet connectivity for remote monitoring and control, which can be a challenge in rural or underdeveloped areas. Also, the setup requires technical knowledge for installation and maintenance, making it less user-friendly for farmers with limited experience in electronics or IoT. Additionally, the initial cost of the hardware components may be high for small-scale farmers. Another concern is the accuracy and calibration of sensors, which can affect system performance over time if not maintained properly.

[2] The paper titled **"Real-Time Crop Prediction based on Soil Analysis using Internet of Things and Machine Learning"** explores the integration of IoT and ML for enhancing agricultural productivity. It primarily focuses on designing a smart system that collects real-time data from soil through sensors (e.g., pH, temperature, and moisture) and uses machine learning algorithms to predict the most suitable crop for cultivation. The model aims to provide timely and accurate recommendations to farmers, thereby improving decision-making and crop yield.The paper is authored by **Yaswanth Bandi, C. Sandeep Kumar, Dr. K. Bhargavi, and C. Deepika**, who bring together expertise in computer science and agricultural applications. They aim to bridge the gap between traditional farming methods and modern technology by leveraging predictive analytics and IoT infrastructure.Despite its promising contributions, the paper has a few drawbacks. One limitation is the reliance on the availability and stability of internet connectivity and power, which may be inconsistent in rural areas. Additionally, the study's dataset may be limited to specific regions or soil types, which can affect the model's generalizability to other agricultural environments. Lastly, the system's effectiveness heavily depends on sensor accuracy and proper calibration, which could be a challenge in field deployment.

[3] The research paper titled **"A Novel Based Crop Prediction using Machine Learning and Internet of Things"** explores the integration of **Machine Learning (ML)** techniques with **Internet of Things (IoT)** technologies to enhance the accuracy of crop prediction systems. It aims to provide farmers with an intelligent system that assists in selecting the most suitable crop for cultivation based on environmental factors such as soil moisture, pH value, temperature, and humidity. By collecting real-time data through sensors and processing it using ML algorithms like Random Forest, Naive Bayes, and K-Nearest Neighbors

(KNN), the system recommends optimal crop choices, thereby improving agricultural productivity and decision-making. The paper is authored by **S. Rajesh, B. Rupa, K. Swetha, and P. Mounika** from the Department of CSE, G. Pulla Reddy Engineering College (Autonomous), Kurnool, India. Their collective effort demonstrates a practical application of AI and IoT in precision agriculture.However, the paper has certain drawbacks. One major limitation is the **lack of detailed dataset explanation and preprocessing techniques**, which are crucial for understanding the robustness and scalability of the model. Additionally, the **system's real-world implementation challenges**, such as sensor calibration, data transmission reliability, and cost-effectiveness for small-scale farmers, are not thoroughly addressed. The paper also does not compare its approach with existing advanced models using deep learning, which could offer improved prediction accuracy.

III. PROPOSED SYSTEM

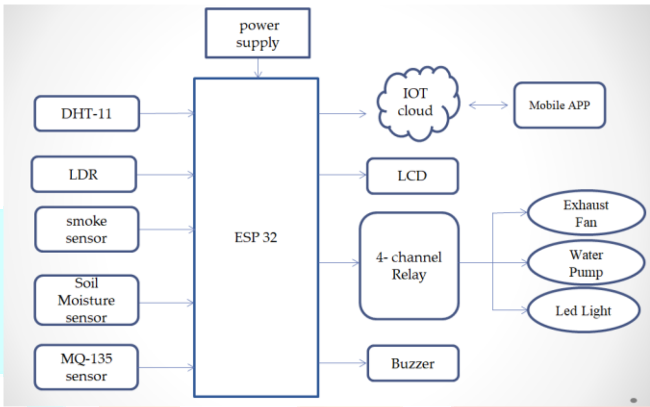
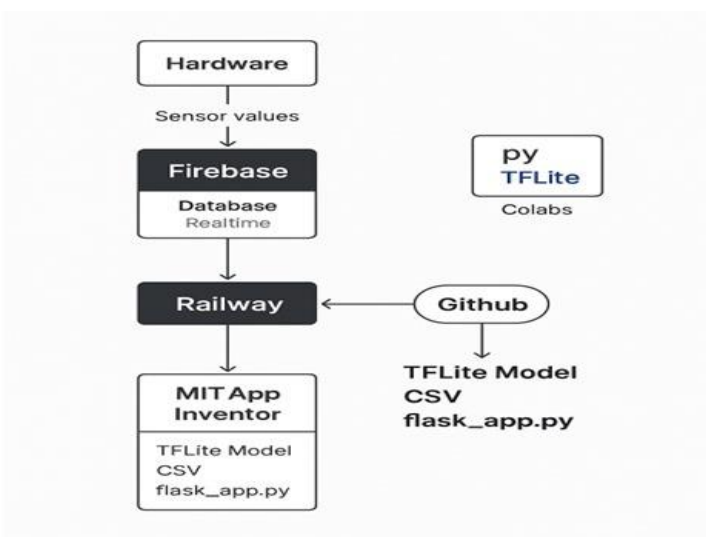


Fig.3.1 : Block Diagram

The proposed greenhouse monitoring system is designed to automate and optimize environmental conditions for efficient crop growth. It incorporates various sensors to monitor key parameters such as temperature, humidity, soil moisture, light intensity, and CO_2 levels. These real-time data readings are processed using a microcontroller or IoT-based system, which enables automated control of greenhouse components like ventilation, irrigation, and lighting.

The system utilizes machine learning algorithms to analyze environmental data and provide predictive insights for better crop yield. Additionally, a web-based or mobile application will allow farmers to remotely monitor and control greenhouse conditions, receive alerts, and make data-driven decisions. Cloud integration ensures secure data storage and facilitates historical analysis for long-term improvements.



This flowchart illustrates the system architecture for crop prediction. Sensor values from the hardware are sent to Firebase in real-time. The trained TensorFlow Lite (TFLite) model, CSV data, and Flask application file are saved on GitHub. Railway is used as the deployment platform to connect Firebase and the MIT App. The MIT App Inventor fetches the model and prediction logic via Railway to make real-time crop suggestions.

IV. METHODOLOGY

Step 1: Sensor Monitoring
The system begins by continuously monitoring various environmental parameters inside the greenhouse. It uses a network of sensors to accurately measure critical factors such as temperature, humidity, soil moisture, light intensity, and CO_2 levels. These sensors provide real-time data that reflects the current growing conditions of the greenhouse environment.

Step 2: Data Analysis
This flowchart illustrates the system architecture for crop prediction. Once sensor data is collected, it is sent to Firebase, where it is stored in real-time. The TFLite model, CSV data, and Flask app are saved in GitHub and deployed using Railway. Railway connects Firebase with the MIT App. The app accesses the model through Railway to provide real-time crop recommendations based on the analyzed sensor data.

Step 3: Crop Recommendation
Based on the results of the data analysis, the system intelligently recommends the most suitable crops to cultivate under the existing environmental conditions. The crop prediction feature considers multiple variables to ensure that the suggested crops will thrive, improve yield, and maintain soil health. This step assists farmers in making accurate and profitable planting decisions.

Step 4: Automatic Control
To maintain optimal growing conditions, the system automatically controls various equipment within the greenhouse. Devices such as ventilation fans, water pumps, and artificial lighting are adjusted in real-time based on sensor readings. This automation ensures that the internal environment remains favorable for plant growth without requiring manual intervention.

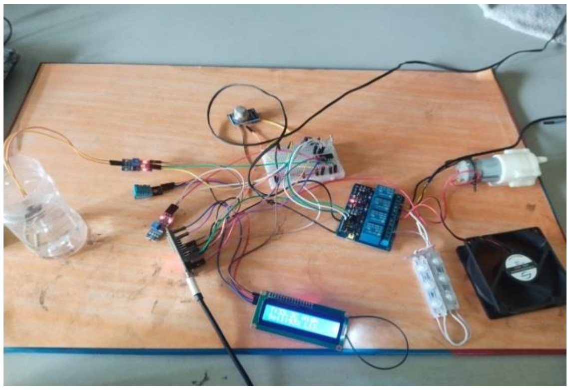
Step 5: Mobile App Integration
The system is integrated with a user-friendly mobile application that provides farmers with easy access to all analyzed data and insights. Through the app, users can view real-time sensor readings, receive crop recommendations, and monitor environmental conditions remotely. This feature empowers farmers to make timely and data-driven decisions for improved agricultural productivity.

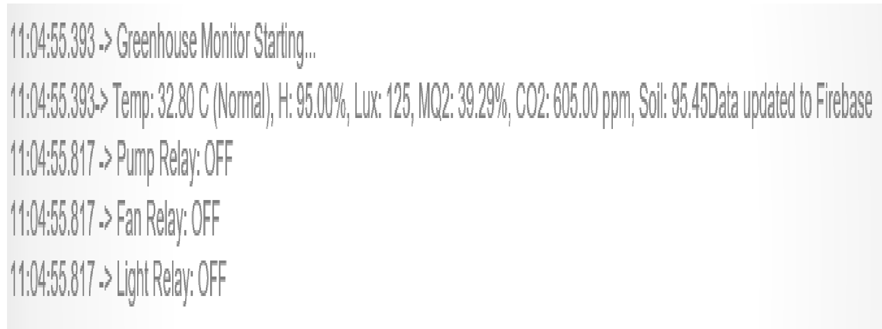
V. RESULTS AND DISCUSSION

The system successfully monitored greenhouse conditions and provided accurate crop recommendations based on environmental factors. Automated controls maintained optimal growing environments, enhancing efficiency and reducing manual effort.

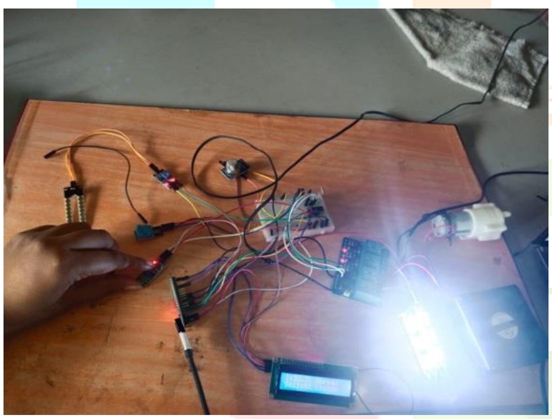
Hardware Implementation and Serial Monitoring Results:

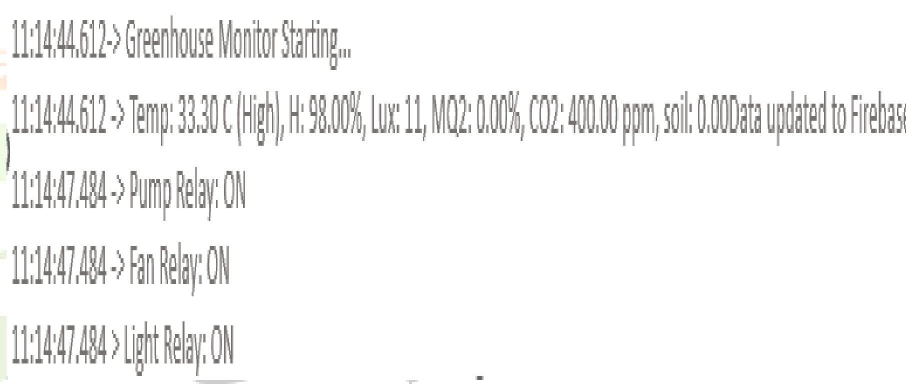
The system is in normal conditions, with the pump, fan, and light relays OFF since the soil moisture level is sufficient.





Due to high temperature and low soil moisture, the system has activated the pump and fan relays, while the light relay is ON.





Hardware Implementation:

In this smart greenhouse setup, all sensors including the DHT11 (temperature & humidity), Soil Moisture sensor, LDR (light), and pH sensor are connected to the ESP32 microcontroller for real-time monitoring. The ESP32 processes the sensor data and controls the actuators accordingly. All actuators such as the exhaust fan, water pump, and LED lights are connected to a 4-channel relay module, which switches them ON or OFF based on environmental conditions. A buzzer and an LCD display are also used to give audio-visual alerts and show real-time values.

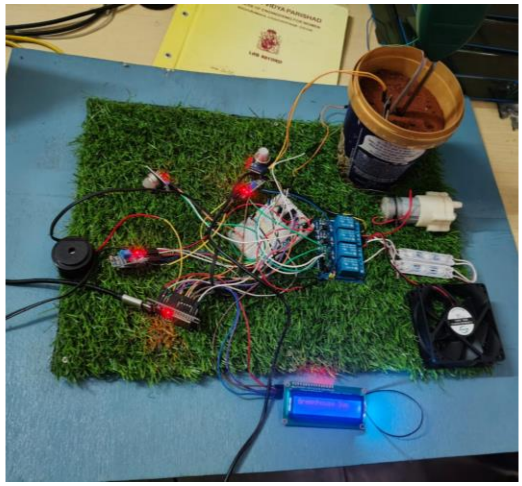


Fig.5.1: **Circuit Diagram of Sensors with Esp32**

Hardware Setup

The final hardware setup of the IoT-based greenhouse monitoring system is housed in a transparent model, integrating sensors for temperature, humidity, light, air quality, smoke, soil moisture, and pH. The ESP32 microcontroller collects and processes the data, displays it on an LCD, and uploads it to the IoT cloud for mobile monitoring. Based on sensor values, devices like the exhaust fan, LED light, and water pump are controlled via a relay module. Real-time system status is also visible through the serial monitor, demonstrating effective automation and smart environmental control.

Fig.5.2 : Hardware setup

NN Model Training Results

The Neural Network (NN) model was trained for 100 epochs using TensorFlow on Google Colab. The dataset was sourced from Kaggle and includes 1,400 records across 14 different crops, with each crop having 100 values. The features used for training include temperature, humidity, soil moisture, pH, and CO_2 levels. The model achieved a test accuracy of 81.79% and a loss of 0.5169, indicating effective learning and good generalization performance.

Training Log Output

The training log displayed accuracy and loss values for each epoch. The model showed consistent improvement with reduced loss and increased accuracy, indicating successful learning.

```
Epoch 91/100
35/35 - 0s - 9ms/step - accuracy: 0.7482 - loss: 0.6597 - val_accuracy: 0.8107 - val_loss: 0.5254
Epoch 92/100
35/35 - 0s - 8ms/step - accuracy: 0.7250 - loss: 0.7103 - val_accuracy: 0.8000 - val_loss: 0.5319
Epoch 93/100
35/35 - 0s - 6ms/step - accuracy: 0.7402 - loss: 0.6879 - val_accuracy: 0.8000 - val_loss: 0.5309
Epoch 94/100
35/35 - 0s - 7ms/step - accuracy: 0.7339 - loss: 0.6792 - val_accuracy: 0.8107 - val_loss: 0.5353
Epoch 95/100
35/35 - 0s - 6ms/step - accuracy: 0.7304 - loss: 0.6843 - val_accuracy: 0.8071 - val_loss: 0.5288
Epoch 96/100
35/35 - 0s - 6ms/step - accuracy: 0.7393 - loss: 0.6632 - val_accuracy: 0.8000 - val_loss: 0.5242
Epoch 97/100
35/35 - 0s - 6ms/step - accuracy: 0.7473 - loss: 0.6933 - val_accuracy: 0.8143 - val_loss: 0.5188
Epoch 98/100
35/35 - 0s - 6ms/step - accuracy: 0.7357 - loss: 0.6746 - val_accuracy: 0.7964 - val_loss: 0.5281
Epoch 99/100
35/35 - 0s - 8ms/step - accuracy: 0.7473 - loss: 0.6725 - val_accuracy: 0.8107 - val_loss: 0.5188
Epoch 100/100
35/35 - 0s - 8ms/step - accuracy: 0.7420 - loss: 0.6816 - val_accuracy: 0.8179 - val_loss: 0.5169
Training time: 39.49 seconds
Test Loss: 0.5169
Test Accuracy: 0.8179
```

Fig.5.3 : Training output

The image shows the final training stages of a machine learning model from epoch 91 to 100. During these epochs, the training accuracy fluctuated slightly, ranging from 72.52% to 74.87%, while the training loss gradually decreased, indicating consistent learning. The validation accuracy remained stable, ranging between 79.64% and 81.79%, suggesting that the model was able to generalize well on unseen data. By the end of training at epoch 100, the model achieved a test accuracy of 81.79% and a test loss of 0.5169, demonstrating solid performance and reliability on the test dataset.

Training Graph:

Accuracy and loss graphs show that the crop prediction model in the greenhouse system learned effectively with high accuracy and minimal overfitting, ensuring reliable classification of crop conditions.

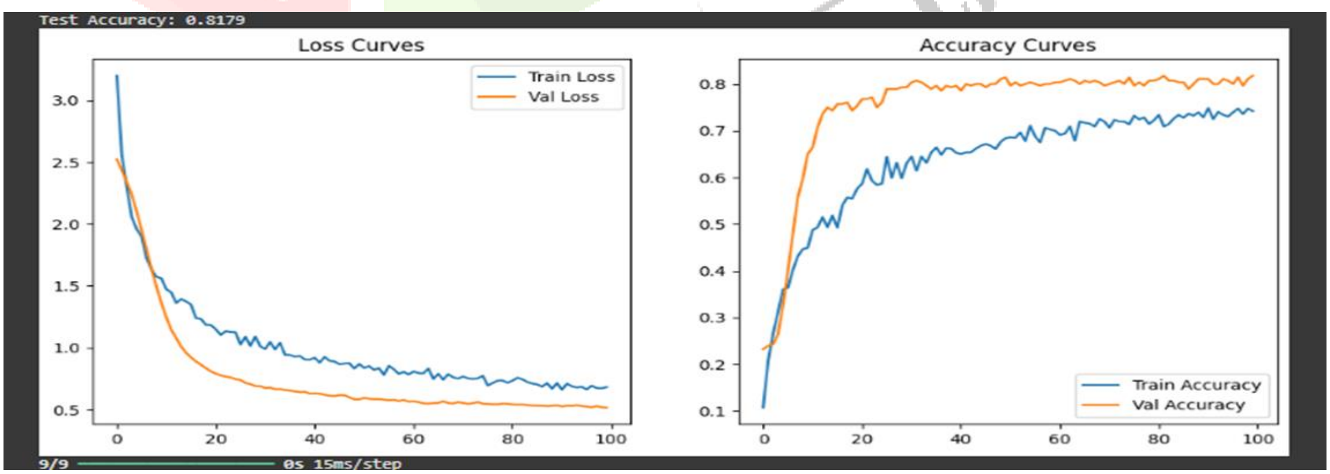


Fig.5.4 : Training Graph

The graphs show the **loss** and **accuracy curves** of a neural network trained over 100 epochs. In the loss curve, both training and validation losses steadily decrease, indicating effective learning and convergence. The accuracy curve shows a sharp rise in both training and validation accuracy, with validation accuracy stabilizing above **80%**, showing good generalization. Overall, the model performs well with no signs of overfitting.

Android APP:

This is the dashboard screen of the MIT App for the greenhouse system. It provides a simple interface with a “Predictions” button to access real-time crop status and monitoring data.

Fig.5.5 : MIT App Dashboard

After clicking the **Predictions** button on the dashboard, this screen displays the real-time sensor values such as temperature, humidity, pH, soil moisture, and sunlight exposure. Based on these inputs, the system analyzes the data and suggests the most suitable crop in this case, **mothbeans** along with a brief explanation comparing the current conditions with trained model data.

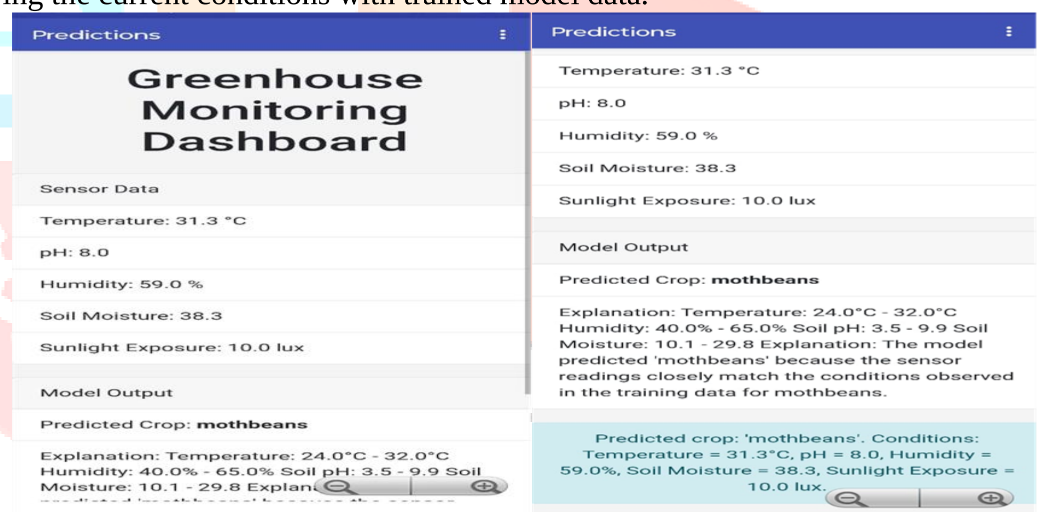


Fig.5.6 : Crop Prediction Result

VI. CONCLUSION

n this project, a smart greenhouse monitoring and crop prediction system was developed using IoT and machine learning technologies. Key environmental parameters such as temperature, humidity, pH, soil moisture, and sunlight were monitored in real-time using various sensors connected to an ESP32 microcontroller. The data was sent to an IoT cloud and accessed through a mobile application with a user-friendly interface. A trained machine learning model analyzed these inputs to suggest the most suitable crop for the given conditions. The system also automated control of devices like fans, water pumps, and lights to maintain ideal growing conditions. Accuracy and loss graphs demonstrated the model’s effective learning with high accuracy and minimal overfitting. This solution proved to be energy-efficient, cost-effective, and scalable for practical use in small- to medium-scale agriculture. It supports sustainable farming by improving decision-making and optimizing resource use. Overall, the system enhances productivity and promotes smart agricultural practices.

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