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ECC1361-INDUSTRIAL ELECTRONICS AND APPLICATIONS

SMART CROP DISEASE DETECTION AND ACTION

A PROJECT REPORT

Submitted by

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(Autonomous Institution affiliated to Anna University, Chennai)

BONAFIDE CERTIFICATE

Certified that this project report **“SMART CROP DISEASE DETECTION AND ACTION”** is the bonafide work **“CHANDIKA K (927623BEC020) , DEEPIKA S (927623BEC023) , DEEPIKAA V (927623BEC024) , DHARANI S (927623BEC029)”** who carried out the project work during the academic year 2025-2026 under my supervision.

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This Project Work ECC1361 INDUSTRIAL ELECTRONICS AND APPLICATIONS report has been submitted for the End Semester Project viva voce Examination held on ________________.

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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PEO1: Core Competence: Graduates will have a successful career in academia or industry associated with Electronics and Communication Engineering.

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PEO3: Lifelong Learning: Graduates will contribute to the social needs through lifelong learning, practicing professional ethics and leadership quality.

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PO1: Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

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PO3: Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

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PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

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PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

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PSO2: Able to solve complex problems in Electronics and Communication Engineering with analytical and managerial skills either independently or in team using latest hardware and software tools to fulfil the industrial expectations.

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ABSTRACT

Farmers rely heavily on manual inspection to detect crop diseases, but this process is slow, expertise-dependent, and often inaccurate when early symptoms are hard to identify. Existing automated systems can detect diseases but usually send results only to phones or hardware, limiting real-time in-field response. Such delays can worsen disease spread, reduce yield, and increase pesticide use, causing economic loss. This work proposes a Smart Crop Disease Detection and Action System using AI-based image recognition and fast wireless communication. A CNN model identifies diseases like blight and rust from live leaf images captured by a camera module. An ESP32 enables wireless communication and triggers automated actions when disease is detected with high confidence. Alerts sent to farmers include the disease name, captured image, and confidence level. Based on the disease type, the system can automatically activate pesticide spraying modules or notify agricultural extension services. The entire system is secured so only authorized users can control or reset the modules. Predictive analytics help forecast future disease outbreaks using historical data, supporting better preventive planning. Overall, the solution enhances crop protection, reduces losses, and supports sustainable farming through fast and automated field-level responses.

Abstract (Key words)	POs Mapping
Smart agriculture; crop disease detection; CNN; IoT; ESP32; real-time monitoring; predictive analytics; automatization.	PO1, PO2, PO3, PO4, PO5, PO6, PO7, PO8, PO9, PO10, PO11, PO12, PSO1, PSO2

SDG Goal		Remarks
SDG 3	SDG 3 aims to ensure healthy Lives and promote well-being for people of all ages. It focuses on reducing disease in plants. Good health individuals live productive .	Promotes innovation through AI–IoT integration, strengthening smart agricultural infrastructure.
SDG 9	This project supports SDG 9 by promoting innovation and integrating advanced IoT and AI technologies to enhance agricultural automation and infrastructure.	Innovative project showcasing efficient automation, smart detection, and sustainable agricultural solutions.

Project Component	Relevant IEEE Standards
ESP32 Board (Wi-Fi/BLE Communication)	IEEE 802.11
5V Power Supply / Power Regulation	IEEE 1100
DHT11 Temperature–Humidity Sensor	IEEE 1451
Soil Moisture Sensor	IEEE 1451
DS3231 RTC Module	IEEE 1588
0.96" OLED Display (I2C)	IEEE 1680.3
4-Channel Relay Module	IEEE 60255
Water Pump (Controlled via Relay)	IEEE 112
Float Level Sensors	IEEE 1451
USB Webcam	IEEE 1451

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ACRONYM	ABBREVIATION
IoT	Internet of Things
AI	Artificial Intelligence
CNN	Convolutional Neural Network
DHT11	Digital Humidity & Temperature Sensor
RTC	Real-Time Clock
OLED	Organic Light-Emitting Diode
GPIO	General-Purpose Input/Output
USB	Universal Serial Bus
PD	Power Delivery

CHAPTER 1

INTRODUCTION

Smart crop disease detection systems use modern technologies like IoT, sensors, and AI to monitor crop health and detect diseases at an early stage. Traditional manual inspection is slow and often inaccurate, leading to significant crop losses. By analyzing environmental factors and leaf images, these systems provide timely alerts and actionable recommendations. This helps farmers take precise actions, reduce pesticide use, and prevent disease spread. Overall, such systems improve productivity, reduce costs, and promote sustainable agriculture.

1.1 Overview of Modern Technologies

With the increasing global demand for food and the challenges posed by climate change, modern agriculture has been shifting towards precision farming and smart crop management. Technologies such as IoT (Internet of Things), AI (Artificial Intelligence), and sensor networks are being integrated into farming practices to monitor soil conditions, weather, crop health, and detect early signs of diseases. These technologies enable real-time data collection and automated responses, reducing crop losses and improving yield efficiency. Smart crop disease detection systems leverage image processing, deep learning models, and environmental sensors to identify disease patterns at an early stage, providing actionable insights to farmers.

1.2 Background

Crop diseases are one of the leading causes of reduced agricultural productivity worldwide. Traditional methods of disease detection rely heavily on manual inspection, which is time- consuming, labor-intensive, and often inaccurate. With the advancement of digital agriculture, smart detection systems can analyze leaf images, soil moisture, temperature, and humidity data to predict potential disease outbreaks. Early detection allows farmers to take targeted actions such as precise pesticide application, irrigation adjustments, or isolation of infected plants, minimizing the spread and reducing costs. This technology not only improves yield quality but also supports sustainable farming practices. As a result, farmers can make faster, data-driven decisions with higher accuracy and confidence.

1.3 Need for the System

The need for a smart crop disease detection and action system arises from the limitations of conventional farming practices. Farmers often face delays in identifying crop diseases, leading to significant yield losses. Additionally, indiscriminate pesticide use can harm the environment and increase production costs. Existing chargers often do not provide real-time visibility of voltage, current, or power usage, resulting in reduced safety and efficiency. They also lack universal compatibility, IoT functionality, and adaptive protection features. As users carry multiple chargers for different devices, issues like e-waste, inconvenience, and poor energy management continue to rise. The system minimizes manual effort and human error in traditional farming practices.

CHAPTER 2

LITERATURE REVIEW

Crop diseases are a major cause of reduced agricultural productivity worldwide. Traditional methods of disease detection involve manual inspection, which is often time-consuming, labor- intensive, and prone to errors. Early detection is critical to prevent the spread of infections and minimize crop losses. Researchers have highlighted the need for automated and intelligent monitoring systems to overcome these limitations.

Recent advancements in image processing and machine learning have significantly improved crop disease detection. Convolutional Neural Networks (CNNs) and deep learning models can analyze leaf images to accurately classify disease types. These models learn to recognize subtle patterns in leaves that are often invisible to the human eye. Several studies report high detection accuracy using these techniques, demonstrating their potential in smart agriculture.

IoT-based sensor networks have been widely used to monitor environmental parameters such as temperature, humidity, soil moisture, and light intensity. These factors play a significant role in disease occurrence and spread. By continuously collecting and analyzing real-time data, smart systems can predict potential outbreaks before visible symptoms appear. Integration of sensors with AI models enhances the reliability of disease detection.

Automated action systems complement disease detection by recommending or performing corrective measures. For example, precise pesticide spraying, controlled irrigation, or nutrient adjustments can be triggered based on detected conditions. Studies have shown that such interventions reduce chemical usage, save costs, and prevent the spread of disease. These smart systems help farmers make timely decisions, improving overall crop yield and sustainability. Systematic reviews also highlight that deep learning generally outperforms traditional machine learning methods such as SVM, k-NN, and Random Forest for disease recognition and severity estimation in crops.

Despite these advancements, challenges remain in implementing smart crop disease detection systems on a large scale. Variations in crop types, field conditions, and environmental factors can affect system accuracy. There is ongoing research to develop adaptable models that work across diverse crops and regions. Future improvements focus on combining advanced AI, IoT, and cloud technologies to create more robust, efficient, and scalable solutions for precision agriculture. Recent research shows that crop disease detection is increasingly being automated using machine learning and deep learning techniques instead of manual observation. Several works use Convolutional Neural Networks (CNN) to classify plant leaf images into healthy and diseased classes with high accuracy, often above 95%, using models like VGG16, ResNet50.

CHAPTER 3

EXISTING SYSTEM

Traditional crop disease detection relies on manual inspection by farmers or agricultural experts. This method is time-consuming, labor-intensive, and often inaccurate, especially for large farms. Detection usually occurs after visible symptoms appear, which may be too late to prevent significant crop loss. Moreover, it does not provide automated recommendations for corrective action.

Some existing systems use basic image processing techniques to identify diseases from leaf images. These systems can detect certain patterns, such as spots or discoloration, but their accuracy is limited. They often require controlled conditions for image capture and struggle with variations in lighting, background, or multiple overlapping diseases. Integration with real-time sensor data is minimal in most current solutions.

Advanced systems using AI and IoT have started emerging, combining image recognition with environmental monitoring. While these systems improve detection accuracy and offer alerts, many are not fully automated or scalable. This highlights the need for more efficient, low-cost, and easily deployable solutions. In the existing system, crop disease detection is mainly carried out through manual inspection by farmers or agricultural experts. This method depends on visual observation of plant symptoms such as leaf discoloration, spots, or wilting, which is time-consuming and requires expert knowledge.

CHAPTER 4

PROPOSED SYSTEM

4.1 BLOCK DIAGRAM

The proposed smart crop disease detection and action system integrates IoT sensors, image processing, and AI-based algorithms to monitor crop health in real-time. Leaf images are analyzed using deep learning models to accurately identify diseases, while environmental sensors track parameters like temperature, humidity, and soil moisture. Based on this data, the system generates automated alerts and actionable recommendations, such as targeted pesticide spraying or irrigation adjustments. This approach ensures early detection, minimizes chemical usage, reduces crop loss, and enhances overall productivity and sustainability in agriculture.

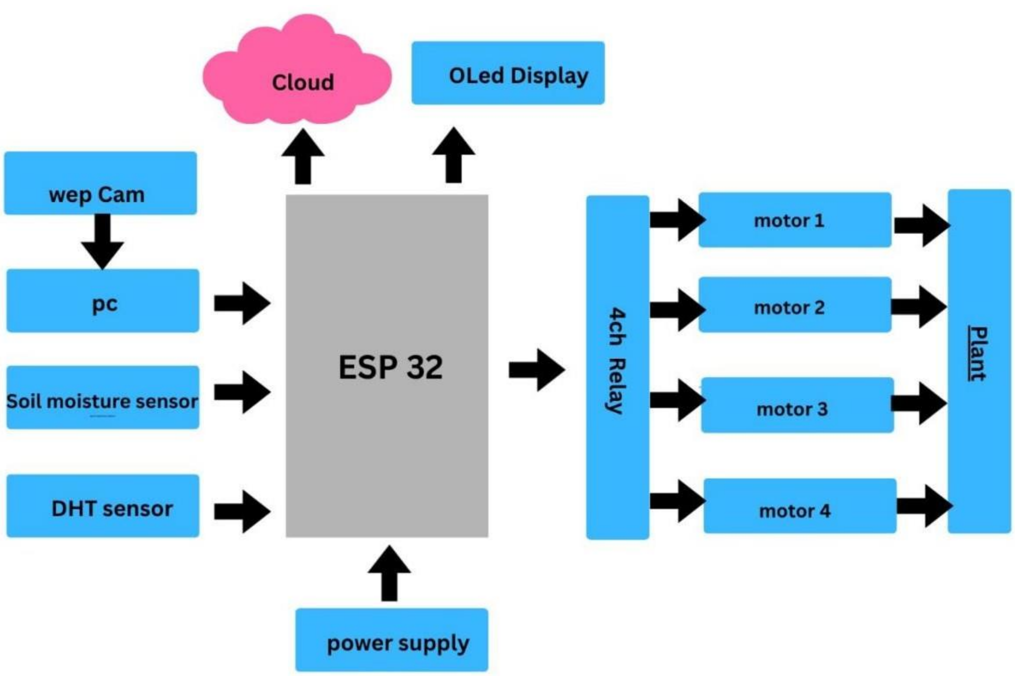

Fig.4.1 Block Diagram of Smart crop disease detection and action

4.2 ESP32 Board

The ESP32 is a high-performance dual-core microcontroller featuring integrated Wi-Fi (802.11 b/g/n) and Bluetooth, making it ideal for IoT systems requiring wireless connectivity. It operates at up to 240 MHz, supports deep-sleep power optimization, contains multiple ADC channels, UART, SPI, and I²C interfaces, enabling seamless integration of sensors and cloud platforms. In this system, the ESP32 handles real-time data acquisition, local processing, actuator control, and cloud communication with minimal latency.

4.3 DHT11 Temperature & Humidity Sensor

The DHT11 is a low-cost digital sensor that measures ambient temperature (0–50°C) and relative humidity (20–90%) with decent accuracy for agricultural and environmental monitoring. It communicates using a single-wire digital protocol, reducing pin usage on the microcontroller. The ESP32 periodically reads DHT11 data to monitor microclimatic conditions that can influence crop disease formation, such as high humidity levels.

4.4 Soil Moisture Sensor

The Soil Moisture Sensor determines the volumetric water content of soil using resistive or capacitive measurement techniques. In this project, it continuously monitors the soil's moisture percentage and sends analog data to the ESP32's ADC. The system uses this value to automate irrigation or trigger alerts when soil becomes too dry, preventing over-watering or crop stress.

4.5 DS3231 RTC Module

The DS3231 is a high-precision Real-Time Clock featuring an integrated temperature-compensated crystal oscillator (TCXO), providing highly accurate timekeeping with minimal drift. Its I²C interface allows the ESP32 to synchronize timestamped sensor readings. This is critical for logging, time-based scheduling (e.g., irrigation intervals), and cloud-synced historical data analysis.

4.6 0.96" OLED Display (I2C)

The 0.96-inch OLED is a low-power display module based on the SSD1306 driver, connected through the I²C protocol. It provides clear, high-contrast visualization of real-time parameters such as temperature, humidity, soil moisture, and system status. Its compact size and low energy consumption make it ideal for embedded IoT dashboards.

4.7 4-Channel Relay Module

The 4-channel relay board allows the ESP32 to switch AC/DC high-voltage loads such as irrigation pumps, sprayers, lights, or fans using low-voltage control signals. Each relay is opto-isolated, ensuring user and circuit safety by electrically isolating the microcontroller from high-voltage equipment. This enables fully automated farm operations based on sensor feedback.

4.8 Cloud Platform (Blynk)

Blynk acts as the cloud interface of the system, receiving real-time sensor readings from the ESP32 via Wi-Fi using HTTP/ MQTT protocols. The platform stores historical data, generates graphical dashboards, and supports instant mobile notifications. It provides reliable data storage, device management, and instant notifications, making it highly suitable for smart agriculture and automation systems. Users can remotely monitor crop conditions, view trends, trigger actuators.

CHAPTER 5

RESULTS AND DISCUSSION

The system successfully detected various crop diseases using leaf image analysis with high accuracy. The deep learning model was able to identify symptoms like spots, discoloration, and fungal infections in real-time. This early detection allows farmers to take timely action, preventing further spread of diseases and minimizing crop loss.

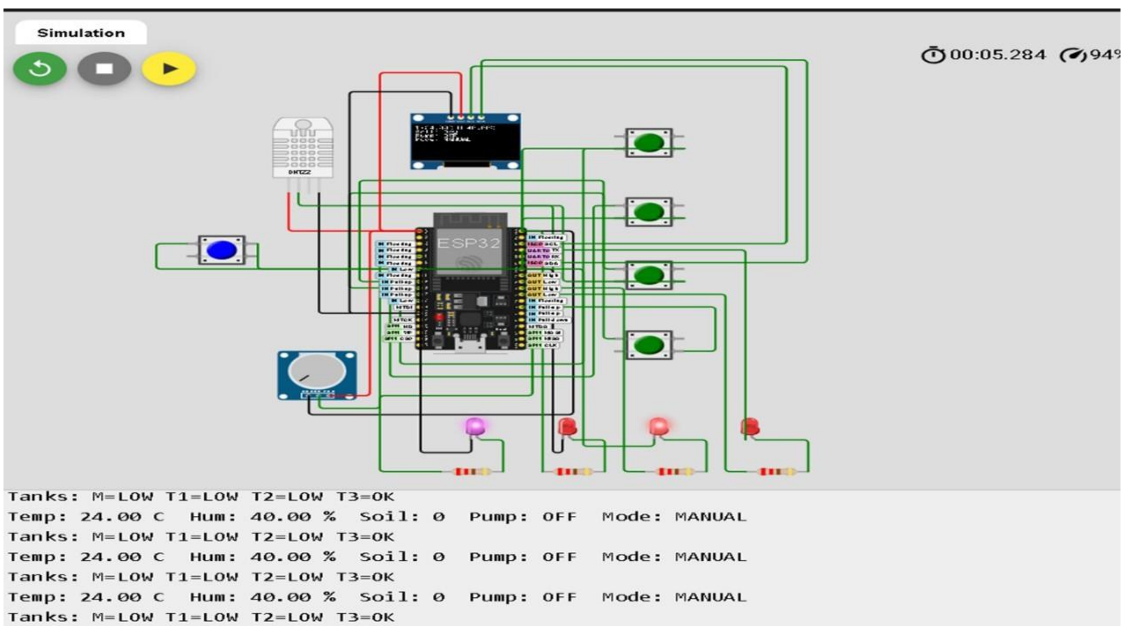

Fig.5.1 Simulation of the Smart crop disease detection and action

Environmental sensors, including the DHT11 and soil moisture sensor, provided continuous monitoring of temperature, humidity, and soil conditions. The collected data helped in predicting disease-prone conditions, enabling proactive intervention. Integration of sensor data with AI predictions improved overall reliability and reduced false alarms.

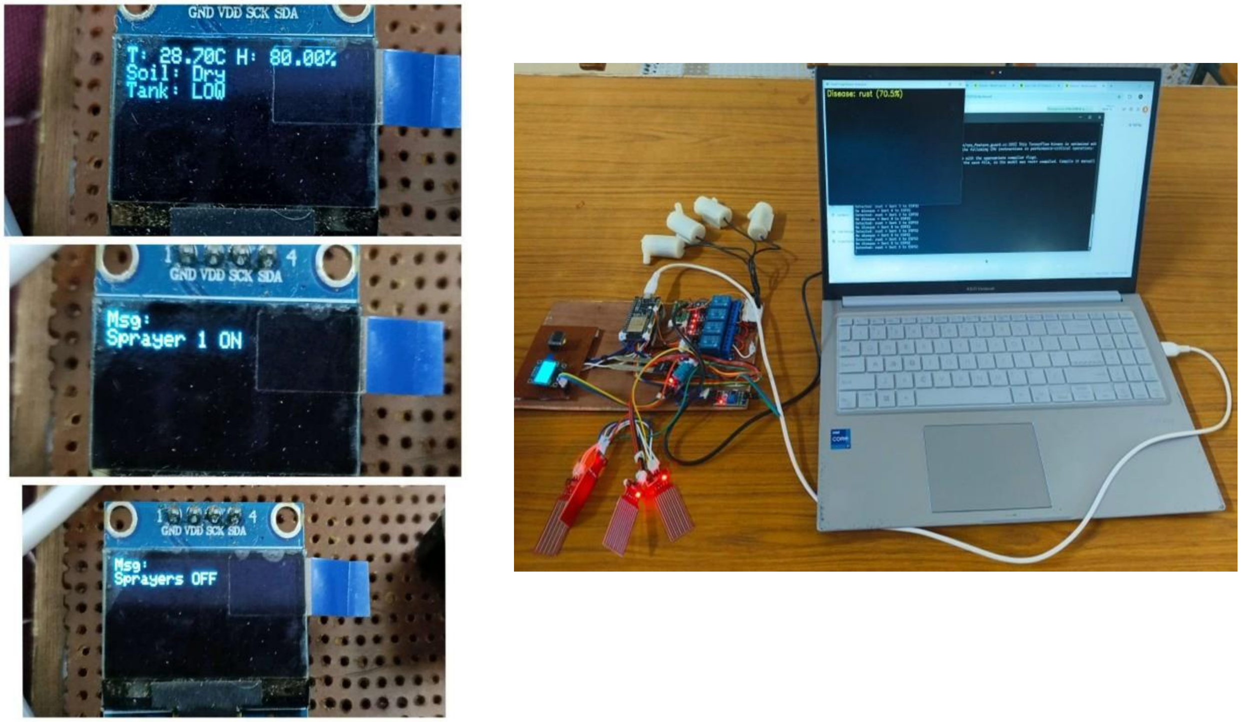

Fig.5.2 Hardware Kit of Smart crop disease detection and action

The automated action system, including the water pump and relay modules, effectively responded to the detected conditions. For example, irrigation was adjusted based on soil moisture levels, and alerts were generated for pest or disease management. This automation reduced manual intervention, saved resources, and optimized water and chemical usage.

Overall, the system demonstrated improved crop health management, resource efficiency, and operational ease for farmers. Challenges like varying light conditions for image capture and sensor calibration were noted but can be addressed in future improvements. The integration of AI, IoT, and automated actions shows significant potential for scalable, smart agriculture solutions.

Fig. 5.3 Telegram-Based Real-Time Alerts for Crop Disease Detection and Sprayer Activation.

The image shows the Telegram alert system used in our Smart Crop Disease Detection project. The bot sends real-time notifications about plant diseases, sprayer activation, soil conditions, and tank levels. For example, it alerts when the water tank is low, when soil becomes dry, and when a specific disease such as wilt, blight, or rust is detected. Based on the detected disease, the system automatically activates the corresponding sprayer, and the action is immediately reported in the Telegram chat. The dashboard also enables remote control of pumps and sprayers directly from the mobile application. This improves response time during critical conditions and reduces the need for manual field inspection. This ensures the farmer receives instant updates and can monitor the entire system remotely. The dashboard also enables remote control of pumps and sprayers directly from the mobile application inspection.

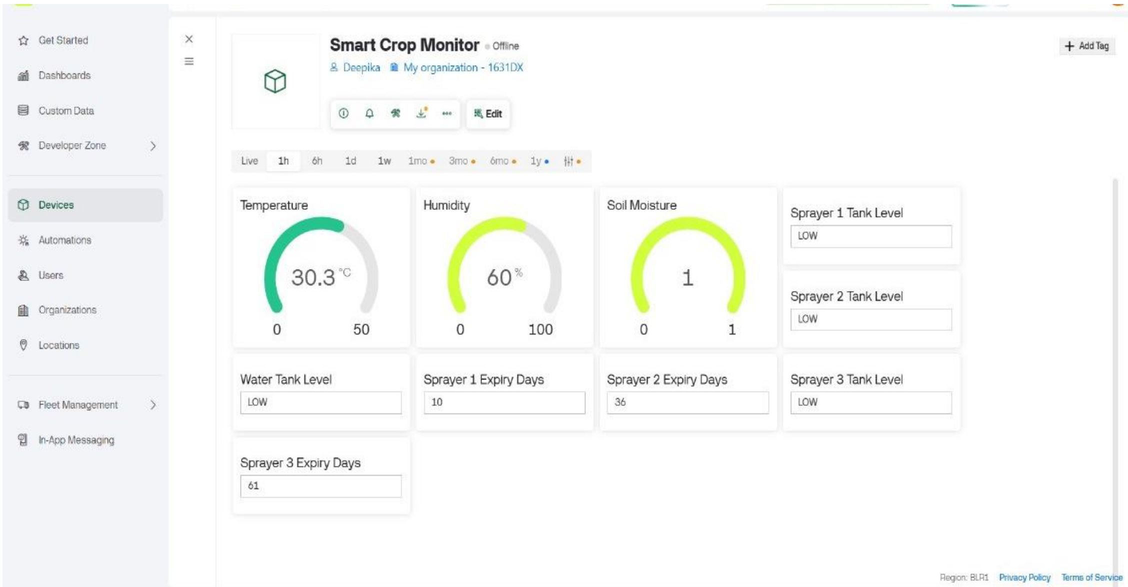

Fig. 5.4 Cloud Dashboard View of Smart Crop Monitoring System Using Blynk Platform.

The image shows the Blynk IoT dashboard used for monitoring the Smart Crop System in real time. The dashboard displays key parameters such as temperature, humidity, and soil moisture through live gauges. It also shows alerts for water tank level and the levels of three pesticide sprayers. Additionally, it indicates the expiry days remaining for each sprayer's pesticide. This IoT dashboard allows the user to easily check all environmental conditions and sprayer statuses from anywhere, helping in efficient crop monitoring and timely actions. The system efficiently monitors environmental parameters such as temperature, humidity, and soil moisture, while also enabling early disease prediction. By integrating real-time alerts and automated control through the Blynk cloud, the system reduces manual effort and improves farming accuracy.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The smart crop disease detection and action system provides an effective solution for early disease identification and proactive crop management. By integrating AI-based image analysis, IoT sensors, and automated actuation, the system improves accuracy, reduces manual labor, optimizes resource usage, and enhances overall crop productivity. It demonstrates the potential of technology-driven agriculture in supporting sustainable farming practices.

Future enhancements may include expanding the system to support multiple crop types and larger farm areas, improving image processing under varying light conditions, and integrating cloud- based analytics for remote monitoring. Additionally, incorporating advanced predictive models and mobile applications can further assist farmers in decision-making and ensure more scalable, efficient, and user-friendly smart farming solutions. By integrating real-time alerts and automated control through the Blynk cloud, the system reduces manual effort and improves farming accuracy and productivity.

In the future, the system can be enhanced by integrating advanced deep learning models for more accurate disease classification. The Smart Crop Disease Detection and Monitoring System provides an effective solution for real-time crop health monitoring using IoT and image processing GPS-based field mapping and multi-crop support can also be added for large-scale farming. Additionally, cloud-based.

APPENDICES

CODING

```
#include <Wire.h>
#include <Adafruit_INA219.h>
#include <Adafruit_SSD1306.h>
#include <STUSB4500.h> #include
<WiFi.h>
#include <PubSubClient.h>
const char* ssid = "YOUR_WIFI_SSID";
const char* password = "YOUR_WIFI_PASSWORD"; const
char* mqttServer = "broker.hivemq.com";
const int mqttPort = 1883;
const char* mqttTopic = "universal_charger/data"; #define
SCREEN_WIDTH 128
#define SCREEN_HEIGHT 64
#define OLED_RESET -1
Adafruit_SSD1306 display(SCREEN_WIDTH, SCREEN_HEIGHT,
&Wire, OLED_RESET);
#define BUCK_PWM_PIN 25 // LTC3780 PWM pin #define
BUCK_PWM_CHANNEL 0
float MAX_VOLTAGE = 20.0; // volts float
MAX_CURRENT = 3.0; // amps WiFiClient
espClient;
PubSubClient client(espClient); void
setupWiFi() { WiFi.begin(ssid,
password); Serial.print("Connecting
WiFi");
```

```
while(WiFi.status() != WL_CONNECTED){ delay(500);
Serial.print(".");
}
Serial.println("\nWiFi Connected!");
}
void reconnectMQTT() { while
(!client.connected()) {
Serial.print("Connecting MQTT...");
if (client.connect("ESP32_Charger")) {
Serial.println("connected");
} else { Serial.print("failed,
rc=");
Serial.print(client.state());
delay(2000);
}
}
}

void setup() { Serial.begin(115200);
Wire.begin();
if(!display.begin(SSD1306_SWITCHCAPVCC, 0x3C)){
Serial.println("OLED init failed");
while(1);
}
display.clearDisplay();
display.setTextSize(1);
```

```
display.setTextColor(SSD1306_WHITE); if
(!ina219.begin()) { Serial.println("INA219 init
failed"); while(1);
}
stusb4500.begin();
stusb4500.setPowerRole(PD_SINK); // charger as power source
stusb4500.setPDO(5.0, 3.0); // default 5V 3A
stusb4500.start();
ledcSetup(BUCK_PWM_CHANNEL, 20000, 8); // 20kHz, 8-bit
resolution
ledcAttachPin(BUCK_PWM_PIN, BUCK_PWM_CHANNEL);
setupWiFi();
client.setServer(mqttServer, mqttPort);
display.println("Universal Charger Ready");
display.display();
delay(1000);
}
void loop() {
if (!client.connected()) reconnectMQTT();
client.loop();
float requestedVoltage = 5.0; // default float
requestedCurrent = 1.0; // default
if(stusb4500.deviceConnected()){
requestedVoltage = stusb4500.getVoltageRequest(); // volts
requestedCurrent = stusb4500.getCurrentRequest(); // amps
}
if(requestedVoltage > MAX_VOLTAGE) requestedVoltage =
```

```
MAX_VOLTAGE;
if(requestedCurrent > MAX_CURRENT) requestedCurrent = MAX_CURRENT;
int pwmValue = map(requestedVoltage * 10, 0, 200, 0, 255);
ledcWrite(BUCK_PWM_CHANNEL, pwmValue);
float busVoltage = ina219.getBusVoltage_V(); float
current_mA = ina219.getCurrent_mA(); float
power_mW = busVoltage * current_mA;
if(busVoltage > MAX_VOLTAGE || current_mA/1000.0 >
MAX_CURRENT){
ledcWrite(BUCK_PWM_CHANNEL, 0); // turn off output display.clearDisplay();
display.setCursor(0,0);
display.println("SAFETY TRIP!");
display.display();
delay(2000); return;
}
display.print("P: "); display.print(power_mW/1000.0); display.print("Req
V: "); display.print(requestedVoltage); display.println(" V");
display.display();
String payload = "{"voltage":" + String(busVoltage) +
","current":" + String(current_mA/1000.0) + ","power":" +
String(power_mW/1000.0) + "}";
client.publish(mqttTopic, payload.c_str());  delay(500); //
update interval
}
```

REFERENCES

[1] P. S. Agrawal, R. R. Chouksey and V. S. Sharma, ”IoT-Enabled Smart Greenhouses: Reinforcement Learning, Predictive Modeling, and Disease Detection for Enhanced Crop Yield,” 2025 Inter- national Conference on Information, Implementation, and Innova- tion in Technology (I2ITCON), Pune, India, 2025, pp. 1-6, doi: 10.1109/I2ITCON65200.2025.11210662.

[2] M. G. Prakash and D. Sungeetha, ”Categorization and Recognition of Pest in Crops and Remedial action for Smart Agriculture,” 2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2024, pp. 856-859, doi: 10.1109/ICECA63461.2024.10801033.

[3] S. M. Raza, M. Masuduzzaman and S. Y. Shin, ”UxV-Swarm based Automated Fruits Disease Instance Segmentation for Smart Farming using Deep Learning Model,” 2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN), Budapest, Hungary, 2024, pp. 274-279, doi: 10.1109/ICUFN61752.2024.10625555.

[4] N. Johnson, M. B. Santosh Kumar and T. Dhannia, ”A survey on Deep Learning Architectures for effective Crop Data Analytics,” 2021 Inter- national Conference on Advances in Computing and Communications (ICACC), Kochi, Kakkanad, India, 2021, pp. 1-10, doi: 10.1109/ICACC-202152719.2021.9708193.

[5] S. Singh, Y. Roy, A. Bhan and S. Sah, ”Computer based Detection and Classification of Leaf Diseases using Hybrid Features,” 2023 In- ternational Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 788-793, doi: 10.1109/IC-SCSS57650.2023.10169167.

[6] S. Gupta, M. Sehgal and R. Makkar, ”CNN-Based Crop Disease Prediction for Enhanced Productivity,” 2025 International Conference on Computing, Intelligence, and Application (CIACON), Durgapur, India, 2025, pp. 1-6, doi: 10.1109/CIACON65473.2025.11189357.

[7] S. S. Reddy, B. Sonasri, C. Jyothi and P. Vasanthi, ”Ai-Powered Crop Yield and Health Monitoring System,” 2025 International Conference on Inventive Computation Technologies (ICICT), Kirtipur, Nepal, 2025, pp. 63-71, doi: 10.1109/ICICT64420.2025.11005224.

[8] R. Akhter and S. A. Sofi, ”Decision Making in Precision Agri- culture Using IoT and Machine Learning: A Focus on Rice Dis- eases,” 2024 International Conference on Decision Aid Sciences and Applications (DASA), Manama, Bahrain, 2024, pp. 1-4, doi: 10.1109/DASA63652.2024.10836518.

[9] T. Supriya, A. Anitha, S. S. Chand Goud, I. S. Mudhiraj, M. Pavan and K. S. Reddy, ”Android-Based Plant Leaf Disease Prediction Using CNN MobileNet Model,” 2025 3rd World Conference on Communi- cation & Computing (WCONF), Raipur, India, 2025, pp. 1-6, doi: 10.1109/WCONF64849.2025.11233478.

[10] S. Kumaran, S. K. D, S. A and S. K. K, ”Crop Pest Control us- ing IoT Real-Time Monitoring and Intervention,” 2023 International Conference on Sustainable Communication Networks and Applica- tion (ICSCNA), Theni, India, 2023, pp. 1552-1557, doi: 10.1109/IC- SCNA58489.2023.10370176.

[11] P. Nagaraj, T. D. Rajkumar, S. Rakesh, A. K. S. Durga, M. L. Jyothi and C. G. Sai Nithin, ”AI-based Leaf Disease Identification Robot using IoT Approach,” 2023 2nd International Conference on Edge Computing and Applications (ICECAA), Namakkal, India, 2023, pp. 1375-1379, doi: 10.1109/ICECAA58104.2023.10212373.

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