RESEARCH PAPER

Smart Agriculture Using ESP32

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ABSTRACT

Agriculture is an important sector that requires continuous monitoring of crop health and field conditions to improve productivity and reduce crop loss. Traditional plant disease identification mainly depends on manual observation by farmers or agricultural experts, which may be time-consuming, less accurate, and difficult to perform continuously in large fields. In this paper, we propose a smart agriculture system using ESP32, ESP32-CAM, and Convolutional Neural Network (CNN) based leaf disease detection to support real-time crop monitoring. The proposed system monitors environmental parameters such as soil moisture, water level, temperature, pump status, and solenoid valve status through an interactive web dashboard. Leaf images are captured using an ESP32-CAM or uploaded manually to the system, and the trained CNN model classifies the disease category from the input image. The system further provides disease description, preventive steps, and treatment recommendations to assist farmers in taking timely action. The integration of IoT-based environmental monitoring and AI-based disease detection improves the efficiency of crop health analysis and supports smart decision-making in agriculture.

Keywords: Smart Agriculture, Leaf Disease Detection, ESP32,ESP32-CAM,Convolutional Neural Network, Environmental Monitoring, IoT, Crop Health.

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INTRODUCTION

Agriculture is a major sector that supports food production, livelihood, and economic development. In recent years, the increasing demand for food, climate variation, water scarcity, and plant diseases have created serious challenges for farmers. Traditional agricultural practices mainly depend on manual field observation and fixed irrigation methods. These methods are time-consuming and may lead to over-irrigation, under-irrigation, delayed disease identification, and inefficient use of resources. Therefore, intelligent and automated solutions are required to improve crop monitoring, reduce human effort, and support timely decision-making in agriculture.

The Internet of Things (IoT) is a growing technological paradigm that offers many benefits in agricultural monitoring and automation. This technology enables sensors, microcontrollers, actuators, and software applications to communicate through wireless networks. IoT-based agriculture systems provide real-time monitoring of field parameters such as soil moisture, temperature, water level, and irrigation status [1], [2], [4]. These systems help farmers observe crop field conditions remotely and take suitable action based on sensor data. Smart irrigation and water management systems using IoT have shown that automated monitoring can improve water usage and reduce wastage [7], [12], [14], [18].

Although IoT-based smart agriculture provides many advantages, most existing systems focus mainly on irrigation control and environmental monitoring [5], [9], [15], [17]. These systems are useful for observing soil and water conditions, but they do not provide complete plant health monitoring. Plant diseases are one of the major causes of crop damage and yield reduction. If diseases are not detected at an early stage, they can spread quickly and affect the overall productivity of the crop. Manual disease identification requires continuous field inspection and expert knowledge, which may not always be available to farmers.

In current research work, plant disease detection has been addressed using image processing and machine learning techniques [3], [13], [16], [20]. Leaf images are analyzed to identify disease symptoms such as color changes, spots, fungal patches, blight marks, and abnormal texture patterns. K-means clustering has been used for agricultural image segmentation and infected region identification [6], [20]. Remote sensing and image-based analysis have also been used for early detection and management of crop diseases [10]. However, many of these systems work independently and are not fully integrated with real-time IoT-based environmental monitoring.

To overcome these limitations, this paper proposes a smart agriculture system that integrates IoT-based environmental monitoring with CNN-based leaf disease detection. The proposed system uses an ESP32 microcontroller to collect field parameters such as soil moisture, water level, and temperature. It also uses an ESP32-CAM and manual image upload feature to capture plant leaf images for disease analysis. The captured image is pre-processed and classified using a Convolutional Neural Network model. The predicted disease result is then displayed on the web dashboard along with disease description, preventive steps, and treatment recommendations.

The proposed architecture aims to provide both environmental awareness and plant health monitoring in a single platform. This system helps farmers monitor field conditions, identify plant diseases, and take timely preventive action. The integration of sensor monitoring, camera-based image acquisition, CNN classification, and dashboard-based output improves the practical usefulness of smart agriculture. Thus, the proposed work supports efficient water management, early disease detection, reduced manual effort, and improved crop health decision-making.

RELATED WORK

Recent advancements in the Internet of Things (IoT) have significantly improved agricultural monitoring and automation systems. IoT-based solutions enable continuous monitoring of environmental parameters such as soil moisture, temperature, humidity, and water levels, thereby supporting efficient resource utilization and smart decision-making in farming. These technologies have opened new opportunities for real-time monitoring systems that go beyond traditional irrigation methods and contribute to sustainable agricultural practices.

Machine learning and data-driven techniques have further enhanced IoT-based agricultural systems by enabling automated analysis and predictive decision-making. Several studies have explored the use of image processing and machine learning algorithms for plant disease detection. In particular, the k-means clustering algorithm has been widely used for image segmentation and classification of plant health conditions. These approaches help in early identification of diseases, reducing crop loss and minimizing the excessive use of pesticides.

In irrigation-focused research, IoT-based smart irrigation systems using microcontrollers such as ESP32 microcontroller have been proposed to automate water management. These systems utilize soil moisture sensors, temperature sensors, and humidity sensors to determine optimal irrigation conditions. By automating water flow based on real-time data, they significantly reduce water wastage and improve crop productivity. However, most of these systems primarily focus on irrigation control and lack integrated plant health monitoring capabilities.

Several healthcare-focused studies also demonstrate the effectiveness of AI-based wearable monitoring for identifying specific physiological conditions. Explainable AI and wearable gait analysis have been used to identify patients with osteopenia and sarcopenia in daily life [5]. Similarly, AI-based wearable gait monitoring has shown promising results in the optimization of Parkinson's disease management [6]. Although these studies are not specifically designed for sports, they show that wearable sensing integrated with intelligent models can support practical continuous monitoring in real-life settings.

Wireless Sensor Networks (WSNs) have also been widely applied in precision agriculture to enable distributed monitoring of environmental conditions. These networks support continuous data collection from multiple locations in a field, improving accuracy and scalability. However, such systems mainly focus on environmental monitoring and do not provide integrated solutions for both disease detection and water management.

In addition, recent studies have highlighted the importance of combining machine learning with IoT for predictive agriculture. Soil moisture prediction models and data analytics techniques have been used to optimize irrigation schedules and improve resource efficiency. While these approaches enhance decision-making, they often rely heavily on historical data and lack real-time adaptive control mechanisms.

Despite these advancements, existing systems face several limitations, including lack of early disease detection, absence of integrated water management during extreme conditions such as rainfall, and limited automation in decision-making. Most solutions address either irrigation or plant health monitoring independently, rather than providing a unified framework.Motivated by these research gaps, the present work proposes an integrated smart agriculture system that combines IoT-based monitoring with machine learning-driven disease detection and automated water level management. The proposed system utilizes real-time image processing, sensor-based monitoring, and intelligent control mechanisms to provide a comprehensive solution for modern farming. This unified approach ensures improved crop health, efficient water usage, and enhanced agricultural productivity.

OUR APPROACH

Architecture

Fig. 1 shows the proposed architecture of the smart agriculture system designed to monitor plant health and manage water levels using IoT and machine learning techniques. The system integrates multiple components including the user, ESP32 controller unit, sensor modules, image processing unit, and cloud platform.

The ESP32 microcontroller acts as the central unit that collects real-time data from sensors such as soil moisture sensor, temperature and humidity sensor, and water level sensor. A camera module is used to capture plant leaf images for disease detection. The collected data is processed and transmitted to the cloud platform for monitoring and decision-making.

The working of the proposed architecture is as follows:

Step 1: The user registers and connects the system through a mobile or web application.

Step 2: Environmental data such as soil moisture, temperature, humidity, and water level are continuously collected using sensors.

Step 3: The ESP32 processes the sensor data and transmits it to the cloud platform.

Step 4: A camera module captures leaf images for disease detection.

Step 5: The captured images are analyzed using the k-means clustering algorithm to identify plant diseases.

Step 6: Based on the analysis, the system decides whether irrigation, drainage, or alert generation is required.

Step 7: The ESP32 controls the relay module to activate the water pump or solenoid valve.

Step 8: The processed data and system status are stored in the cloud.

Step 9: Alerts are sent to the user through SMS or email.

Step 10: The user can remotely monitor and control the system.

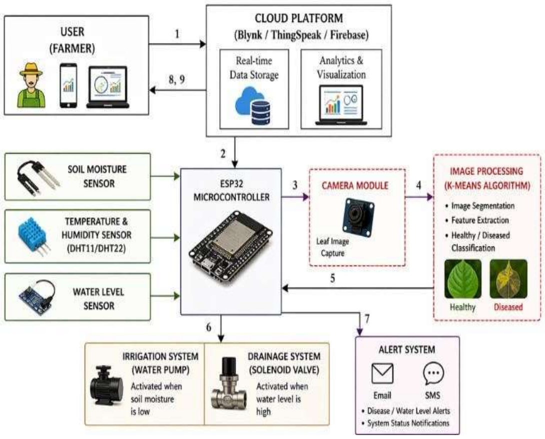


Fig.1 System architecture

The architecture consists of multiple interconnected modules including the user interface, ESP32 controller unit, sensor layer, image processing module, control system, and cloud platform. The ESP32 microcontroller acts as the core processing unit that collects real-time data from various sensors and communicates with external systems via Wi-Fi. The system supports bidirectional communication, where sensor data is sent to the cloud and control commands can be issued remotely by the user. This ensures efficient monitoring and management of agricultural activities without physical presence in the field.

Data Acquisition Module

The data acquisition module plays a crucial role in collecting real-time environmental data required for decision-making. The system utilizes multiple sensors:

Soil Moisture Sensor: Measures the volumetric water content in soil, helping determine irrigation needs.

Temperature and Humidity Sensor (DHT11/DHT22): Monitors atmospheric conditions that influence plant growth and disease formation.

Water Level Sensor: Detects excess water accumulation to prevent waterlogging conditions.

The ESP32 reads sensor values at regular intervals using ADC and digital GPIO pins. These readings are calibrated and filtered to remove noise, ensuring accurate measurements. The collected data is then transmitted to the cloud for further processing and visualization.

Image Processing & Disease Detection

The proposed system integrates an image processing module to enable early detection of plant diseases. A camera module captures images of plant leaves, which are processed using Python-based tools such as OpenCV and NumPy.The k-means clustering algorithm is applied to segment the image into clusters based on color intensity and texture features. This segmentation helps in identifying infected regions, such as spots, discoloration, or abnormal growth patterns.

After segmentation, the system classifies the plant condition into healthy or diseased categories. The results are then transmitted to the ESP32 for further action. This approach reduces dependency on manual inspection and improves the accuracy and speed of disease detection.

Decision Making & Control System

The ESP32 microcontroller acts as the decision-making unit of the system. It processes sensor data and disease detection results to determine appropriate control actions.

A threshold-based logic is implemented:

- If soil moisture < threshold → irrigation is activated
- If water level > threshold → drainage is activated
- If disease detected → alert is generated

The ESP32 generates control signals to drive actuators through a relay module. This automated decision-making mechanism ensures optimal resource utilization and reduces human intervention.

Early Disease Prediction (AI) requires an uploaded image — use the form below.

Fig. 02. Dashboard ScreenShot

Automated Irrigation & Drainage System

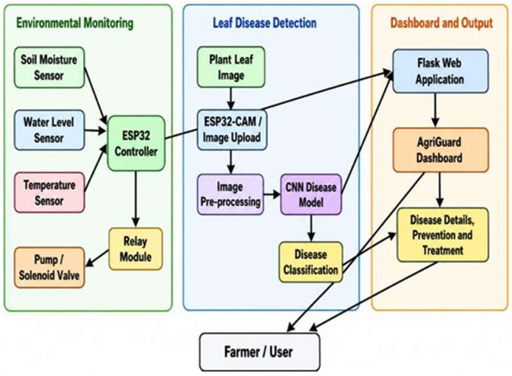
The system incorporates an automated water management mechanism to maintain optimal soil conditions. The irrigation system consists of a water pump, while the drainage system uses a solenoid valve.When soil moisture falls below the required level, the ESP32 activates the pump to supply water to the field. Conversely, when excess water is detected, the solenoid valve is opened to drain water. This automation prevents both under-irrigation and overirrigation, ensuring efficient water usage. It also helps in maintaining soil health and preventing crop damage caused by water imbalance.

Cloud Integration & Monitoring

The system is integrated with cloud platforms such as Blynk, ThingSpeak, or Firebase for real-time data monitoring and storage. The ESP32 transmits sensor data to the cloud using Wi-Fi connectivity. The cloud platform provides: • Real-time data visualization • Historical data analysis • Remote monitoring interface Users can access the system through a mobile or web application to view parameters such as soil moisture, temperature, humidity, and water level. This enables farmers to make informed decisions based on real-time insights.

Alert & Notification System

The system includes an intelligent alert mechanism to notify users about critical conditions. Alerts are generated when: • Soil moisture is too low • Water level is too high • Disease is detected Notifications are sent via SMS or email, ensuring that the user is informed immediately. This feature enables timely intervention and helps in reducing crop losses. H. Overall System Workflow.



The overall system workflow of the proposed smart agriculture system is designed as a continuous and intelligent process that integrates sensing, processing, decision-making, and actuation. The system operates in a cyclic manner to ensure real-time monitoring and efficient control of agricultural parameters.

Initially, the workflow begins with the data acquisition phase, where multiple sensors deployed in the field continuously monitor environmental conditions. The soil moisture sensor measures the water content in the soil, the temperature and humidity sensor captures atmospheric conditions, and the water level sensor detects excess water accumulation. These sensors provide real-time analog and digital signals to the ESP32 microcontroller.

Once the data is collected, it enters the data preprocessing stage, where the ESP32 filters noise and converts raw sensor readings into meaningful values. Calibration techniques are applied to ensure accuracy and reliability of the sensor outputs. This processed data forms the basis for further analysis.

Simultaneously, the image acquisition process is initiated using the camera module. The system captures leaf images either periodically or based on user request. These images are then forwarded to the image processing module for analysis.

In the image processing and analysis stage, the captured leaf images are processed using the k-means clustering algorithm. The algorithm segments the image into clusters based on color and texture features, helping to identify diseased regions. The output is classified into healthy or diseased categories and sent back to the ESP32 for further action.

The workflow then proceeds to the decision-making stage, where the ESP32 evaluates both sensor data and disease detection results. A rule-based logic is applied:

- If soil moisture is below the threshold → irrigation is required
- If water level exceeds the limit → drainage is required
- If disease is detected → alert is generated

Based on these conditions, the system determines the appropriate control actions.

EXPERIMENTAL RESULTS

The proposed smart agriculture system was implemented as a complete hardware-software prototype for plant disease detection and environmental monitoring. The implementation includes CNN-based leaf disease classification, manual image upload, ESP32-CAM based live image capture, ESP32-based environmental sensor monitoring, pump and solenoid status display, and web dashboard integration. Experimental evaluation was performed by observing the environmental parameters displayed on the dashboard and analyzing how these parameters support crop health monitoring.

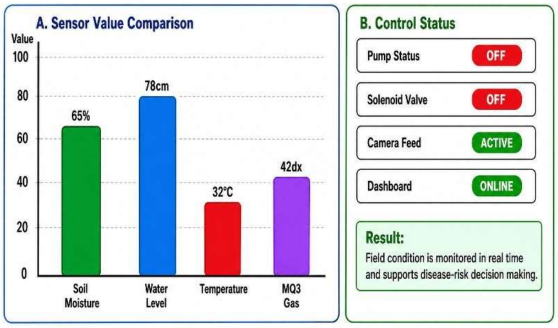
Environmrntal Monitoring Result

The environmental monitoring module was developed using an ESP32 microcontroller and sensor-based field observation. The system monitors soil moisture, water level, temperature, pump status, and solenoid valve status. These parameters are displayed on the AgriGuard dashboard and are used to understand the crop field condition. The environmental monitoring module supports the disease detection system by providing additional field-condition information that may influence plant health and disease development

The environmental monitoring module was evaluated considering the following five parameters:

a)SoilMoisture
b)WaterLevel
c)Temperature
d)PumpStatus
e) Solenoid Valve Status

The ESP32 microcontroller is used to collect the sensor values from the agricultural field. These values are transmitted to the web dashboard and displayed in real time. In the proposed system, the environmental result is used to understand the field condition and support the leaf disease detection process. The monitored values help the farmer identify whether the plant is growing under suitable environmental conditions.



Field condition is monitored in real time and supports disease-risk decision making.

Fig. 04. Monitoring result

Soil Moisture

Soil moisture is one of the most important parameters in smart agriculture because it indicates the availability of water in the soil. Fig. 05 shows the soil moisture monitoring result of the proposed system. When the soil moisture value is low, the crop may require irrigation. When the soil moisture value is sufficient, unnecessary irrigation can be avoided.

The result shows that the proposed system can continuously observe soil moisture variation and display the values on the dashboard. This helps the farmer make timely irrigation decisions and reduces water wastage. Soil moisture monitoring also supports plant disease prevention because excess or insufficient moisture may affect plant growth and increase disease risk.

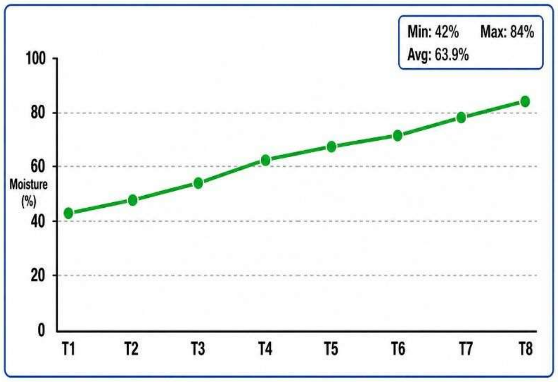


Fig. 05. Soil Moisture Monitoring result

Water Level

Water level monitoring is used to identify the amount of water present in the field or storage tank. Fig. 06 shows the water level monitoring result. The water level value helps in detecting excess water conditions and supports proper water management. If the water level is very high, it may lead to waterlogging, root damage, and increased disease formation.

The experimental result shows that the proposed system can monitor water level changes and provide useful information for field management. By observing the water level, the system helps prevent over-irrigation and supports better crop growth.

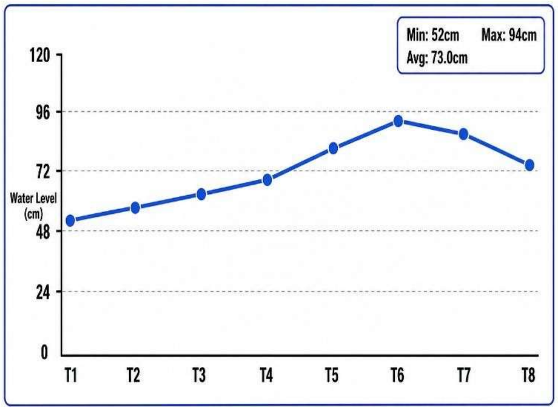


Fig. 06. Water level Monitoring result

Temperature

Temperature is an important environmental factor that affects plant growth and disease spread. Fig. 07 shows the temperature monitoring result of the proposed system. High temperature or sudden temperature changes may create stress in plants and can support the development of certain diseases.

The result confirms that the system can display temperature values through the web dashboard. By monitoring temperature along with disease prediction, the proposed system provides better awareness of field conditions. This helps farmers understand whether environmental changes may affect crop health.

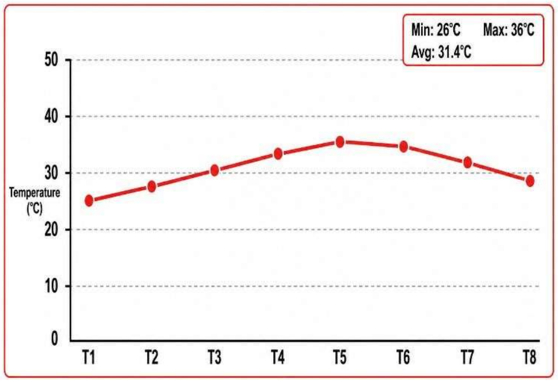


Fig. 07. Temperature Monitoring result

Pump and Solenoid Valve Status

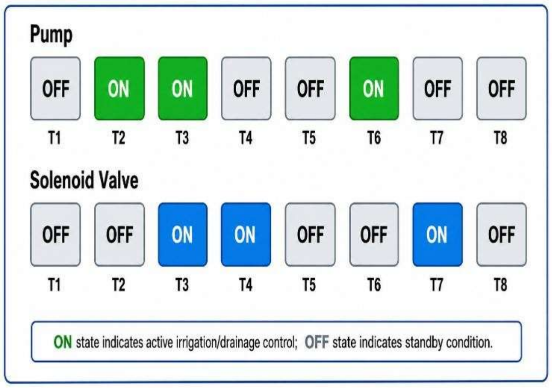


Fig. 08. Pump & Solenoid valve result

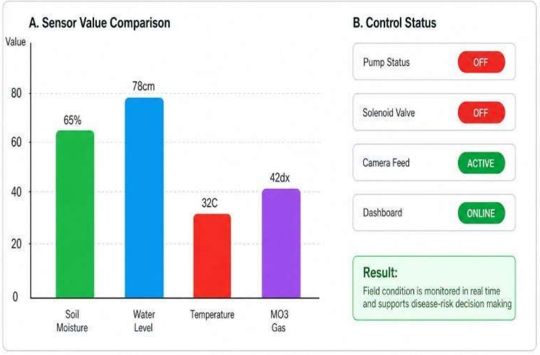
The pump and solenoid valve are used for irrigation and water control. Fig. 08 shows the pump and solenoid valve status result. The pump status indicates whether irrigation is active or inactive. The solenoid valve status indicates whether water flow control or drainage control is active.

The result shows that the dashboard can display ON and OFF states of the pump and solenoid valve. This allows the farmer to monitor the irrigation process and verify whether the control devices are functioning properly. When soil moisture is low, the pump can be activated for irrigation. When water level is high, the solenoid valve can be used to control excess water.

e) Integrated Environmental Dashboard Result

Fig. 09 shows the integrated environmental monitoring result of the proposed smart agriculture dashboard. The dashboard displays soil moisture, water level, temperature, pump status, solenoid valve status, and camera monitoring features in a single interface.

This integrated view helps the user understand the current field condition without checking each sensor separately.



Result:
Field condition is monitored in real time and supports disease-risk decision making

Fig. 09. Integrated environmental Monitoring result

The proposed system also includes a fallback testing method. When the ESP32 device is connected, live environmental readings are received from the hardware. During testing, if the ESP32 is unavailable, simulated values are displayed to verify the dashboard interface and monitoring workflow.

PARAMETER	STATUS	PURPOSE
Soil moisture	40%-90%	To identify soil water availability
Water Level	50cm-100cm	To detect excess water
Temperature	20°C - 38°C	To monitor field climate
Pump Status	ON / OFF	To indicate irrigation acticity
Solenoid Valve	ON / OFF	To indicate water control activity

TABLE I. MODEL PERFORMANCE SUMMARY

Experimental results in Table I show the environmental parameters monitored by the proposed system. The results confirm that the system can observe soil moisture, water level, temperature, pump status, and solenoid valve status through the AgriGuard dashboard. These parameters help in identifying unfavorable field conditions and support timely agricultural decision-making.

Overall, the environmental monitoring result shows that the proposed system is capable of combining sensor-based field observation with CNN-based leaf disease detection. The environmental module helps farmers maintain proper irrigation, avoid waterlogging, monitor temperature variation, and understand field conditions that may influence plant disease development.

Leaf Disease Detection Result

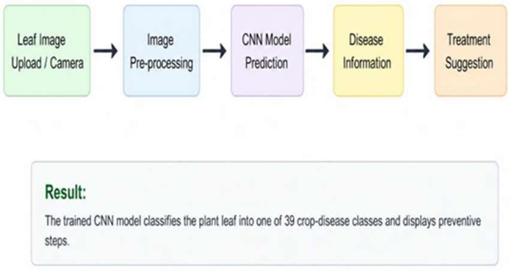
The leaf disease detection module was implemented using a Convolutional Neural Network (CNN) model trained to classify plant leaf images into 39 crop-disease categories. The proposed system accepts input through two methods: manual image upload and ESP32-CAM based live image capture. The captured or uploaded leaf image is pre-processed and resized to 224 x 224 pixels before being passed to the CNN model for classification. The leaf disease detection module was evaluated considering the following four parameters:

a) Image Acquisition
b) Image Pre-processing
c) CNN Disease Classification
d) Disease Information and Treatment Recommendation

Image Acquisition

Fig. 10 shows the workflow of the leaf disease detection module in the proposed system. The input leaf image is obtained either through manual upload or from the live camera module. In manual diagnosis, the user uploads a plant leaf image through the AgriGuard dashboard. In camera-based diagnosis, the ESP32CAM captures the leaf image and sends it to the Flask web application for analysis.

The image acquisition stage plays an important role because the quality of the input image directly affects disease prediction. A clear leaf image helps the CNN model identify disease symptoms such as spots, color changes, fungal patches, and damaged leaf regions.



Result:
The trained CNN model classifies the plant leaf into one of 39 crop-disease classes and displays preventive steps.

Fig. 10. Leaf disease detection workflow b) Image Pre-processing After image acquisition, the input image is converted into RGB format and resized to 224 x 224 pixels. This fixed image size is required because the CNN model expects a uniform input dimension. The

image is then converted into tensor format before being passed to the trained model. The pre-processing step improves the consistency of the prediction process. Since images may be captured from different distances, lighting conditions, and camera angles, resizing and format conversion help the model process all images in a common structure. c) CNN Disease Classification Fig. 11 shows the CNN prediction result for a sample leaf image. The CNN model analyzes the visual features of the leaf and predicts the most suitable disease class. The implemented model contains convolution layers, batch normalization, max pooling, dropout, and fully connected layers. These layers help the model extract important features such as leaf color, texture, disease spots, and infected patterns. The model classifies the input image into one of the available disease categories such as Apple scab, Apple black rot, Corn common rust, Grape black rot, Potato early blight, Tomato early blight, Tomato late blight, Tomato leaf mold, Tomato mosaic virus, and healthy leaf classes. The prediction result is then matched with the disease information stored in the system database.

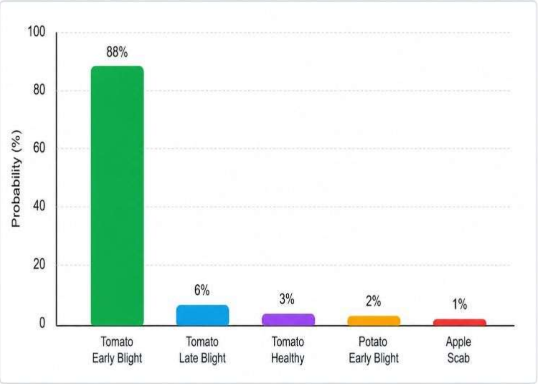
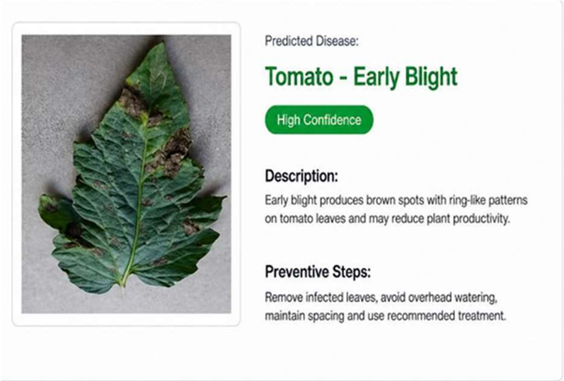


Fig 11. CNN prediction distribution

Disease Information and Treatment Recommendation

Fig. 12 shows the disease detection output displayed in the proposed dashboard. After predicting the disease class, the system displays the disease name, disease description, preventive steps, and recommended supplement or treatment. This helps farmers understand the detected disease and take suitable action at an early stage.



Predicted Disease:

Tomato - Early Blight

Description:

Early blight produces brown spots with ring-like patterns on tomato leaves and may reduce plant productivity.

Preventive Steps:

Remove infected leaves, avoid overhead watering, maintain spacing and use recommended treatment.

Fig 12. Disease detection result The recommendation output is generated using the stored disease information and supplement information files. The system also provides early disease prediction support using an AI-based analysis module, which gives possible early symptoms, risk level, and preventive actions for mild disease conditions.

Module	Input	Processing Method	Output
Manual Diagnosis	Uploaded leaf image	CNN classification	Disease name and preventive steps
Camera Diagnosis	ESP32CAM image	CNN classification	Live disease detection result
Early Prediction	Uploaded leaf image	AI-based visual analysis	Early symptoms and risk level
Recommendation	Predicted disease class	CSV-based information retrieval	Treatment and supplement suggestion

TABLE II. Leaf disease detection module summary

CONCLUSION

On the proposed work, an intelligent smart agriculture system for environmental monitoring and leaf disease detection using ESP32, ESP32-CAM, and CNN-based image classification. The proposed system was developed to support farmers by combining real-time field condition monitoring with automated plant disease identification. The system monitors important environmental parameters such as soil moisture, water level, temperature, pump status, and solenoid valve status through an interactive web dashboard. In addition, the system detects plant leaf diseases using uploaded images or live camera-captured images. The implemented prototype demonstrated that environmental monitoring and AI-based disease detection can be successfully integrated into a single smart agriculture platform. The CNN model classifies plant leaf images into multiple crop-disease categories and displays the disease name, description, preventive steps, and treatment recommendations. The ESP32-CAM based image capture feature improves the practical usability of the system by allowing live leaf image analysis. The dashboard also provides environmental values, camera monitoring, manual diagnosis, and early disease prediction support in one interface.

The current work establishes a useful foundation for smart farming and crop health monitoring. The system helps farmers understand both plant health and field conditions, which are important for timely agricultural decision-making. By combining sensor-based monitoring with CNN-based disease prediction, the proposed system can reduce manual inspection effort, support early disease detection, improve irrigation awareness, and help prevent crop damage. As future work, the system can be improved by increasing the size of the real-field image dataset, improving model accuracy under different lighting conditions, adding mobile application support, enabling cloud-based data storage, and integrating automatic irrigation control based on sensor thresholds. Overall, the proposed smart agriculture system demonstrates the feasibility of building an intelligent, low-cost, and practical plant health monitoring platform using IoT, computer vision, and deep learning.

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