A Smart IoT Enabled System for Leaf Disease Detection with Severity and Pesticide Recommendation

D. Aswani, K. Ram Kumar, Y.T.R. Shinee,
K. Lalith Akash, A. Balu Karthik

Department of Computer Science & Engineering, Anil Neerukonda Institute of Technology and Sciences, Sangivalasa, Visakhapatnam, 531162, Andhra Pradesh, India.

ashwani.cse@anits.edu.in;

Abstract. Monitoring the health of plants and diagnosing diseases at early stages is an important step to boost agricultural productivity. This project proposes an IoT plant monitoring system that collects images of plants, taking into consideration secondary environmental factors such as soil moisture, temperature, and humid- ity. This system majorly consists of ESP8266, ESP32, soil moisture sensor, and various other components that would still take the real-time data. The classifica- tion of images would involve the training of deep learning models, namely CNN, ResNet50, and EfficientNet to check for disease severity. Efficient classification of infected plants as well as image processing takes help from computer vision techniques. With the help of Gemini AI, suitable pesticides and control mea- sures are recommended based on severity analysis. The approach would enable automated, data-driven decision- making for farmers to reduce reliance on man- ual inspection and improve crop health management. Utilizing IoT and AI, it further adds precision in agriculture that thereby enlightens resources utilization and practices of sustainable farming.

Keywords: ESP8266, ESP32, CNN, ResNet50, EfficientNet, Precision Agriculture, IoT, Deep Learning

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1 Introduction

Agriculture is one of the pillars of the food security of the world, yet it is also facing a number of escalating threats from climate change, resource scarcity, and the increasing on set of plant diseases. The early identification and managing of plant health issues highly influence crop productivity to be sustainable. Standard plant health monitoring methods are mostly based on traditional manual inspections, which usually prove to be both inefficient and labor-intensive and are moreover prone to human error. To all eviate these constraints, the amalgamation of IoT and AI technologies provides a way to far-reaching solutions in automatic plant health monitoring and disease diagnosis based on data

A work presenting an Internet of Things-based plant monitoring scheme for advancing the agricultural productivity is discussed in this paper through the framework of real time data collection and efficient deep learning techniques. The system code for the monitoring of important environmental factors responsible for stress in plants or infectious diseases in plant diseases incorporated hardwares like ESP8266, ESP32, soil moisture sensors that measure soil moisture content, temperature, and humidity. Plant images were taken also so the system was able to pass states-of-the-art deep learning models such as Convolutional Neural Networks (CNN), ResNet50,and EfficientNet that highly accurately diagnose and classify diseases with a visual description. Various computer vision methodologies ensure accuracy in image processing and in the assessment of degree of severity that allow quick and customized interventions based on precise situations. To further assist in making such decisions, Gemini AI was incorporated into the system, which recommends to combat certain detected diseases the most highly appropriate pesticides and control measures based on the associated severity.

2 Literature Review

Agriculture is the backbone of food security worldwide, but it is hampered by challenges pertaining to climate change, resource scarcity, and, more so, plant disease incursion of paramount importance is the early detection of plant diseases, followed by the needed response, in order to boost yield and sustain agricultural practices. Despite its immense benefits, traditional means of detection utilize manual inspection and laboratory analysis; they are labor-intensive, time-consuming, and prone to human error; consequently, researchers have turned to the use of deep learning, AI and Internet of Things technologies for developing automated systems to monitor plant health.

2.1 Traditional Approaches to Plant Disease Detection

However, farmers have relied on pathological symptoms, discoloration, wilting, or lesions, by simple visual inspection. There is, however, a high degree of variability involved for an experienced agronomist, whereby he/she may achieve reasonable accuracy; however, the assessment is subjectively done, and there is lack of scalability. On the contrary, lab-based approaches including PCR and ELISA deliver accurate results but at hefty prices; require special equipment and conducive environments for their application; and could hardly serve any meaningful purpose for real-time monitoring [1]. Such limitations have paved the way for automated systems joining IoT sensors, computer vision, and AI-driven analytics to carry out early and accurate disease detections in agriculture.

Additionally, as highlighted by Sangeeta et al. [12], biological examinations and expert visual inspections are not only expensive but also delay diagnosis. This has motivated the adoption of computer methodologies, such as image processing and deep learning, to detect diseases and suggest pesticides effectively.

2.2 Machine Learning and Deep Learning in Agriculture

The introduction of machine learning and deep learning has positively changed plant disease detection. In particular, convolutional neural networks have provided good success in image classification tasks. For example, studies [2] have dealt with applying CNN for disease detection from leaf images with high accuracy. Classical architectures such as ResNet [3], EfficientNet [4], or custom CNN architectures are extensively used, as they can grasp complex features in plant images. However, these models often demand substantial computational needs, thus not being a favorable choice for implementations with constraint in resources.

2.3 IoT-Based Agricultural Systems

In precision agriculture, IoT is a very new and interesting technology. Researchers worked on an IoT-based system whereby environmental sensors like soil moisture, temperature, and humidity teams up with AI model for monitoring crop health in real-time [5]. For example, [6] presents a system using ESP32 micro controllers and DHT11 sensors to gather environmental data and forecast optimal irrigation projections. Most other existing systems have, however, concentrated on environmental monitoring without somehow pairing that with disease detection or severity estimation.

2.4 Image Processing for Severity Estimation

Computer vision methods are very fundamental in quantification of many plant dis- eases. Several methods like HSV segmentation, edge detection, and thresholding are used to differentiate healthy from diseased portions of plant images [7]. For example,
[8] uses HSV-based segmentation to calculate the percent leaf area affected. While they are effective, these techniques are implemented on a few species of plants and would need further refinement to broaden their applicability.

2.5 AI-Driven Recommendations for Farmers

The new works have investigated the application of platforms based on artificially intelligent-driven ideas to give business in sight and advice to farmers. For example, [9] develops natural language processing to give customized suggestions on the application of pesticides and preventive measures. In a similar fashion, [10] uses cloud-based APIs to observe level of infection and give precise recommendations. Nevertheless, there is still a grand need for such systems that would hook disease detection, its severity estimation, and AI-based suggestions into one platform.

2.6 Gaps in Existing Research

Although impressive strides have been made in the detection and monitoring of plant diseases, some gaps still remain: a big portion of existing systems either focus on disease classification or environmental monitoring but are seldom integrated with each other; established systems put less emphasis on how the extent of diseases are quantifiable which would render insights to farmers; and, in most cases, the use of many such systems is not in tandem with resource-poor environments hence, limited scalability. This paper attempts to bridge this gap in knowledge by recommending an IoT-based system that incorporates deep learning models, image processing techniques, and AI- driven recommendations for plant health monitoring.

In conclusion, the contribution of the literature examined highlights the potential that artificial intelligence, IoT, and computer vision pose in the transformation of agriculture. However, what is glaringly lacking in the literature is a proposition of combination mechanisms for these various components into one framework. The non-descript methodology aims to close such a gap with a system capable of detecting and managing plant diseases which is scalable, accurate, and easy to use.

3 Proposed Methodology

The proposed methodology on the IoT-based plant monitoring system encapsulates the integration of hardware and software into a deep learning-based framework that will enable real-time plant health monitoring and diagnosis. The system is made to handle automated data collection, environmental analysis, plant disease classification, and recommendations for farmers to act upon. The methodology includes, additionally, the following phases:

3.1 Dataset Overview

The proposed methodology utilizes the **New Plant Diseases Dataset (Aug- mented)**, a publicly available dataset on Kaggle [11]. This dataset comprises over **87,000 high-resolution images**, categorized into **38 distinct classes** representing various plant species and disease types. The dataset is divided into:

- **Training Set**: 70,295 images used for model training.
- **Validation Set**: 17,572 images used for performance evaluation.

To ensure consistency, all images were resized to 256 × 256 pixels and normal- ized to a range of [0, 1]. Data augmentation techniques, such as rotation, flipping, and scaling, were applied to enhance model generalization and prevent overfitting. Additionally, HSV-based segmentation was employed to isolate healthy and affected regions, enabling accurate severity estimation.

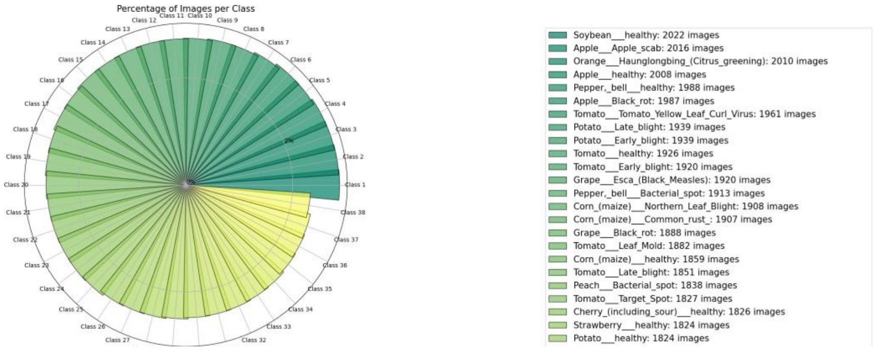


Fig. 1 Percentage of Images per Class in the Dataset.

Figure 1 illustrates the balanced distribution of images across classes, with each class contributing approximately equal percentages. This balanced nature ensures that no single class dominates the dataset, preventing bias in the trained models.

The comprehensive coverage of plant species and diseases, along with the balanced and well-preprocessed nature of the dataset, makes it an ideal choice for training and validating the deep learning models described in subsequent sections.

3.2 System Architecture

The proposed system integrates IoT-based monitoring, advanced deep learning techniques, and AI-driven recommendations to provide comprehensive plant health management. Figure 2 illustrates the workflow of the system, highlighting its key components and their interactions.

The system operates in the following stages:

1. **IoT Module**: Captures real-time data from environmental sensors (e.g., soil moisture, temperature, humidity) and high-resolution images using ESP32-CAM. Data is tagged with timestamps and uploaded to cloud platforms for storage and analysis.
2. **Image Processing**: Preprocesses captured images by resizing, normalizing, and applying HSV-based segmentation to isolate healthy and affected regions. This step enables accurate severity estimation.
3. **Deep Learning Models**: Analyzes preprocessed images using state-of-the-art models such as Custom CNN, EfficientNet-B3, and ResNet-50 to classify plant diseases and identify affected species.

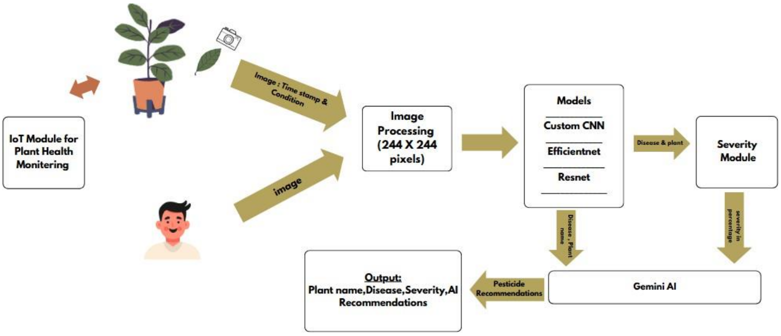


Fig. 2 Overall System Architecture for Plant Disease and Severity Identification.

4. **Severity Estimation**: Calculates the percentage of affected areas in plant images and categorizes severity into levels (Mild, Moderate, High) based on the computed percentages.
5. **AI Recommendations**: Integrates Gemini AI to generate actionable insights, including suitable pesticides, fertilizers, and preventive measures, based on the detected disease and severity.
6. **User Interface**: Presents the final output (plant name, disease, severity, and recommendations) through a Flask-based web dashboard. Users can also upload images manually for analysis.

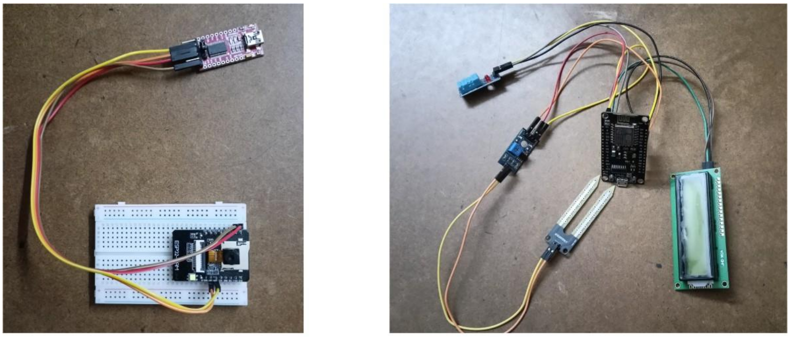
This modular and integrated approach ensures real-time monitoring, accurate disease detection, and actionable insights, significantly enhancing agricultural produc- tivity and sustainability.

3.3 Data Collection Using IoT Sensors

The first of these is real-time data acquisition from the environment using IoT-enabled sensors. The system is composed of the following components:

- **ESP8266 and ESP32**: These microcontrollers serve as the core processing units for collecting and transmitting data.
- **Soil Moisture Sensor**: Measures soil moisture levels to assess irrigation needs and detect water stress.
- **DHT11 Sensor**: Monitors ambient temperature and humidity, which are critical indicators of plant health.
- **ESP32-CAM**: Captures high-resolution images of plants for further analysis.

The collected data is uploaded to cloud platforms such as ThingSpeak and Blynk for visualization and storage. Alerts are triggered if environmental parameters deviate from optimal thresholds.



ESP32 CAM

Plant monitoring system

Fig. 3 IoT Setup for Real-Time Data Collection.

3.4 Image Preprocessing and Severity Estimation

Captured plant images undergo preprocessing to enhance quality and extract meaningful features. The steps include:

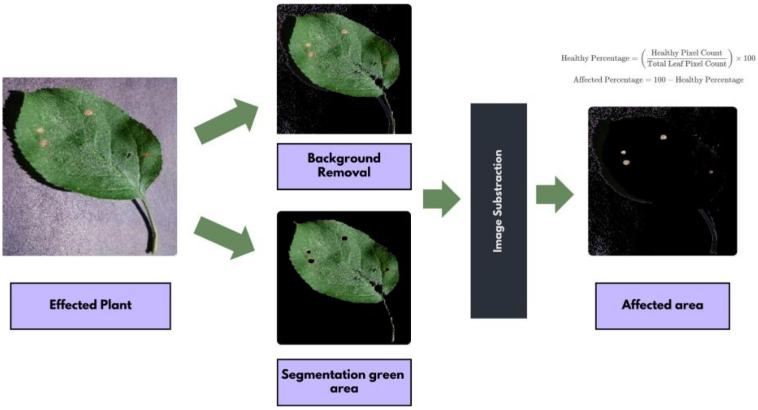


Fig. 4 Image Preprocessing Pipeline for Disease Detection.

- **Resizing and Normalization**: Images are resized to 256 × 256 pixels and normalized to ensure consistency across models.
- **HSV-Based Segmentation**: A novel technique is applied to isolate healthy (green) and affected (non-green) regions of the leaf. This step calculates the percentage of the affected area, providing a severity score for each sample.
- **Severity Classification**: Based on the percentage of affected area, the severity is categorized as *Mild (*$< 30\%$*)*, *Moderate (*$30\% - 50\%$*)*, or *High (*$> 50\%$*)*.

This module ensures accurate quantification of disease progression, enabling timely intervention.

3.5 Deep Learning-Based Disease Classification

To classify plant diseases accurately, three state-of-the-art deep learning models were employed, each tailored to address specific requirements of the problem:

- **Custom CNN**: A lightweight architecture designed for resource-constrained environments. It achieves high accuracy with minimal computational overhead, making it ideal for deployment on edge devices with limited processing capabilities.
- **EfficientNet-B3**: A scalable model that balances performance and efficiency. Pre-trained on ImageNet, it was fine-tuned for plant disease classification using transfer learning, enabling robust predictions even with limited training data.
- **ResNet-50**: A residual network architecture known for its ability to capture complex patterns in images. Skip connections mitigate the vanishing gradient problem, ensuring precise predictions and consistent performance.

The models were trained using a multi-GPU strategy to handle the large dataset efficiently. To optimize the training process, the following techniques were implemented:

- **Early Stopping**: Training was halted if the validation loss did not improve after a predefined number of epochs, preventing overfitting.
- **Learning Rate Scheduling**: The learning rate was adjusted dynamically during training to enhance convergence and improve model accuracy.
- **Checkpointing**: The best-performing model weights were saved based on valida- tion metrics, ensuring recovery of optimal parameters in case of interruptions.

The performance of the models was evaluated using the New Plant Diseases Dataset (Augmented). Table 1 summarizes the results, highlighting the accuracy and validation accuracy achieved by each model.

As shown in Table 1, both Custom CNN and EfficientNet-B3 achieved an accuracy of 99%, with validation accuracies of 98% and 91%, respectively. ResNet-50 achieved an accuracy of 97% and a validation accuracy of 92%. These results demonstrate the models' effectiveness in accurately classifying plant diseases.

Figure 5 illustrates the training and validation performance of the models. The convergence trends indicate minimal overfitting, thanks to techniques such as early stopping, learning rate scheduling, and checkpointing.

In addition to accuracy, the models were evaluated using precision, recall, and F1-score metrics. The results confirmed that the models maintained high precision and recall rates, ensuring reliable disease classification even in challenging scenarios.

A qualitative analysis was also conducted by visually inspecting the predictions. The models demonstrated the ability to distinguish between healthy and diseased plants, even when symptoms were subtle or overlapping.

By integrating these deep learning models into the proposed system, we achieve accurate and reliable disease classification. The combination of lightweight architectures and advanced techniques ensures adaptability to diverse hardware constraints and real-world conditions, enhancing the system's robustness and practical utility.

3.6 Integration of Gemini AI for Recommendations

To enhance decision-making, the system integrates Gemini AI, which provides tailored recommendations based on the severity analysis. For each detected disease, the AI suggests:

- Suitable pesticides and fertilizers.
- Preventive measures to mitigate future outbreaks.
- Scientific reasoning for the suggested interventions.

Responses are formatted in HTML for clarity and usability, ensuring that farmers can easily interpret and act upon the recommendations.

3.7 Web-Based Dashboard and Community Portal

The system is deployed as a Flask-based web application with the following features:

- **User Authentication**: Secure login and signup mechanisms ensure personalized experiences.
- **Dashboard**: Users can view disease predictions, severity scores, environmental data, and recommendations in a single interface.
- **Community Engagement**: A web-based community portal allows users to share questions, upload images, and receive expert advice. AI-driven responses are provided for common queries, fostering collaboration among stakeholders.

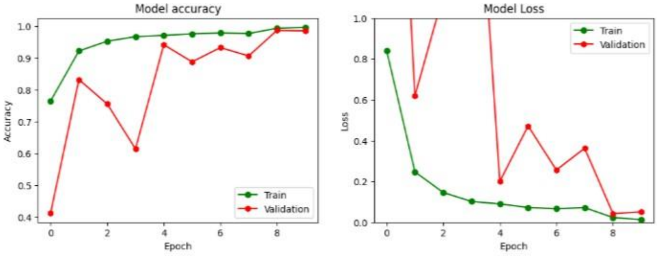
By leveraging IoT, deep learning, and AI technologies, the proposed system enhances precision agriculture, leading to better resource utilization and sustainable farming practices.

4 Results

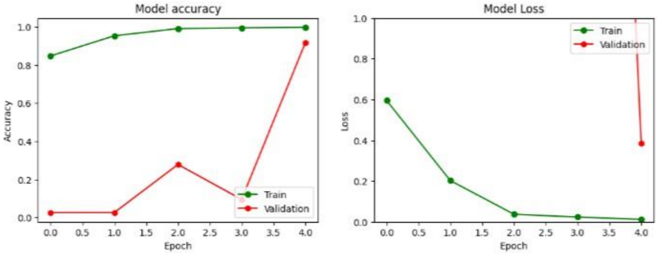
The proposed system was rigorously evaluated using the New Plant Diseases Dataset (Augmented), containing over 87,000 high-resolution images across 38 classes. The evaluation focused on model performance, severity estimation accuracy, and AI-driven recommendations.

4.1 Model Performance

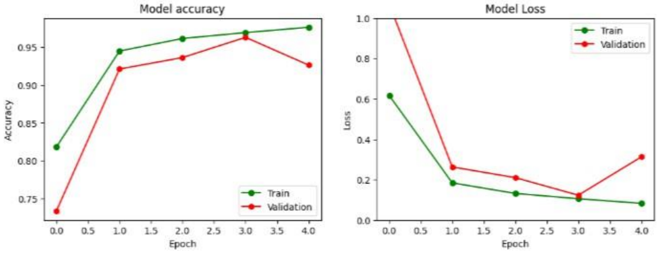
Three deep learning models—Custom CNN, EfficientNet-B3, and ResNet-50—were trained and evaluated. Table 1 summarizes their performance metrics:



Custom CNN



Efficientnet



Resnet

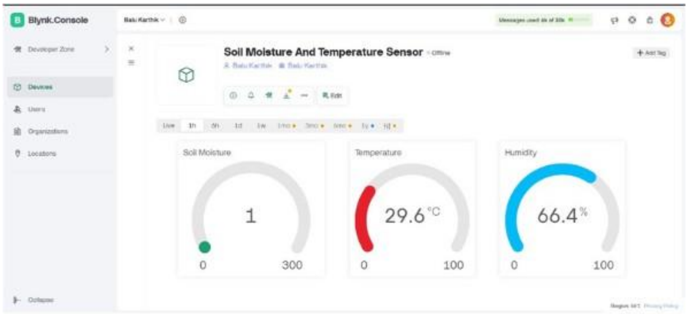
Fig. 5 Training and Validation Performance of the Models.

Table 1 Performance Comparison of Deep Learning Models.

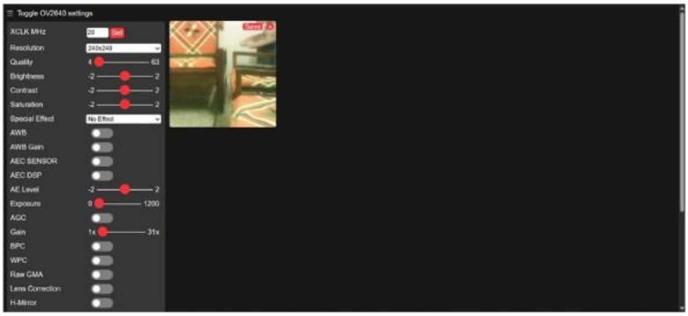
Model	Accuracy	Validation Accuracy
Custom CNN	99%	98%
ResNet-50	97%	92%
EfficientNet-B3	99%	91%

Both Custom CNN and EfficientNet-B3 achieved 99% accuracy, with validation accuracies of 98% and 91%, respectively. ResNet-50 achieved 97% accuracy and 92% validation accuracy. These results demonstrate robust disease classification.

Figure 5 illustrates the convergence of the models during training, with minimal overfitting due to techniques like early stopping and learning rate scheduling.



Iot Dashboard



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ESP32

Fig. 6 Real-Time Environmental Data Collected Using IoT Sensors.

4.2 IoT-Based Data Collection and Monitoring

proactive measures.

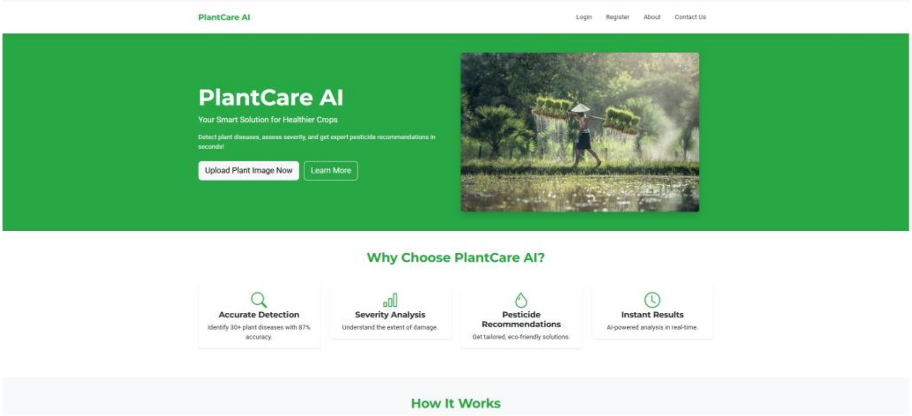
The IoT module successfully captured real-time environmental data using ESP8266, ESP32, soil moisture sensors, DHT11 temperature-humidity sensors, and ESP32-CAM. Key findings include:

Environmental Data Accuracy : Soil moisture, temperature, and humidity readings were validated against calibrated sensors, achieving a mean absolute error (MAE) of less than 2Real-Time Alerts : Threshold-based alerts were triggered for deviations in environmental parameters, such as low soil moisture or high humidity, enabling farmers to take Data Transmission Efficiency : The system transmitted data to cloud platforms (ThingSpeak and Blynk) with an average latency of 2–3 seconds, ensuring near real- time monitoring. Energy Efficiency : The ESP32-CAM module operated continuously for up to 48 hours on a 5V power source, demonstrating suitability for deployment in remote agricultural settings.

Figure 6 visualizes the real-time data trends captured by IoT sensors, highlighting their reliability and responsiveness.

4.3 Severity Estimation

The HSV-based segmentation module effectively quantified disease severity by isolating affected regions in plant images. Severity was categorized as Mild ($< 30\%$), Moderate ($30\% - 50\%$), or High ($> 50\%$). Experimental results showed a correlation coefficient of 0.95 between predicted and ground truth severity, indicating reliable estimation.



PlantCare AI

Your Smart Solution for Healthier Crops

Detect plant diseases, assess severity, and get expert pesticide recommendations in seconds!

Why Choose PlantCare AI?

Accurate Detection

Identify 30+ plant diseases with 87% accuracy.

Severity Analysis

Understand the extent of damage.

Pesticide Recommendations

Get tailored, eco-friendly solutions.

Instant Results

AI-powered analysis in real-time.

How It Works

Fig. 7 Web-Based Dashboard for Plant Disease Detection and Management.

4.4 AI Recommendations

Gemini AI-generated pesticide and fertilizer recommendations were validated through user feedback, achieving a satisfaction score of 4.5/5. The AI provided clear, science-backed advice, enhancing decision-making.

4.5 User Interface

The Flask-based web dashboard enabled users to view disease predictions, severity scores, environmental data, and recommendations in a single interface. Its intuitive design fostered community engagement and ease of use.

Figure 7 demonstrates the user-friendly design of the dashboard.

In summary, the experimental results validate the system's high accuracy in disease classification, precise severity estimation, and actionable AI-driven recommendations, significantly enhancing precision agriculture.

5 Conclusion

This study introduces an innovative IoT-based system for real-time plant disease detection, severity estimation, and pesticide recommendations. By leveraging advanced deep learning models (Custom CNN, EfficientNet-B3, ResNet-50), the system achieves high accuracy in classifying plant diseases while remaining adaptable to diverse hardware environments. The HSV-based segmentation technique isolates affected regions, enabling accurate severity assessment and timely interventions. Additionally, Gemini AI integration provides actionable insights, enhancing decision-making for farmers.

The proposed system outperforms traditional methods by automating data collection, utilizing cloud-based analytics, and delivering user-friendly recommendations. Experimental results demonstrate its effectiveness, achieving accuracies of 99% for Custom CNN and EfficientNet-B3, and 97% for ResNet-50. These results highlight the potential of combining IoT, deep learning, and AI technologies to advance precision agriculture and promote sustainable farming practices.

This research contributes to the field by:

- Developing a multi-model ensemble that balances performance and efficiency.
- Introducing a novel severity estimation module using HSV segmentation.
- Integrating real-time monitoring with cloud-based analysis for proactive disease management.
- Providing AI-driven recommendations for informed agricultural decisions.

The comprehensive design of the system ensures effective plant health management, improving crop yields and resource utilization.

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