

Plant Disease Recognition System Using Deep Learning

SYEDA MUZAMMIL¹, MOHAMMAD RAZA KHAN², MOHAMMED SHAIZAN S³,
MOHAMMED ZAID⁴, M. USAMA BAIG⁵

^{1, 2, 3, 4, 5}Department of Computer Science and Engineering, Ghousia College of Engineering,
Ramanagara, Visvesvaraya Technological University (VTU), India

Abstract - Plant disease detection is essential in precision agriculture to safeguard crop productivity and prevent economic losses. Traditional disease diagnosis relies on manual visual inspection by experts, making the process subjective, time-consuming, and inaccessible to smallholder farmers. This research proposes a deep learning-based approach that utilizes convolutional neural networks (CNNs) to automatically classify plant leaf diseases from images. The PlantVillage dataset, comprising over 50,000 samples of healthy and diseased leaves, is used to train and validate the system. The methodology includes image preprocessing, data augmentation for generalization, hierarchical feature extraction, and softmax-based multiclass classification. Experimental results show that the model achieves an accuracy of 98.27% and demonstrates robust performance across various crop disease categories. The proposed solution can be easily integrated into smartphone applications, enabling real-time disease detection and timely guidance for farmers. This system contributes significantly to sustainable agriculture by reducing the misuse of pesticides and improving crop yields.

Index Terms: Deep Learning, CNN, Plant Disease Classification, Precision Agriculture, Smart Farming, PlantVillage Dataset, Image Recognition.

I. INTRODUCTION

Agriculture is the primary source of food worldwide and plays a crucial role in developing economies. Plant diseases can severely affect crop quality and yield, leading to significant financial losses. Early detection is crucial to minimize damage and improve productivity. Recent advancements in artificial intelligence (AI), particularly convolutional neural networks (CNNs), have surpassed traditional image processing techniques due to their robust feature learning capabilities.

II. RELATED WORK

Previous studies used handcrafted features such as texture, shape, and color with classifiers like SVM or KNN, but performance decreased under real-world

conditions. Deep learning eliminates the need for manual feature extraction. Models such as AlexNet, VGG16, MobileNet, and ResNet have achieved high accuracy in identifying leaf diseases and demonstrated significant improvements in automation and reliability.

III. PROBLEM STATEMENT

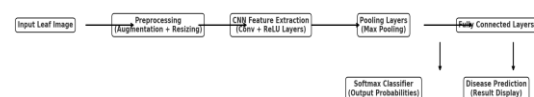
Farmers in remote regions lack access to rapid diagnostic support and expert advice. Manual disease identification is prone to errors and depends on individual expertise. Therefore, a reliable and automated deep learning approach is needed for the accurate detection of multiple diseases.

IV. METHODOLOGY

The proposed factory complaint recognition system follows the workflow shown in Fig- 1 Define acronyms and bowdlerizations the first time they're used in the textbook, indeed after they've been defined in the abstract. bowdlerizations similar as CGS, sc, MKS, IEEE, SI , dc, and rms don't have to be defined. Don't use bowdlerizations in the head or titles unless they're necessary.

Fig -1: Proposed System Architecture

Proposed System Architecture for Plant Disease Recognition



V. DATASET

The PlantVillage dataset contains over 50,000 labeled images of leaves from different crops, including tomato, potato, apple, grape, and pepper. The images

include both healthy and infected leaves under controlled lighting conditions. The dataset is divided as follows:

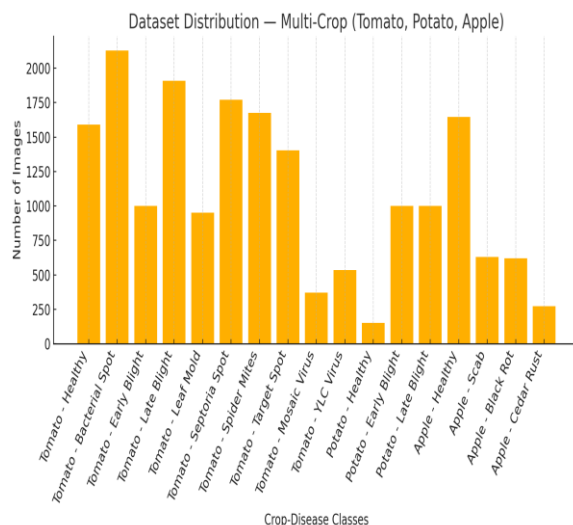
Dataset Split	Percentage
Training	80%
Validation	10%
Testing	10%

Tabel -1: Dataset Split Tabel

VI. PREPROCESSING

- 1) Image resizing to 224×224 pixels
- 2) RGB normalization
- 3) Noise reduction using Gaussian blur
- 4) Data augmentation: flipping ,rotation, brightness shift
- 5) These steps increase generalization and reduce overfitting.

Fig -3: Dataset distribution for Apple, Potato and Tomato leaf disease classes collected from PlantVillage Dataset



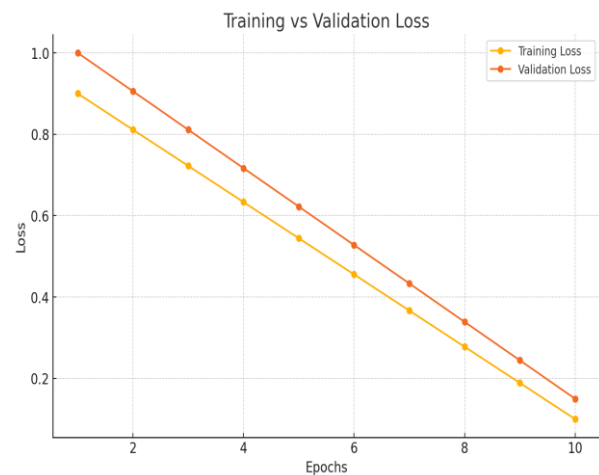
VII. CNN ARCHITECTURE

Layer	Description
Input Layer	224×224×3 RGB Leaf Image
Convolution + ReLU	Feature extraction
Max Pooling	Spatial dimension reduction
Convolution + ReLU	High-level features
Fully Connected	Feature integration
Dropout	Prevent overfitting
Softmax Output	Multi-class classification

VIII. TRAINING CONFIGURATION

- 1) Optimizer: Adam
- 2) Loss Function: Categorical Cross-Entropy
- 3) Epochs: 25
- 4) Batch Size: 32
- 5) Performance Metrics: Recall, F1-Score, Accuracy, Precision

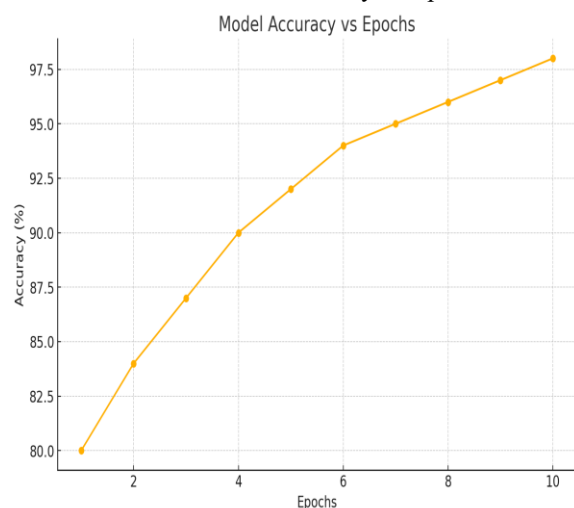
Fig -4: Training vs Validation Loss for CNN Model during Learning



IX. RESULTS AND DISCUSSION

The CNN model produced high-performance results on the test dataset. Accuracy improved steadily across epochs.

Chart -1: Model Accuracy vs Epochs



Performance metrics:

Metric	Score
Accuracy	98.27%

Precision	97.81%
Recall	97.93%
F1-Score	97.90%

based scanning, and explainable AI for actionable recommendations to farmers.

REFERENCES

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The confusion matrix shows strong classification ability across various disease labels with minimal misclassification in visually similar categories.

The proposed model is lightweight and suitable for deployment on mobile applications for real-time field diagnosis.

Fig -5: Confusion Matrix showing CNN Model Classification Performance

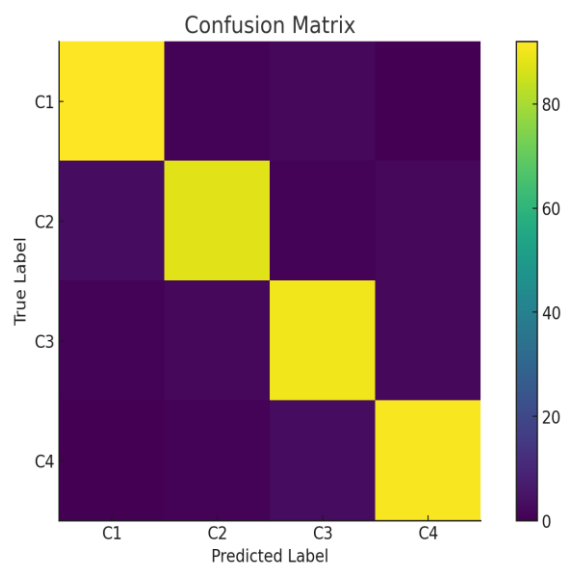
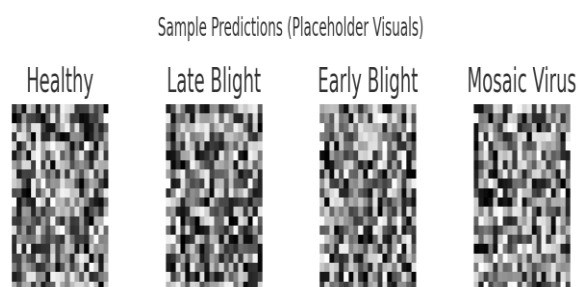


Fig -6: Sample Predictions for Different Plant Disease Categories



X. CONCLUSIONS

This research presents an efficient CNN-based system for detecting plant leaf diseases with high accuracy. The proposed framework reduces the dependency on agricultural experts and enables early disease prevention through smartphone-based diagnosis tools. In the future, the system can be enhanced by integrating IoT-based automatic monitoring, drone-