A STUDY ON DISEASE DETECTION AND REMEDY IDENTIFICATION IN LEAVES

Midhun P Mathew
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
midhunpmathew@amaljyothi.ac.in

Aksa Ann Jacob
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
aksaannjacob2026@cs.ajce.in

Adarsh S
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
adarshs2026@cs.ajce.in

Aaron Tom Viji
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
aarontomviji2026@cs.ajce.in

Aleena Varghese
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
aleenavarghese2026@cs.ajce.in

Abstract - Plant diseases significantly impact agricultural productivity, leading to major crop losses. Early detection and timely treatment are essential to minimize damage. This project introduces a Machine Learning-based mobile application for detecting diseases in tomato, grape, mango, and corn leaves using Convolutional Neural Networks (CNNs) with over 95% accuracy. Once detected, the system suggests appropriate treatments like fungicide application, pruning, or improved irrigation.

Implemented with TensorFlow, OpenCV, and the PlantVillage dataset, the app allows farmers to capture leaf images for real-time diagnosis and treatment recommendations. It also features a mapping system for locating nearby remedy stores and a stock management system for shop owners to update product availability and prices. By integrating AI, smart farming, and marketplace features, this project enhances efficiency, reduces crop losses, and improves overall agricultural productivity.

Keywords: *Plant disease detection, Machine Learning, Convolutional Neural Networks (CNNs), TensorFlow, OpenCV, PlantVillage dataset, Smart farming, Agricultural productivity, Remedy recommendation, Mapping system, Stock management.*

I.INTRODUCTION

Plant diseases significantly impact agricultural productivity, leading to reduced yields and economic losses. Traditional manual inspections are time-consuming and error-prone, especially in remote areas. This study presents a mobile-based AI system for real-time disease detection in tomato(Bacterial_spot,,Early_blight,Late_blight,Septoria_leaf-spot), grape(black_measles,leaf blight(isariopsis leaf spot)), mango(Bacterial Cranker,Gall Midge,Powdery Mildew and corn(common_rust,gray_leaf_spot,northern_leaf_blight) leaves using Convolutional Neural Networks (CNNs) with over 95% accuracy. The system analyzes leaf images, classifies diseases, and suggests treatments like fungicide application and crop rotation. Additionally, it includes a mapping feature to locate nearby stores selling remedies and a stock management system for real-time product availability and pricing. By integrating AI with smart farming, this solution enhances early detection, reduces crop losses, and improves agricultural sustainability.

II.LITERATURE REVIEW

Over the years, researchers have explored various ways to detect plant diseases more accurately and efficiently. In the beginning, most studies relied on **traditional image processing techniques** like contrast enhancement, noise removal, and segmentation. Rathod et al. [1] and Kundu et al. [12] experimented with these techniques alongside machine learning (ML) models such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and K-Nearest Neighbors (KNN). While these methods showed promise, their accuracy was often limited by the need for manual feature extraction.

As technology progressed, **machine learning models** became more popular for plant disease detection. Researchers like Tulshan et al. [3] and Indumathi et al. [4] explored different ML algorithms, including SVM and Random Forest, to classify plant diseases with improved accuracy. Sujatha et al. [11] and Annabel et al. [10] compared various ML techniques and highlighted their ability to reduce manual work while enhancing prediction reliability.

However, the real breakthrough came with **deep learning, particularly Convolutional Neural Networks (CNNs)**. These models eliminated the need for manual feature extraction and delivered much higher accuracy. Militante et al. [5] demonstrated how CNNs could automatically analyze leaf images and detect diseases with high precision. Researchers like Sarkar et al. [7] and Joshi et al. [19] compared traditional ML models with deep learning approaches like ResNet and VGG-16, showing that deep learning consistently outperformed older techniques. Durmuş et al. [9] successfully applied deep learning architectures such as AlexNet and SqueezeNet for real-time farm use.

Some studies took things further by developing **custom datasets and hybrid models**. For instance, Goncharov et al. [8] used a Deep Siamese Convolutional Network specifically designed for grape disease detection, achieving over 90% accuracy. Praneeth et al. [13] tested CNNs against ML models for soybean disease detection, finding that CNNs performed best with 96% accuracy. Tm et al. [16] and Oo et al. [17] applied CNNs for tomato leaf disease detection, consistently surpassing 95% accuracy—making them highly reliable for early diagnosis.

Finally, recent research has focused on **evaluating and optimizing these techniques**. Kumar et al. [18] and Ramesh et al. [20] reviewed different plant disease detection methods, confirming that deep learning models consistently outperform traditional approaches. Gavhale et al. [6] reported that neural networks can achieve over 90% accuracy, while Khirade et al. [14] emphasized the importance of image segmentation and feature extraction in boosting classification performance.

In short, plant disease detection has come a long way—from basic image processing to sophisticated deep learning models capable of real-time diagnosis. As research continues, AI-powered systems are becoming increasingly reliable, helping farmers detect plant diseases early and take timely action to protect their crops.

III.METHODOLOGY

This project implements a deep learning-based approach for plant disease detection using a Convolutional Neural Network (CNN) with transfer learning. The model leverages InceptionV3 as a feature extractor and is trained on an image dataset containing diseased and healthy leaves. The methodology comprises data preprocessing, augmentation, model training, and evaluation, as detailed below:

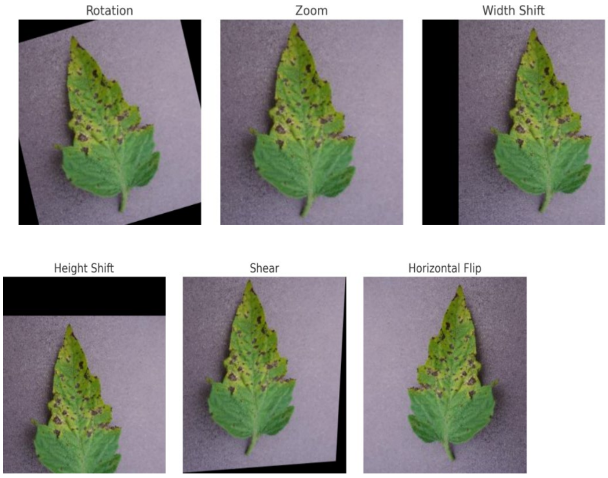
3.1 Data Preprocessing and Augmentation

To enhance the model's robustness and improve generalization, image preprocessing and data augmentation techniques are applied using ImageDataGenerator. The dataset consists of images categorized into different classes representing various plant diseases.

- Image Size: All images are resized to 299 × 299 pixels to match the input requirements of the InceptionV3 model.
- Batch Size: A batch size of 32 is used during training and validation.
- Data Augmentation: The following augmentations are applied to introduce variability in training data:
  - Rescaling: Pixel values are normalized to the range [0, 1] by dividing by 255.
  - Rotation: Images are randomly rotated within a 20-degree range.
  - Zoom: Random zooming up to 15%.
  - Width and Height Shift: Images are randomly shifted 20% along the width and height.

- Shear Transformation: Applied with a 15% shear range.
- Horizontal Flipping: Enabled to make the model robust to orientation changes.
- Fill Mode: Constant fill mode is used to handle empty pixels generated from transformations.

The dataset is divided into training, validation, and test sets, ensuring effective model evaluation.



Here are the applied transformations on the uploaded image:

1. Rotation – Random rotation within ±20 degrees.
2. Zoom – Random zooming up to 15%.
3. Width Shift – Image shifted horizontally by 20%.
4. Height Shift – Image shifted vertically by 20%.
5. Shear Transformation – Applied within a ±15% range.
6. Horizontal Flipping – Flipped along the horizontal axis.

3.2 Model Architecture and Training

The classification model is based on InceptionV3, a powerful deep-learning architecture pre-trained on the ImageNet dataset.

- Base Model:
  - The InceptionV3 network is used as a feature extractor with include_top=False, meaning the fully connected layers of the original model are removed.
  - The input shape is set to **(299, 299, 3)** for compatibility with InceptionV3.
- Layer Freezing Strategy:
  - 250 layers are frozen, retaining pre-trained weights for better feature extraction.
  - The remaining layers are left trainable to fine-tune the model for plant disease classification.
- Fully Connected Layers:
  - A GlobalAveragePooling2D layer is added to reduce the dimensionality of feature maps.
  - A fully connected Dense layer with 128 neurons and ReLU activation is added.
  - A Dropout layer (30%) is used to prevent overfitting.
  - A final Dense layer is added with softmax activation, where the number of output neurons corresponds to the number of plant disease classes.

3.3 Training Parameters

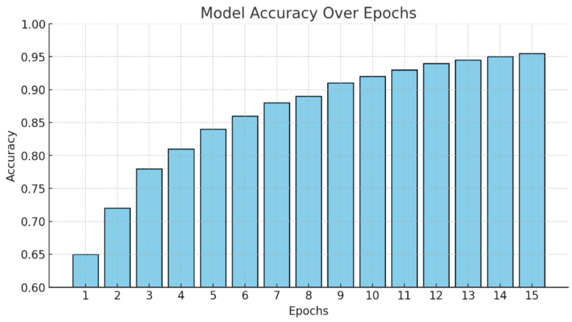
The model is compiled and trained with the following parameters:

- Optimizer: Adam optimizer with a learning rate of 0.0001 -0.00001 is used for adaptive learning.
- Loss Function: sparse_categorical_crossentropy, suitable for multi-class classification.
- Evaluation Metric: Accuracy is used to track performance.
- Number of Epochs: The model is trained for 10-20 epochs.

The trained model is saved as `h5` for later inference.

3.4 Model Evaluation

After training, the model is evaluated using the test dataset to determine its generalization capability. The test accuracy is computed and analyzed to ensure high reliability in disease classification.



IV. CONCLUSION

- ML-Based Disease Detection:
  - The project introduces an advanced Machine Learning-based approach for early plant disease detection in tomato, grape, mango, and corn leaves.
  - Utilizes Convolutional Neural Networks (CNNs) with over 95% accuracy for precise disease classification.
- Technologies Used:
  - Implements TensorFlow, OpenCV, and the PlantVillage dataset for robust image processing and feature extraction.
  - Ensures high reliability and efficiency in disease detection.
- Mobile-Based Accessibility:
  - Farmers can capture leaf images using a mobile application for instant disease diagnosis.
  - Provides real-time treatment recommendations to assist in effective disease management.
- Marketplace and Procurement System:
  - Integrates a mapping feature to help farmers locate nearby stores selling recommended remedies.
  - Includes a stock management system that allows shop owners to update product availability and pricing.
- Impact on Agriculture:
  - Enhances agricultural productivity by reducing crop losses and improving disease management.
  - Promotes sustainable farming practices by equipping farmers with real-time decision-making support.
  - Contributes to a resilient and efficient agricultural system through AI-driven solutions.

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