

Plant Disease Detection from Leaf Images Using Deep Learning

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Abstract—Agriculture is the backbone of food security in many countries, and plant diseases are a major threat to crop productivity. Early and accurate identification of plant diseases is critical for reducing crop loss and ensuring sustainable farming. Traditional manual detection methods are time-consuming, error-prone, and inaccessible in remote areas. This paper presents an automated plant disease detection system using Deep Learning techniques, specifically Convolutional Neural Networks (CNN), MobileNetV2, and VGG16/VGG19 architectures. Leaf images are preprocessed through resizing, normalization, and data augmentation. The system classifies diseased and healthy plant leaves across multiple categories with high accuracy. The VGG16-based transfer learning model achieved a test accuracy of 90.72%, while MobileNetV2 reached 86.12%. The trained model is integrated into a Flask web application with JWT authentication and a Groq AI-powered recommendation engine for real-time agronomic advice. Results demonstrate that deep learning significantly outperforms traditional machine learning and provides a practical, scalable tool for precision agriculture.

Index Terms—*Plant Disease Detection, Deep Learning, CNN, VGG16, MobileNetV2, Transfer Learning, Image Classification, TensorFlow, Flask, Precision Agriculture.*

I. INTRODUCTION

Agriculture plays a vital role in ensuring food security and economic stability worldwide. Plant diseases remain one of the most significant threats to crop production, causing substantial losses in yield and quality each year. Early and accurate detection of these diseases is essential to prevent their spread and minimize economic damage. Traditionally, plant disease identification is performed manually by agricultural experts—a process that is both time-consuming and often inaccurate, particularly in rural regions where expert access is limited.

With the rapid advancement of Artificial Intelligence (AI), Deep Learning has emerged as a powerful tool for image-based disease detection. Convolutional Neural Networks (CNNs) can now analyze leaf images and automatically learn discriminative features such as color variations, irregular spots, texture changes, and lesion patterns from large labeled datasets. The proposed system takes leaf images as input and predicts the disease category, supporting farmers in making timely, data-driven decisions.

This research proposes a deep learning pipeline combining a custom CNN baseline, MobileNetV2, and VGG16/VGG19 transfer learning models trained on a curated subset of the PlantVillage dataset. A Flask-based web application with JWT authentication and a Groq AI-powered recommendation engine enables real-world deployment. By automating disease diagnosis, the system reduces human effort, lowers diagnostic errors, and has the potential to significantly improve agricultural productivity across diverse farming environments.

II. LITERATURE SURVEY

A. Multi-Scale CNN for Plant Disease Classification (Pant & Kumar, 2025)

Pant and Kumar demonstrated multi-scale CNN architectures for robust leaf disease detection using the PlantVillage dataset, achieving high classification accuracy by extracting features at multiple resolution levels. Their study confirmed that multi-scale feature extraction is superior to single-scale approaches for detecting visually similar diseases.

B. Vision Transformer for Plant Disease Detection (Gupta et al., 2024)

Gupta et al. conducted a comparative study of Vision Transformers (ViT) and CNN models, showing that ViTs offer competitive performance when sufficient training data is available, while CNNs remain more efficient for resource-constrained deployment. This informed the decision to prioritize CNN-based architectures in the proposed system.

C. Lightweight CNN for Mobile Deployment (Kumar et al., 2024)

Kumar et al. introduced a lightweight CNN optimized for mobile and edge deployment, reducing model size without significant accuracy loss. This work validates the use of MobileNetV2 in the proposed system as a practical option for farmers using smartphones in the field.

D. Real-Time Detection Using YOLOv8 (Wang & Zhao, 2025)

Wang and Zhao applied the YOLOv8 framework for real-time leaf disease detection, achieving fast inference speeds suitable for drone-based agricultural monitoring. Their results demonstrate the potential of detection architectures for multi-lesion scenarios.

E. Data Augmentation and CNN Robustness (Huang et al., 2024)

Huang et al. demonstrated that extensive data augmentation techniques including rotation, flipping, color jitter, and zoom substantially improve CNN robustness and reduce overfitting when working with limited labeled datasets. These findings informed the augmentation strategy used in the proposed system.

III. EXISTING SYSTEM AND LIMITATIONS

Earlier plant disease identification systems relied primarily on traditional machine learning combined with manual feature extraction. Researchers employed Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and basic Artificial Neural Networks (ANNs). Features including color histograms, texture descriptors (HOG, SIFT), and vein patterns were manually crafted and fed into classifiers. While these methods achieved moderate accuracy in controlled settings, their performance depended heavily on the quality of feature engineering.

The key disadvantages of existing systems are: (1) Lower recognition accuracy on small or imbalanced datasets; (2) Dependence on manual feature extraction which is time-consuming and error-prone; (3) High training time and GPU dependency for deep architectures; (4) Risk of overfitting due to limited data diversity; and (5) Reduced performance under real-world environmental variations such as lighting changes, occlusion, and background clutter.

IV. PROPOSED SYSTEM

The proposed system introduces a deep learning-based pipeline for accurate and automated plant disease identification from leaf images. Unlike traditional methods, the model automatically extracts relevant features from raw images without relying on manual feature engineering. The system begins with preprocessing: resizing leaf images to 224x224 pixels, normalizing pixel values to [0,1], and applying data augmentation such as rotation, flipping, scaling, and brightness adjustment to increase dataset diversity and model generalization.

The CNN architecture consists of multiple convolutional layers for hierarchical feature extraction, pooling layers for dimensionality reduction, and dropout layers to prevent overfitting. Fully connected dense layers with Softmax activation perform the final multi-class classification. Transfer learning using pre-trained VGG16/VGG19 and MobileNetV2 models leverages features learned from large-scale ImageNet data, enhancing accuracy especially for underrepresented disease classes.

A. System Objectives

The specific objectives of the proposed system are as follows:

- Automatically classify leaf images as healthy or diseased using deep learning without manual feature extraction.
- Apply transfer learning with VGG16/VGG19 and MobileNetV2 to maximize classification accuracy while reducing training time.
- Deploy the trained model as a Flask web application with JWT-secured endpoints for real-time leaf disease prediction.
- Integrate a Groq LLM-based recommendation engine to provide expert agronomic treatment advice alongside predictions.
- Empower farmers with a scalable, cost-effective tool that supports early disease detection and crop loss prevention.

B. System Modules

The proposed system comprises seven primary modules:

- Image Acquisition Module: Collects plant leaf images from publicly available datasets or captured using cameras and mobile devices.
- Image Preprocessing Module: Performs resizing to 224x224 pixels, normalization, noise removal, and data augmentation to ensure input uniformity.
- Dataset Management Module: Organizes and labels images by disease category; splits data into training (70%) and testing (30%) subsets.
- Feature Extraction Module: CNN convolutional layers automatically extract spatial features such as color patterns, texture, edges, and lesion shapes.
- Disease Classification Module: Trained deep learning model classifies leaves into healthy or specific disease categories with high accuracy.
- Model Training and Evaluation Module: Trains the CNN using Adam optimizer for 25 epochs; evaluates using accuracy, precision, recall, F1-score, and confusion matrix.
- Prediction and Result Display Module: Flask web interface allows users to upload leaf images and receive instant predictions with AI-generated treatment recommendations.

V. SYSTEM DESIGN AND ARCHITECTURE

A. CNN Architecture

The custom CNN model is built using the Keras Sequential API. It consists of two convolutional blocks, each comprising a Conv2D layer (32 and 64 filters respectively, 3x3 kernel, ReLU activation, He uniform initialization), Batch Normalization, MaxPooling2D (2x2), and Dropout (0.25). Feature maps are then flattened and passed through fully connected Dense layers with Softmax output for multi-class probability estimation. Total trainable parameters: approximately 5.11 million.

B. Transfer Learning: VGG19 and MobileNetV2

Two pre-trained models are fine-tuned on the plant disease dataset. VGG19 (weights=imagenet, include_top=False) is loaded with its 20,024,384 base parameters frozen. A custom classification head comprising GlobalAveragePooling2D, Dense(256, ReLU), Dropout(0.5), and Dense(num_classes, Softmax) is appended. MobileNetV2 follows the same strategy, providing a lightweight alternative with approximately 2.3 million parameters suitable for edge deployment. Both models are compiled with Adam optimizer, categorical cross-entropy loss, and trained for 25 epochs with batch size 128.

VI. IMPLEMENTATION

A. Dataset

A curated subset of the PlantVillage dataset containing 5,433 labeled leaf images across 7 disease categories is used: Apple Black Rot (301), Apple Cedar Apple Rust (300), Blueberry Healthy (300), Apple Apple Scab (167), Grape Leaf Blight (157), Tomato Septoria Leaf Spot, and Tomato Healthy. Training tensor shape: (3798, 224, 224, 3); test tensor shape: (1635, 224, 224, 3).

B. Software and Hardware Requirements

The system is developed in Python 3.8+ using the Anaconda distribution and Jupyter Notebook IDE. Core deep learning frameworks include TensorFlow 2.12.0 and Keras. Image processing relies on OpenCV, Pillow, and NumPy. The web application stack includes Flask, Flask-JWT-Extended, and Werkzeug. Visualization uses Matplotlib and Seaborn. Hardware: Intel Core i5-2450M (2.50 GHz), 8 GB RAM, 250 GB storage.

C. Flask Web Application

The deployment backend is built using Flask. JWT authentication secures the prediction endpoint. The /predict route accepts leaf image uploads, preprocesses them using OpenCV, and runs inference on the loaded VGG16 model (plant_vgg16.h5). The /recommend route queries the Groq Llama-3.3-70B model for expert treatment advice based on the predicted disease label. An HTML/JavaScript frontend provides login, image upload, analysis, and result display pages with real-time feedback.

VII. RESULTS AND PERFORMANCE EVALUATION

Three deep learning models were trained and evaluated on the plant disease dataset. The VGG19-based transfer learning model achieved the highest test accuracy of 90.72%, outperforming both the custom CNN (approximately 65%) and MobileNetV2 (86.12%). Notably, both VGG19 and MobileNetV2 achieved 100% training accuracy. Table I summarizes the comparative results.

TABLE I. Model Performance Comparison

Model	Train Acc.	Test Acc.
Custom CNN	~72%	~65%
MobileNetV2	100%	86.12%
VGG16/VGG19	100%	90.72%

MobileNetV2 offers the best trade-off between accuracy (86.12%) and model size (2.3M parameters), making it the preferred choice for mobile or edge deployment. Classification reports confirm that VGG19 achieves precision above 0.88 and recall above 0.90 across all major disease categories. Occasional misclassification between visually similar diseases (Apple Scab vs. Apple Black Rot) can be addressed through targeted augmentation and additional data collection.

VIII. FUTURE SCOPE

The proposed system establishes a strong foundation for several future enhancements. Real-time disease monitoring using drone or satellite imagery combined with the trained models can enable large-scale field surveillance. Integration of multispectral and hyperspectral imaging would allow detection of diseases before visible symptoms appear, enabling truly predictive disease management.

IoT integration can create a fully automated smart agriculture ecosystem where sensors monitor soil moisture, temperature, and humidity alongside leaf images. Federated learning can enable model improvement across diverse farms without sharing sensitive data. The system can be extended to cover additional crop species and region-specific plant pathogens, improving global applicability and supporting sustainable food production goals.

IX. CONCLUSION

This paper presents a comprehensive deep learning-based system for automated plant disease detection from leaf images. The system integrates a custom CNN baseline with VGG19 and MobileNetV2 transfer learning models, achieving a peak test accuracy of 90.72% with VGG19. The complete pipeline from image preprocessing, model training, and performance evaluation to Flask-based web deployment with AI-powered recommendations demonstrates the practical viability of deep learning for precision agriculture.

The system significantly reduces dependence on manual expert inspection, provides faster and more consistent disease diagnoses, and is deployable on both servers and mobile devices. The integration of a Groq LLM-based recommendation engine provides actionable agronomic advice beyond mere classification. Overall, this work demonstrates that deep learning is a transformative technology for modern agriculture, offering accurate, scalable, and cost-effective solutions that can improve crop management and food security at scale.

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