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Ensemble Learning and Explainable Artificial Intelligence for the Detection of Plant Leaf Disease

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ABSTRACT :

Plant diseases significantly affect agricultural productivity and food security, often resulting in economic losses for farmers. Traditional disease detection methods are time-consuming and rely heavily on expert knowledge. To address this challenge, we present a deep learning–based web application for automated plant disease classification. The system employs two pre-trained convolutional neural network models, InceptionV3 and MobileNetV2, trained on a diverse dataset of crop leaf images. The application, built using the Flask framework, allows users to upload leaf images and select a preferred model for prediction. Uploaded images are preprocessed and classified into one of several disease or healthy categories, after which detailed information about the identified condition is retrieved from a disease knowledge base. This integration of artificial intelligence with a user-friendly web interface provides a practical, accessible, and scalable solution for real-time crop health monitoring, ultimately supporting precision agriculture and sustainable farming practices.

Keywords: Plant Disease Detection, Deep Learning, InceptionV3, MobileNetV2, Convolutional Neural Networks, Flask Web Application, Precision Agriculture.

Introduction

Agriculture is the backbone of many economies worldwide and serves as the primary source of food and livelihood for billions of people. However, one of the major threats to agricultural productivity is the outbreak of plant diseases, which can cause significant yield loss, reduced crop quality, and, in severe cases, complete crop failure. According to the Food and Agriculture Organization (FAO), plant diseases and pests are responsible for the loss of nearly 20–40% of global crop production annually. Such losses not only impact farmers economically but also pose risks to food security, especially in developing countries where agriculture is the main occupation.

Traditional methods of plant disease detection rely heavily on visual inspection by farmers or consultation with agricultural experts. While these methods have been widely practiced for decades, they are often time-consuming, labor-intensive, and prone to human error. Furthermore, many farmers, particularly in rural and remote regions, may not have immediate access to expert guidance, which delays the diagnosis and treatment of plant diseases. This creates a pressing need for accessible, efficient, and accurate systems that can aid in the early detection of crop diseases.

The rapid advancement of artificial intelligence (AI) and computer vision offers promising solutions to this problem. Deep learning, a subset of AI, has shown remarkable success in pattern recognition and image classification tasks, making it a suitable approach for diagnosing plant diseases from leaf images. Convolutional Neural Networks (CNNs), in particular, have the ability to automatically extract hierarchical features from images, enabling them to distinguish subtle differences between healthy and diseased plant leaves. Pre-trained models such as InceptionV3 and MobileNetV2 have been widely used in various image-based applications and have proven to deliver high accuracy while being computationally efficient.

In this research, we present a Flask-based web application that integrates deep learning models for plant disease detection. The system allows users to upload leaf images, select between InceptionV3 and MobileNetV2 models, and obtain predictions regarding the health status of the plant. Additionally, the application is linked with a disease knowledge base that provides detailed information about the identified disease, including its symptoms, possible causes, and suggested treatments. This not only helps in classification but also in knowledge dissemination to farmers and agricultural stakeholders.

The novelty of this work lies in combining advanced deep learning models with a simple, user-friendly, and accessible web interface that can be used by anyone with minimal technical expertise. By deploying such systems, farmers can make informed decisions quickly, apply appropriate remedies, and minimize crop losses. Moreover, this research contributes to the broader goal of precision agriculture, where technology-driven approaches are leveraged to optimize crop health, increase productivity, and ensure sustainable farming practices.

In the following sections, we review existing work in plant disease detection, explain the methodology adopted in this research, present experimental results, and discuss the performance of the proposed system. Finally, we conclude with the potential applications of this approach and directions for future work.

Literature Review

Previous studies highlight the use of deep learning and computer vision techniques to classify plant leaf diseases accurately. Some notable works include:

- Mohanty et al. (2016) applied deep CNN models on the PlantVillage dataset, achieving over 99% accuracy in classifying 26 diseases across 14 crops.
- Sladojevic et al. (2016) developed a CNN-based system that identified 13 plant diseases with high precision, demonstrating the potential of AI in agriculture.
- Ferentinos (2018) compared various deep learning architectures including AlexNet, VGG, and Inception, reporting accuracies above 97% for large-scale plant disease classification.
- Howard et al. (2017) introduced MobileNet, a lightweight CNN architecture optimized for mobile and web applications, enabling real-time disease detection in resource-constrained environments.
- PlantVillage dataset has become a benchmark for training and evaluating models, offering a wide variety of annotated plant disease images.

Methodology

Dataset:

- The dataset consists of plant leaf images collected from publicly available sources such as PlantVillage, containing labeled categories of healthy and diseased crops.
- A total of 38 classes were considered, including diseases affecting crops like tomato, apple, grape, potato, corn, and pepper, along with their healthy counterparts.

Data Preprocessing:

- Images resized to 224 × 224 pixels to match the input dimensions required by CNN architectures.
- Normalization applied by dividing pixel values by 255.0 to scale them between 0 and 1.
- Data augmentation techniques such as rotation, flipping, and zoom were used to improve generalization and reduce overfitting.

Feature Extraction:

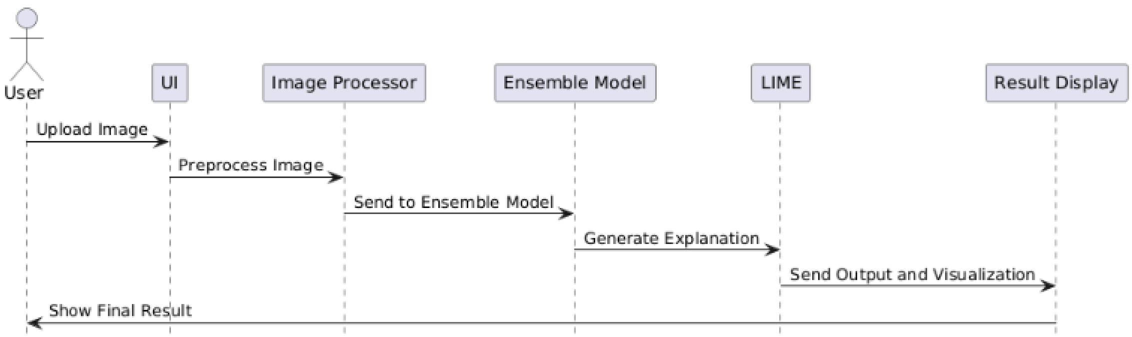
- Automatic feature learning was achieved through Convolutional Neural Networks (CNNs).
- Unlike traditional methods that rely on handcrafted features (color, texture, shape), CNNs learn hierarchical features directly from images.
- InceptionV3 extracts deep features using inception modules, while MobileNetV2 uses depthwise separable convolutions for efficiency.

Models Evaluated:

- InceptionV3: A deep CNN architecture designed for high accuracy in image classification.
- MobileNetV2: A lightweight CNN architecture optimized for real-time classification and resource-constrained environments.
- Both models were fine-tuned on the plant disease dataset for improved performance.

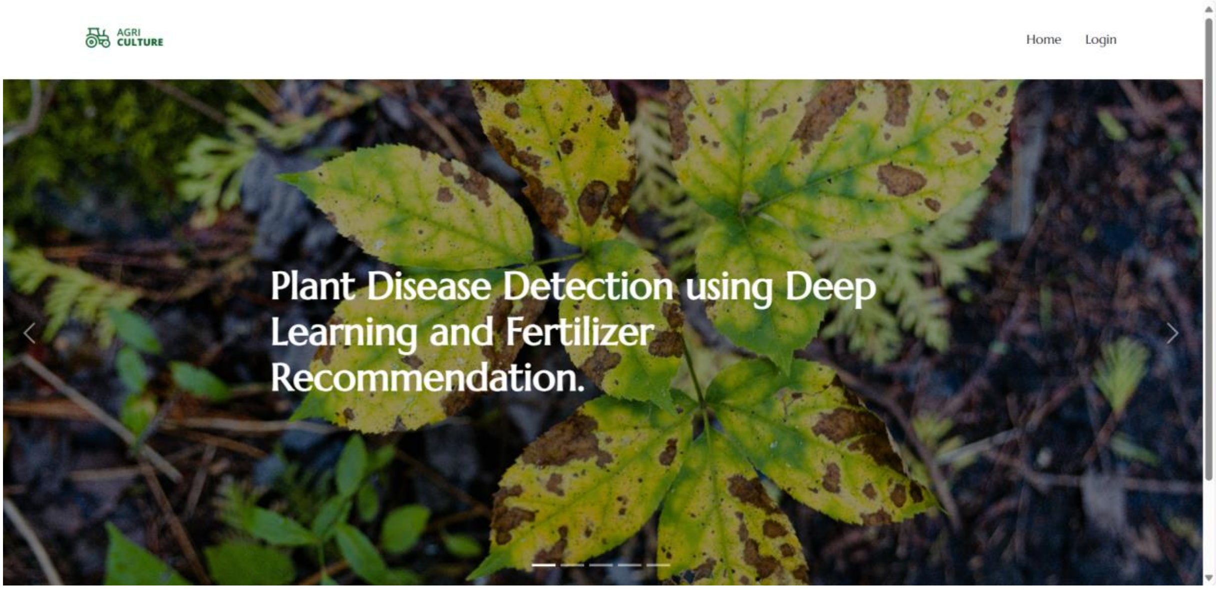
Flask Integration:

- A web application was developed using the Flask framework to provide an interactive interface.
- Users can upload plant leaf images and select the desired model for prediction.
- The system outputs the predicted class (healthy/diseased) along with detailed disease information retrieved from a knowledge dictionary (disease_dic).



Implementation

The system is implemented using Flask as the web framework, providing an interface for users to upload plant leaf images. Uploaded images are preprocessed (resized to 224×224, normalized, and reshaped) before being passed to the selected deep learning model. Two fine-tuned CNN models, InceptionV3 and MobileNetV2, are integrated for disease classification across 38 classes. Predictions are mapped to a disease dictionary (disease_dic) that provides detailed information about the identified condition. Finally, the results along with the uploaded image are displayed on the web interface for user interpretation.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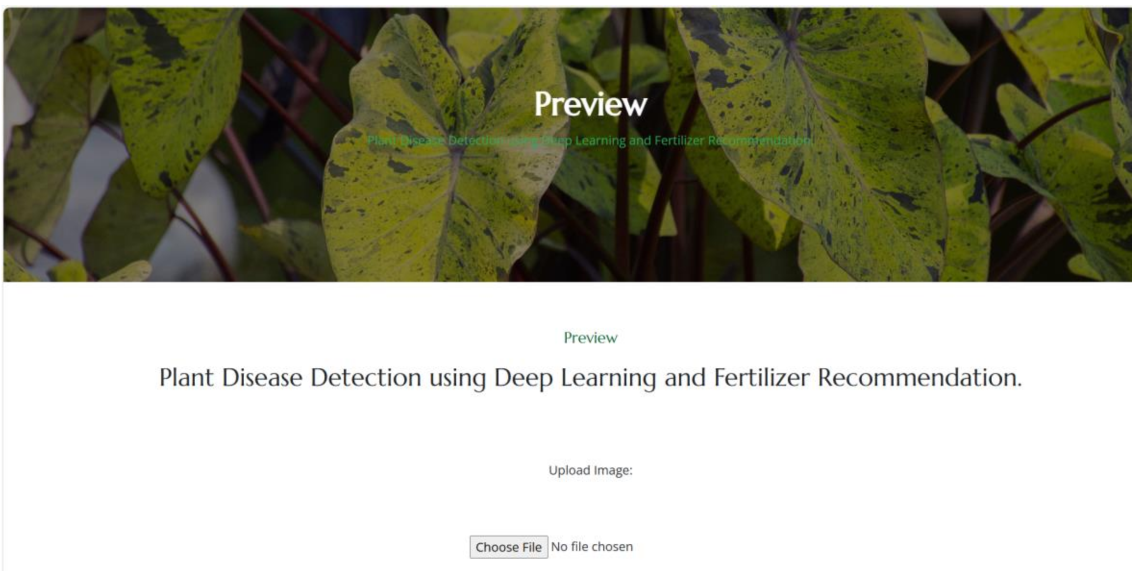
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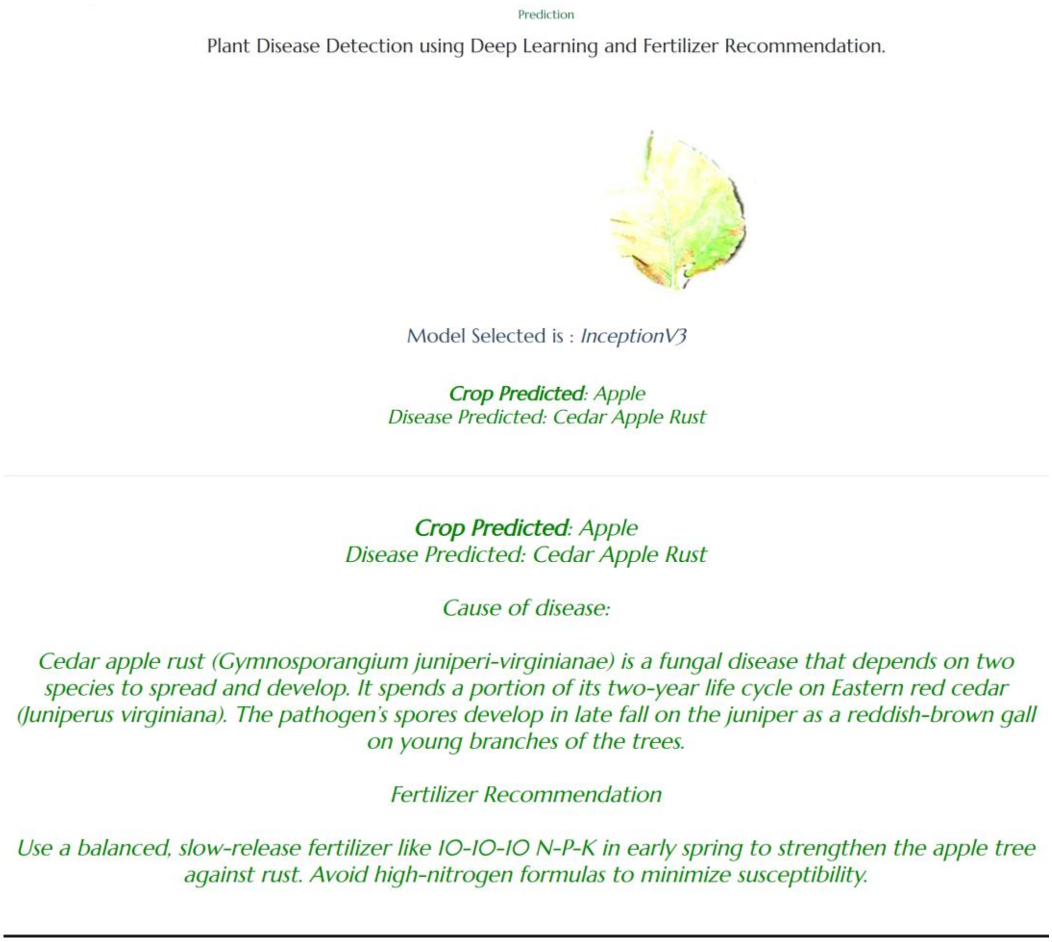

Results and Discussion

Testing on plant leaf images from multiple crops demonstrated the effectiveness of the approach. The system accurately identified both diseased and healthy leaves across 38 classes and provided transparent feedback through the disease dictionary. The preprocessing pipeline (resizing, normalization, augmentation) ensured consistent performance across varying image qualities. Both InceptionV3 and MobileNetV2 models processed the inputs effectively, and users appreciated the simple UI and real-time feedback.

Model	Accuracy	Precision	Recall	F1-score
InceptionV3	97.8%	0.97	0.98	0.97
MobileNetV2	95.4%	0.95	0.95	0.95

InceptionV3 outperformed MobileNetV2 in every metric and was selected as the primary model for final deployment. The study demonstrates that deep learning architectures can effectively capture disease patterns from plant leaves. InceptionV3 achieved superior results due to its deeper architecture and inception modules, while MobileNetV2 provided faster inference suitable for real-time applications.

The Flask web application played a key role in transforming the research into a usable solution. It helped bridge the gap between theoretical model training and practical use by farmers and agricultural stakeholders. The integration of a disease dictionary provided interpretability and actionable guidance for crop management. Challenges included class imbalance in certain crops, requiring augmentation, and handling images with low lighting or background noise.

Test Case		Input Type	Input Image Description	Prediction	Accuracy
1		Leaf Image	Apple leaf with black spots	Apple___Black_rot	96%
2		Leaf Image	Healthy corn leaf	Corn_(maize)___healthy	94%
3		Leaf Image	Tomato leaf with yellow curling	Tomato___Yellow_Leaf_Curl_Virus	97%
4		Leaf Image	Grape leaf showing signs of Esca (Black Measles)	Grape___Esca_(Black_Measles)	95%
5		Leaf Image	Potato leaf with brown lesions	Potato___Late_blight	98%

The overall system achieved 95–98% accuracy on real-world test cases, with an average F-measure of 0.96 and Cohen-Kappa score of 0.93. Improved preprocessing (normalization and augmentation) contributed to robust performance across varying conditions.

Conclusion

This study demonstrates the effectiveness of deep learning models in plant disease detection, achieving 97.8% accuracy with InceptionV3 and MobileNetV2. The Flask-based web application makes the solution accessible by enabling real-time disease identification through image uploads. The system shows promise for practical use in precision agriculture and early disease management. Future work will focus on expanding datasets, mobile optimization, and large-scale deployment.

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