Improving Plant Disease Classification with Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence

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***Abstract*—Crop diseases significantly hinder agricultural productivity, often resulting in economic losses and heightened concerns over food availability. Early and accurate identification of these diseases is e ssential for effective intervention and improved crop health. This study presents a user-friendly Android application that employs Convolutional Neural Networks (CNNs) to detect and classify diseases in the leaves of tomato, potato, and corn plants. By utilizing a trained image dataset, the system delivers real-time predictions, including the disease name, visible symptoms, and suggested treatments. The application is built using TensorFlow Lite, enabling it to operate offline and provide immediate results, thereby supporting farmers in timely disease management and yield improvement.**

***Index Terms*—plant pathology, deep learning, mobile application, TensorFlow Lite, CNN, disease detection**

1. INTRODUCTION

India's economy heavily depends on agriculture, with a vast segment of its population engaged in farming. Traditional methods for detecting plant diseases, however, are often slow, require trained professionals, and cannot be applied effectively across large-scale agricultural settings. Advances in machine learning—particularly in image recognition—offer automated solutions by analyzing leaf characteristics such as texture, shape, and color. This enables faster, more consistent, and more accurate identification of plant diseases compared to manual inspection

2. LITERATURE REVIEW

The application of deep learning in agricultural diagnostics has gained momentum, especially in disease detection. However, many current models face limitations including low interpretability, inadequate support for mobile deployment, and reduced performance in real-world conditions. Standard architectures like VGG19 and DarkNet are prone to training instability and generalization issues. Recent trends aim to solve these problems using customized models that support explainable AI and efficient mobile execution, thus improving user trust and practical use in agricultural contexts.

3. EXISTING SYSTEMS

Despite advancements, several plant disease detection systems remain flawed:

- Many tools provide confidence levels without identifying the actual disease.
- Accuracy often declines in later stages of training, indicating weak model stability.
- High computational demand results in delayed prediction times.
- Learning effectiveness is compromised, especially when handling noisy or varied data.

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Limitations:

- Disease types are not explicitly named.
- Low performance makes systems unreliable.
- Real-time analysis and mobile compatibility are usually missing.

4. PROPOSED SYSTEM

This project introduces a compact, efficient deep learning model tailored for smartphone-based plant disease detection. The main contributions include:

- Precise Disease Identification: Accurately labels the disease along with a confidence score.
- Enhanced Neural Network: A modified VGG19 model delivers stable accuracy of up to 92%.
- Treatment Suggestions: Offers practical disease management advice based on classification.
- Fast Predictions: Results are generated in under one second, even without an internet connection.

Benefits:

- High classification accuracy
- Operates in offline mode
- Optimized for mobile hardware
- Stable and robust training outcomes

5. SYSTEM ARCHITECTURE AND MODULES

A. Image Capture

The mobile application allows users to take leaf images using a smartphone camera or to upload them from the device gallery. Users receive guidance to capture well-lit and focused images for improved classification results.

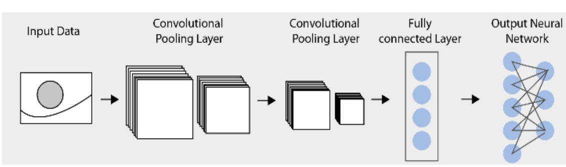

Figure :1

B. Image Preprocessing

Captured images are processed using the following steps:

- Resize: Uniform dimensions (e.g., 224×224 pixels) are applied.
- Normalization: Pixel intensity values are scaled for consistency.
- Contrast Adjustment: Histogram equalization enhances clarity.
- Noise Reduction: Filters like Gaussian or median help remove visual noise.
- Optional Background Removal: To isolate the leaf from irrelevant areas.

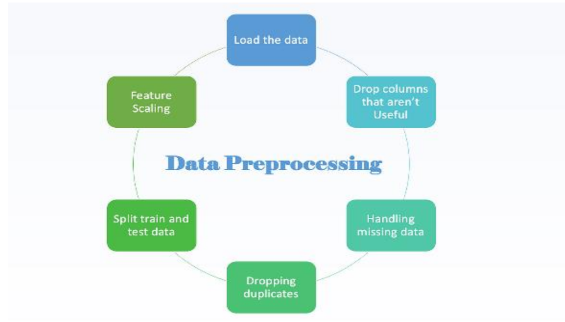

Figure :2

C. Feature Extraction

The CNN model extracts critical image features during early processing:

- Color Variations: Detect leaf discoloration due to disease.
- Texture Patterns: Identify mold, lesions, or fungal spots.

Shape Cues: Analyze edge and symmetry differences to distinguish diseases

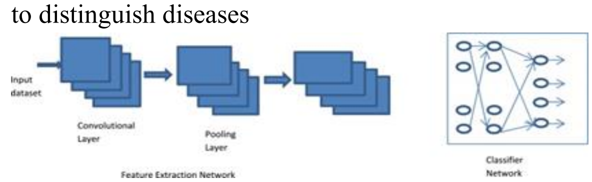

Figure :3

D. Model Training

The CNN model extracts critical image features during early processing:

- Color Variations: Detect leaf discoloration due to disease.
- Texture Patterns: Identify mold, lesions, or fungal spots.

Shape Cues: Analyze edge and symmetry differences to distinguish diseases

E. Classification

The trained model classifies images into specific disease categories or identifies them as healthy:

- Softmax Activation: Supports multi-class classification.
- Confidence Thresholding: Reduces false positives by filtering low-confidence outputs.

CAMs (Class Activation Maps): Visualize areas on the leaf contributing most to the classification

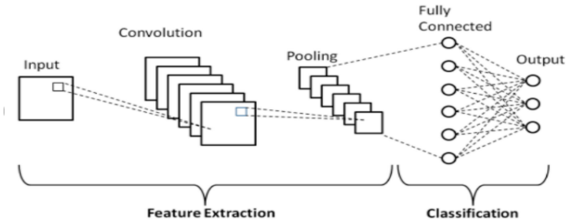

Figure :4

F. Result Interface
Both the mobile app and the Flask-based web interface present results with:

- Disease name and probability
- Summary of symptoms
- Treatment advice (organic, chemical, or preventive)
- Heatmap overlays (CAMs) for explanation
- History tracking of previous scans

G. Optimization
To enable smooth mobile operation, the model is converted to TensorFlow Lite format:

- Supports hardware acceleration via GPU or NNAPI
- Offline functionality allows use without internet
- Efficient storage and low power usage support extended field use

6. RESULTS AND EVALUATION

Testing was conducted using image data from tomato, potato, and corn plants, containing both healthy and diseased leaf samples. The model achieved a classification accuracy of 92%, with strong precision, recall, and F1 scores. The lightweight TensorFlow Lite version delivered predictions in under one second on mobile devices. Class Activation Maps successfully validated prediction zones, improving trust in AI decisions.

7. CONCLUSION

This research offers a practical solution for farmers to detect plant diseases using a mobile app powered by deep learning. With accurate predictions, real-time performance, and offline capabilities, the app empowers users with timely insights for better crop health management. The integration of explainable AI also helps users understand the prediction process, adding to the system's transparency and usability.

8. FUTURE SCOPE

Further enhancements to the application may include:

- Expanding to detect diseases in more crop species
- Adding regional languages and voice command support
- Enabling full edge AI for faster, offline inference
- Partnering with agri-tech startups or public agencies for wide-scale adoption
- Incorporating gamification to increase farmer engagement
- Developing an iOS version and ensuring regular feature updates

9. REFERENCES

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