A CNN-Based Framework for Accurate Detection of Plant Leaf Diseases

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Abstract This study demonstrates how plant diseases significantly threaten global agricultural productivity and food security. This paper presents a deep learning-based mobile application that can detect plant diseases from leaf images using Convolutional Neural Networks (CNNs). The system was trained on a dataset comprising 38 classes of healthy and diseased plants leaves. The proposed solution combines image pre-processing, feature extraction using CNNs, and mobile deployment using a lightweight interface. The experimental results demonstrated high classification accuracy, low latency inference, and practical feasibility for real-world agricultural settings. The app further integrates features such as offline access, disease-specific treatment recommendations, and image-history tracking for farmer support.

Keywords: plant disease detection, deep learning, convolutional neural network (CNN), mobile application, image classification, agricultural AI, precision farming.

INTRODUCTION

Agriculture remains the backbone of many economies, particularly in developing countries where a significant portion of the population depends on farming for their livelihood. However, plant diseases present a major obstacle to sustainable agricultural production, leading to severe losses in crop yield, increased production costs, and food insecurity. Accurate and timely diagnosis and control of plant diseases is crucial for maintaining healthy crops and ensuring agricultural sustainability.

Traditional disease detection methods involve manual observations by agricultural experts or pathologists. While effective under controlled conditions, these techniques are prone to human error, are often inaccessible to rural farmers, and lack scalability for large-scale farming. The increasing penetration of smartphones, combined with advancements in artificial intelligence, has created new opportunities for accessible and intelligent disease-detection tools.

Deep learning, a subset of artificial intelligence, has been successful in computer vision tasks such as convolutional Neural Networks (CNNs) in leaves. CNN-based models trained on large datasets can extract hierarchical features from images. highly effective in identifying complex patterns, such as disease symptoms, in plants that classify plant diseases with high accuracy, even under varying environmental conditions.

This study proposes a deep-learning-powered mobile application for plant disease detection using CNNs. The system supports the classification of 38 different plant disease classes using leaf image inputs. The application is designed to operate efficiently on mobile devices, offering farmers real-time diagnostic capabilities without the need for internet connectivity. In addition, the app provides users with recommendations for treatment and preventive measures, thus enhancing its utility beyond mere identification.

I. LITERATURE REVIEW

The Plant-Village Dataset and Baseline CNN Models Mohanty et al. (2016) conducted pioneering work using the publicly available Plant-Village dataset, which contains over 50,000 images across 38 classes of plant species and diseases. They trained Alex Net and Google Net architectures and achieved classification accuracies exceeding 99% on a clean test set.

Although effective, the models were evaluated under ideal conditions with simple backgrounds, limiting their generalization.

One of the earliest and most influential studies was conducted by Mohanty et al., who utilized the Plant Village dataset, which is a comprehensive image repository containing over 54,000 labeled images spanning 38 disease classes across 14 crop species. They applied the Alex Net and Google Net architectures and achieved a classification accuracy of over 99% under ideal lighting and background conditions. While these results were promising, the models struggled to generalize when exposed to noisy, real-world data from farms.

To address this gap, Ferentinos employed Transfer Learning To use deeper architectures such as VGG16 and ResNet50, pre-trained on ImageNet. Fine-tuning these models on augmented datasets yielded better generalization across diverse environmental conditions. The use of transfer learning not only accelerates training, but also reduces dependency on large labeled datasets, which is an important consideration in agricultural AI, where field-level annotations are scarce.

Lightweight Architectures for Mobile Deployment Recognizing the growing need for portable solutions designed a CNN tailored for mobile inference. Their work on tomato disease detection emphasized low-latency processing and efficient memory usage. Their Android application allows farmers to capture leaf images and receive disease predictions offline, which is particularly useful in connectivity-constrained rural regions. This inspired further research into model pruning, quantization, and efficient CNNs such as Mobile Net and Squeeze Net for edge deployment.

II. METHEDOLOGY

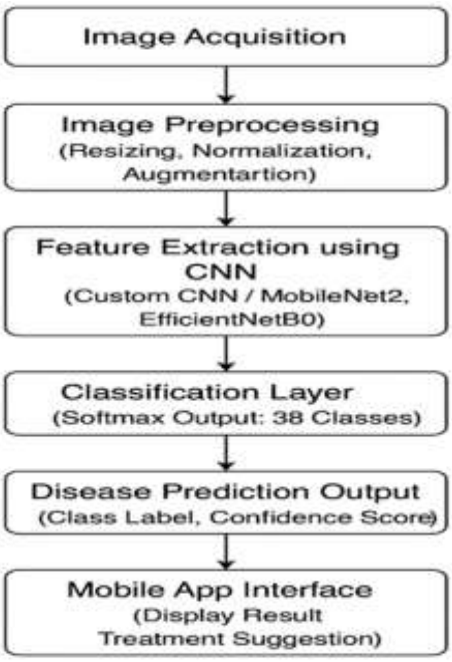

Fig 1 Block Diagram

This section delineates the methodological framework adopted for plant disease detection, encompassing the dataset characteristics, preprocessing steps, CNN architecture design, training protocol, and mobile deployment strategy.

A. Dataset Description: The Plant Village dataset, an open-access benchmark curated by Hughes and Salathé, was

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used in this study. It comprises approximately 54,303 RGB images of healthy and diseased leaves, spanning 14 crop species and 38 disease categories. The dataset was selected for its diversity and standardized image acquisition conditions, including uniform backgrounds and controlled lighting. All images were resized to 224 × 224 pixels to match the input dimensions of conventional CNN models.

B. Data Preprocessing and Augmentation: To enhance the model's generalizability and robustness to real-world conditions, preprocessing was conducted as follows:

- Normalization: Pixel values were scaled to the range [0, 1] and normalized using channel-wise mean and standard deviation values from the ImageNet dataset.
- Data Augmentation**:** Techniques including random rotation (±20°), horizontal and vertical flipping, zooming (range: 0.8–1.2×), and brightness modulation were applied. These augmentations were implemented to simulate environmental variability such as inconsistent lighting, diverse leaf orientations, and complex backgrounds encountered in field imagery.

C. Training Procedure: The model was trained using categorical cross-entropy as the loss function and the Adam optimizer with an initial learning rate of 0.0001. Training was conducted for 50 epochs with a batch size of 32. Early stopping based on the validation loss was employed to prevent over fitting. The training framework was implemented in Tensor Flow 2.x, with Keras a the high-level API. To address class imbalance, class weighting and focal loss have been investigated as alternative strategies.

The trained model was converted to TensorFlow Lite format for deployment on Android-based smartphones. The mobile application was developed using Android Studio and incorporates the following features: a graphical interface that allows users to capture or select leaf images. On-device inference utilization, enabling offline functionality in connectivity-constrained regions.

Fig 2 Snapshot of Plant Village Dataset

Fig 3: Snapshot of VS Code Dashboard

III. RESULT AND DISCUSSION

Fig 4: Output Fig 5: Output

This section presents the experimental results obtained from the training and evaluation of the proposed deep learning-based plant disease detection system. The performance of the developed model was analyzed with respect to classification accuracy, generalization capability, and real-world applicability. The feasibility of mobile deployment was also assessed. A. Experimental Setup: The system was trained and tested on a publicly The experiments were conducted using the Plant Village dataset, which was split into training (80%), validation (10%), and testing (10%) sets. All models were trained using TensorFlow on a system with NVIDIA GPU acceleration. Performance metrics, such as accuracy, precision, recall, and F1-score were computed to evaluate the classification capabilities of the models. In addition, the model size and inference time were measured to determine mobile compatibility.

IV. CONCLUSION

This paper presents a deep learning-based approach for automated plant disease detection that leverages convolutional neural networks and transfer learning techniques. By utilizing the Plant Village dataset and applying extensive preprocessing and augmentation methods, the system achieved a high classification accuracy across 38 distinct disease classes. Lightweight models such as MobileNetV2 and EfficientNetB0 demonstrated strong performance with low inference times and minimal storage requirements, making them suitable for mobile deployment in agricultural settings. Although the results are promising, challenges remain in adapting the system to complex real-world environments characterized by noisy backgrounds and variable lighting conditions. Future work will focus on expanding the dataset with field-captured images, improving robustness through domain adaptation, and incorporating multimodal features, such as environmental data. Additionally, enhancements, such as multilingual interfaces and voice-enabled support, will be explored to increase accessibility and usability among diverse user groups.

V. REFERENCES

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