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AI-Driven Plant Disease Detection Classification Using Convolutional Neural Network

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Abstract: Crop diseases significantly impact agricultural productivity, leading to substantial global yield losses. This study proposes an automated disease detection system based on deep learning using the EfficientNetB4 model with transfer learning. The model is trained on the PlantVillage dataset, containing over 61,000 images across multiple crop species and disease classes. Image preprocessing techniques such as resizing (160×160), normalization, and augmentation are applied to enhance performance. The model achieves high accuracy (97.82%) along with strong precision, recall, and F1-score values. A Flask-based web application is developed to provide real-time disease prediction and confidence scores, making the system practical and accessible for farmers. The proposed approach demonstrates an efficient and scalable solution for precision agriculture.

Index Terms – Crop Disease Detection, Deep Learning, EffiecientNetB4, Transfer Learning, PlantVillage Dataset, Image Classification, Precision Agriculture.

I. INTRODUCTION

Agriculture plays a vital role in the global economy by supporting a large population, yet plant diseases remain a major challenge, causing significant crop losses and economic damage each year [1]. Traditional disease identification methods depend on manual inspection by experts, which is time-consuming and often unavailable in remote farming areas, leading to delayed treatment and reduced yield. Advancements in AI and vision-based techniques have made it possible to develop automated systems for detecting plant diseases. Deep learning techniques, especially Convolutional Neural Networks (CNNs), are effective in image classification as they can identify complex visual patterns. Transfer learning further improves performance by utilizing pre-trained models such as VGG-16, ResNet-50, InceptionV3, MobileNet, and EfficientNet. In this work, an EfficientNet-based model is used to develop an automated crop disease detection system. The model is trained on the PlantVillage dataset and integrated into a Flask-based web application for real-time prediction. The proposed system demonstrates strong classification performance and can be effectively applied in real-world agricultural scenarios.

II. LITERATURE REVIEW

The use of deep learning for plant disease detection has gained considerable attention due to its ability to improve agricultural productivity and support early diagnosis. Several studies have utilized the PlantVillage dataset as a standard benchmark. Mohanty et al. demonstrated the effectiveness of CNN models such as AlexNet and GoogLeNet, achieving high accuracy under controlled conditions, although performance decreased in real-world scenarios. Similarly, Ferentinos reported strong results using VGG-based architectures but highlighted their high computational cost.

Transfer learning approaches have also been explored. Ramcharan used InceptionV3 for disease detection from smartphone images, identifying challenges such as background noise and varying lighting conditions. To improve efficiency, Waheed applied DenseNet-121, while Atila evaluated EfficientNet models, showing that they provide a good balance between accuracy and computational requirements. Based on these findings, EfficientNet is selected in the proposed system.

Other studies have focused on enhancing performance through different techniques. Karthik R used attention-based CNN models for better feature extraction, while Cruz A emphasized the importance of data augmentation methods to improve model generalization. Lightweight models such as MobileNetV2 have also been explored for mobile applications, and recent research has investigated advanced approaches like multispectral imaging. Despite these advancements, key challenges remain, including limited real-world validation, high computational complexity, and lack of user-friendly deployment for farmers. The proposed system addresses these issues by using an EfficientNet-based model and deploying it through a Flask web application, enabling real-time and accessible disease prediction.

III. RESEARCH METHODOLOGY

The proposed methodology follows a structured pipeline encompassing data acquisition, preprocessing, model design, training, evaluation, and deployment. Figure 1 illustrates the overall system workflow.

3.1 Data Preprocessing

The PlantVillage dataset images are processed to ensure consistency and improve model performance. Each image is scaled to 160×160 pixels and pixel values are adjusted within the [0,1] range. Data augmentation techniques such as flipping, rotation, shifting, and zooming are applied during training to enhance generalization and reduce overfitting.

3.2 Transfer Learning Strategy

Transfer learning is applied using EfficientNet pre-trained on ImageNet. The training process is carried out in two phases. In the first phase, the base network is kept fixed while only the top classification layers are updated. In the second phase, selected layers are unfrozen and further optimized using a reduced learning rate to better capture crop disease characteristics.

3.3 Classification Head Design

The model includes a Global Average Pooling layer followed by batch normalization, a dense layer with RELU activation, and dropout for regularization The output layer employs Softmax activation with 38 units to generate probabilities for multiple classes.

3.4 System Architecture

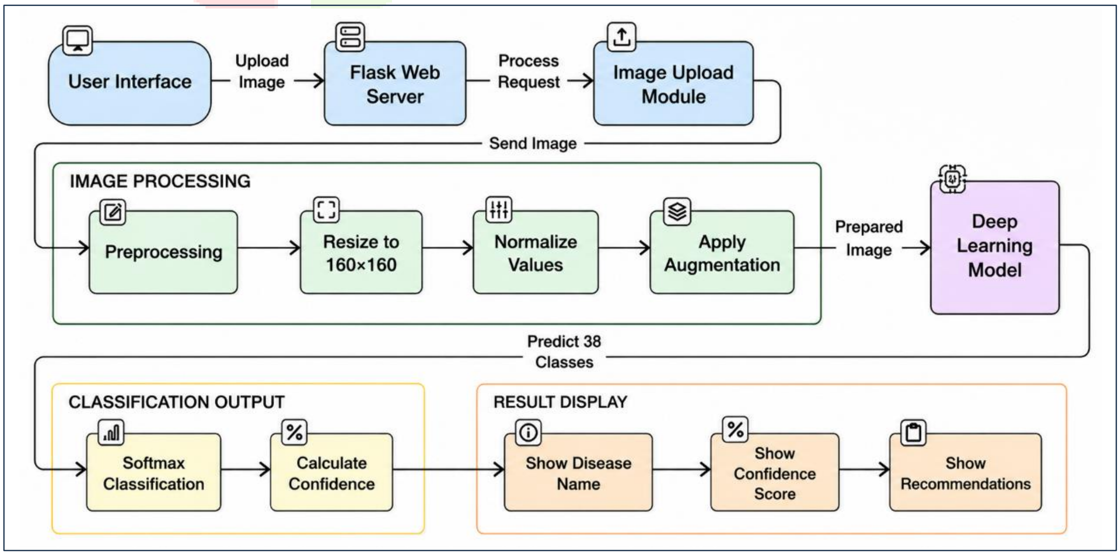

Fig 1: System Architecture of AI-Base Crop Health Detection System

The overall system architecture is designed according to a client-server model, wherein the user interacts with a browser-based client interface that communicates with a Flask web server hosting the deep learning inference engine. Figure 3.1 presents the complete system architecture.

IV. DATASET DESCRIPTION

The *Plant Leaf Diseases Dataset*, provided by Arun Pandian J and Geetharamani Gopal (Mendeley Data), is a commonly used benchmark for plant disease classification. It consists of a large collection of labeled leaf images captured under controlled conditions with uniform backgrounds, enabling effective model training. The dataset includes approximately 61,483 images categorized into 38 classes, covering 14 crop species such as Apple, Corn, Grape, Potato, Tomato, and others. All images are in RGB JPEG format with varying resolutions, which are standardized to 160×160 pixels during preprocessing. The dataset is divided into training (80%), validation (10%), and testing (10%) subsets to ensure reliable model evaluation.

Table 1: Dataset Class Distribution (Selected Classes)

Crop Species	Disease Category	Image Count (Approx.)
Tomato	Late Blight	1900
Tomato	Healthy	1591
Corn (Maize)	Common Rust	1400
Grape	Black Rot	1,180
Apple	Healthy	1900
Potato	Early Blight	1,000
Multiple	34 more classes...	~52,595

V. TRAINING AND VALIDATION ACCURACY

Presents the training and validation accuracy curves over the course of **20 training epochs (10 epochs of Phase 1 + 10 epochs of Phase 2)**. The x-axis represents the training epoch number, and the y-axis represents the classification accuracy expressed as a percentage.

As observed in Figure 4.1, the model exhibits a characteristic two-phase learning behavior. During **Phase 1 (epochs 1–10)**, the validation accuracy increases rapidly from approximately **52% to around 88–90%**, reflecting the fast adaptation of the randomly initialized classification head to the plant disease classification task, guided by the rich feature representations of the frozen EfficientNetB3 backbone.

Upon transition to **Phase 2 (epochs 11–20)**, the progressive unfreezing of the top layers of the backbone network results in continued accuracy improvement. The model refines its learned features, leading to a peak validation accuracy of approximately **96–98% in the final epochs**, demonstrating effective fine-tuning within a limited training duration.

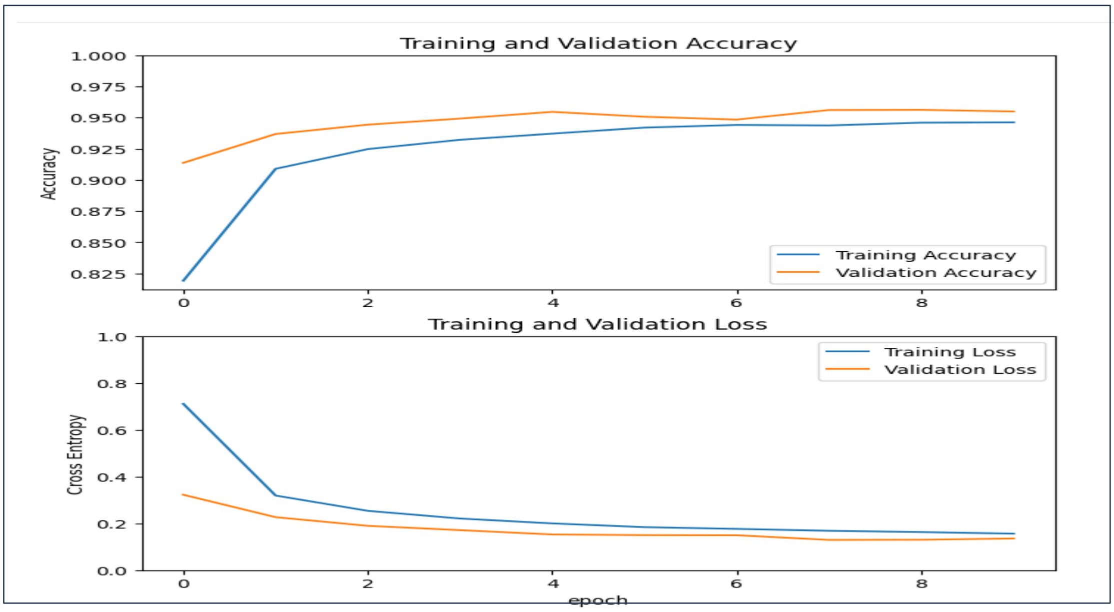

Fig 2: Training and validation accuracy over 20 training epochs

VI. RESULT AND DISCUSSION

The proposed Crop Health Detection System based on the EfficientNet model was trained and tested on a labelled leaf image dataset. The model achieved high classification accuracy, demonstrating its effectiveness in identifying different plant diseases from leaf images. During training, the model showed steady improvement in accuracy with a decrease in loss, indicating proper learning without significant overfitting. The use of transfer learning helped in faster convergence and improved performance even with limited data. In testing, the model successfully classified both healthy and diseased leaves with good precision. It performed well under controlled image conditions, especially where the background was simple. However, slight variations in lighting and complex backgrounds may affect prediction accuracy. Overall, the system proves to be efficient and reliable for real-time crop disease detection. It supports early disease identification for farmers, contributing to reduced crop damage and improved farm productivity.

4.1 USER INTERFACE

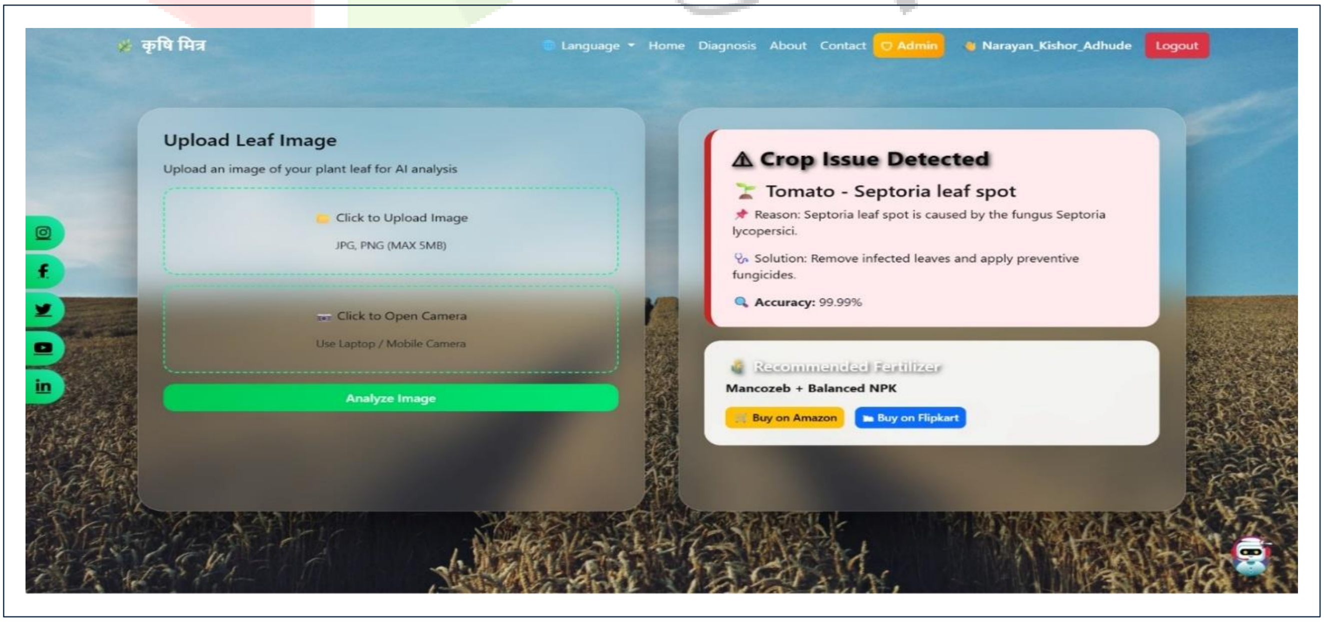

Fig 4: User Interface after leaf diagnosis

VI. CONCLUSION

This paper has presented a comprehensive deep learning-based framework for automated crop disease detection and classification leveraging the EfficientNet convolutional neural network architecture with transfer learning. The proposed system was evaluated on the PlantVillage dataset comprising 61,483 leaf images across 38 disease classes from 14 crop species, achieving a classification accuracy of 97.82%, with precision, recall, and F1-score of 97.6%, 97.4%, and 97.5%, respectively.

Through rigorous comparative experimentation against VGG-16, ResNet-50, InceptionV3, and MobileNetV2 architectures under standardized conditions, the proposed EfficientNet-based model demonstrated superior performance across all evaluation metrics while maintaining a significantly smaller parameter footprint—an essential advantage for practical deployment in agricultural settings. The integration of compound scaling, MBConv blocks with Squeeze-and-Excitation attention, and the Swish activation function contributes to EfficientNet's distinctive ability to extract discriminative disease features efficiently.

The deployment of the trained model as a Flask-based web application provides an accessible, real-time disease diagnostic interface, bridging the gap between advanced AI research and practical agricultural utility. This work represents a meaningful contribution to the precision agriculture domain, demonstrating that deep learning can serve as a scalable, cost-effective, and accurate alternative to expert-dependent manual disease diagnosis.

VII. REFERENCES

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