

Transfer Learning-based Multi-Class Plant Disease Detection Using MobileNetV2 and EfficientNet-B0

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Abstract

An early and precise identification of plant diseases helps to increase the efficiency of farming operations and minimize the economic losses associated with plant diseases. Nevertheless, applying deep learning models for plant disease identification in an agricultural setting poses certain difficulties due to high computational costs and insufficient edge device computing power. This paper presents a transfer learning-based framework for multi-class plant disease detection using MobileNetV2 and EfficientNet-B0 models. For the purpose of research, the PlantVillage dataset including potato, bell pepper, and tomato leaves was used. Images from this source underwent pre-processing that included resizing, normalizing, and augmenting images. Both transfer learning approach and fine-tuning helped to modify pre-trained CNNs for multi-class classification of different diseases affecting plants' leaves. Experiments have shown that EfficientNet-B0 model performed much better with accuracy of 95.7% and AUC of 0.98. Moreover, the proposed algorithm was exported as a TensorFlow Lite model and implemented in the Streamlit application for efficient edge deployment.

Keywords: Plant Leaf Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Lightweight Models, Transfer Learning, Multi-Class Classification.

1. Introduction

Agricultural practices play a crucial role in securing food safety and economic sustainability on an international level. Diseases in plants are responsible for impacting the yield and overall quality of crops, resulting in considerable economic costs and lower agricultural efficiency. Visual identification techniques are typically employed to recognize plant diseases; however, this approach is prone to inaccuracies, since it involves a manual process and is time consuming. Moreover, the presence of specialist personnel to detect diseases might not always be available for large-scale farms.

Advancements in artificial intelligence and computer vision technologies have facilitated the design of automatic plant disease recognition models. Deep learning models based on CNN were proven highly successful in extracting visual features of disease from images of leaves. Handcrafted visual features engineering was no longer required thanks to such models, which led to an improvement in classification performance. However, the application of deep learning CNN models was associated with high computational needs and high memory consumption.

With the appearance of edge computing technologies, more chances for implementing the intelligent disease diagnosis system appeared. Lightweight neural network models like MobileNetV2 and EfficientNet-B0 are explicitly optimized for ensuring excellent classification accuracy without increasing computational complexity. Such features allow performing real-time disease diagnostics using edge computing, which makes this solution not depend on cloud-based computing infrastructures.

Despite the numerous research projects on deep learning plant disease detection, balancing between accuracy and computational complexity still remains a problem. Moreover, practical application of the agricultural solution requires models, which are able to demonstrate high-performance levels even when working under low computational capabilities. With this idea in mind, the following work tries to prove that lightweight transfer learning models can be effectively used for classifying multi-class plants diseases.

The primary objective of this study is to develop and evaluate a transfer learning-based framework for multi-class plant disease detection using MobileNetV2 and EfficientNet-B0 architectures with further evaluation of the classification results on potato, bell pepper, and

tomato leaf images. The framework will include image preprocessing, transferring learning, performance assessment stages, and TensorFlow Lite model deployment.

2. Literature Review

The use of deep learning algorithms and edge computing technologies for plant diseases detection has been gaining increasing interest lately because of the opportunity to boost agricultural productivity through fast and accurate disease recognition. One of the main directions in plant disease detection research involves the development of light models and architectures that are efficient, interpretable, and are capable of running on edge computing devices.

Al Kafi et al. [1] presented LeafAI – a plant disease detection system based on an explainable artificial intelligence architecture and tailored specifically for edge computing systems. The authors implemented a hybrid two-step method in which at first, with the help of a machine learning model, healthy leaves were distinguished from those that had any diseases, and only after that, with the help of a deep learning model, the diseases themselves were recognized. Deepa et al. [2] developed L-Net – a light deep learning model for multicrop leaf disease classification. This model leveraged the advantages of depthwise separable convolutions as well as optimized activation mechanism to minimize the number of calculations required for each inference while maintaining high prediction accuracy. It was tested on edge computing platforms such as Raspberry Pi and Jetson Nano.

The paper by Gunasekaran et al. [3] provides a detailed literature analysis on the use of lightweight deep learning methods to detect diseases on tomatoes. This study underlines the significance of finding an adequate balance between the accuracy and computational efficiency needed for deployment of edge systems. Challenges such as environmental factors, the diversity of data sets, and explainability of models were described, alongside the rising popularity of edge AI in precision agriculture. The paper by Ahamed et al. [4] examines the usage of CNNs in conjunction with edge computing for disease detection in plants. It was shown in this paper that using CNN algorithms for disease identification allows achieving higher accuracy rates than manual diagnosis. At the same time, the difficulties related to the application of deep learning models to edge environments were analyzed.

Gonçalves et al. [5] focuses on creating edge-friendly models for detection of pest outbreaks in vineyards. The study demonstrates that lightweight neural networks may be used for identifying agricultural pests without placing significant demands on computational resources. Hasan et al. [6] developed a deep learning architecture to detect cross-domain diseases in plants, which incorporated the use of ensemble learning, knowledge distillation, and model quantization methods. This framework enhanced model performance in cross-domain data while achieving significant reductions in model sizes to facilitate its implementation on low-end edge devices.

Khan et al. [7] developed an edge-optimized plant disease detector. Their objective was to minimize the model's computational complexity without compromising accuracy of the predictions made by their models. The results of the study showed that deep learning models could be effectively implemented on mobile agricultural devices for disease detection. Gookyi et al. [8] examined the deployment of various deep learning models via the Edge Impulse platform to detect disease among tomato leaves. In their study, they highlighted the usefulness of edge computing capabilities in enhancing fast and accurate disease diagnoses while reducing the need for network access.

Another relevant study by Javaid et al. [9] involved an explainable edge AI approach using MobileNetV2 and gradient-based saliency maps for plant disease detection. By incorporating explainability techniques, this paper made it possible to visualize areas affected by disease in leaf images and increase users' trust. Rashid et al. [10] discussed the idea of employing an ensemble learning framework with explainable AI for leaf disease detection.

This study used an ensemble learning technique to improve prediction robustness and relied on explainability methods to analyze the reasoning behind the model's decisions. Thus, showed that a combination of an ensemble learning framework and explainable AI could significantly increase both the efficiency and interpretability of models. Despite many successful applications of deep learning for plant disease detection, a number of issues still remain unresolved. Among these problems, one can name maintaining high prediction accuracy in real-world conditions, simplifying models for edge implementation, dealing with imbalanced data sets, and increasing interpretability.

3. Methodology

The proposed workflow (Figure 1) adopted uses lightweight neural network structures along with transfer learning to carry out accurate classification of plant leaf diseases using minimal computing resources required for deployment at edge. The overall methodology consists of Dataset collection, Image preprocessing, Splitting of the datasets, Model training through transfer learning, Disease classification, Performance evaluation and Model Deployment.

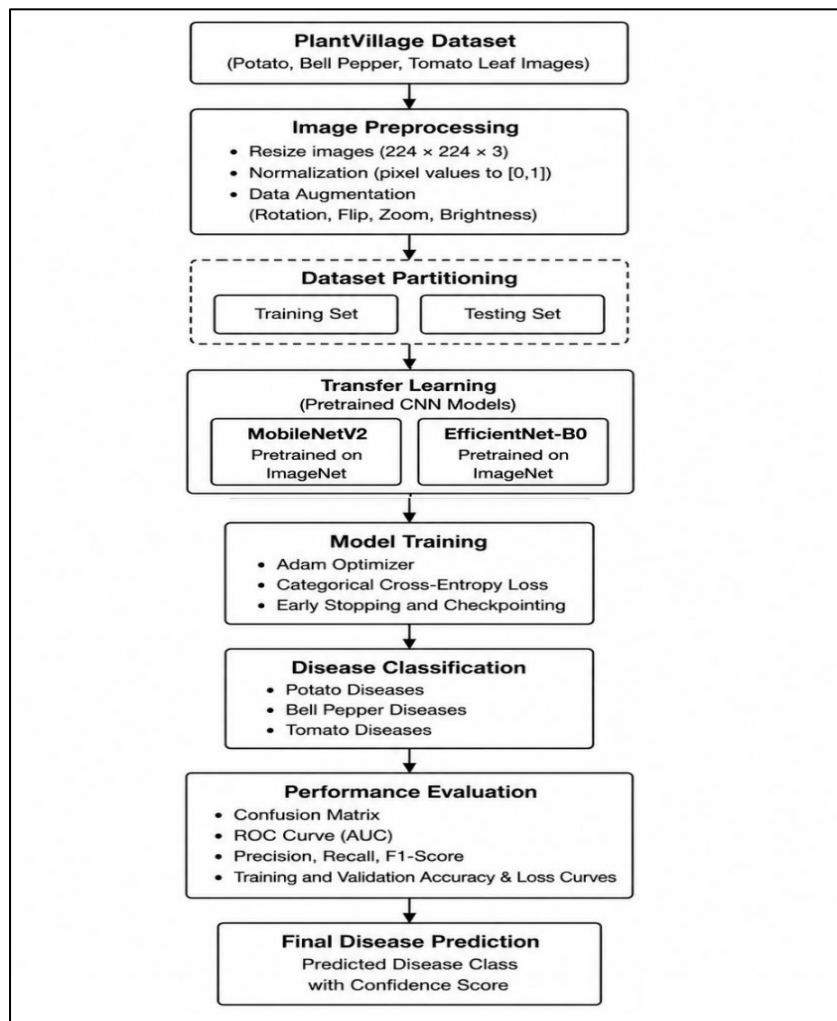


Figure 1. Transfer Learning-Based Framework for Multi-Class Plant Disease Detection

3.1 Dataset Acquisition and Preparation

The experiments have been performed using the PlantVillage dataset [11], which is an openly available dataset and often referred to as a benchmark for studying plant disease classification. This dataset consists of about 54,300 RGB images of healthy and sick plant

leaves captured in well-defined laboratory settings. The dataset involves 38 different categories of crop diseases, including 14 different crops and several types of diseases, such as fungal infection, bacterial infection, virus infection, and mite-related infections.

In this paper, datasets pertaining to three important crops, namely, potatoes, bell peppers, and tomatoes, have been utilized. The potato dataset includes three classes: Healthy, Early Blight, and Late Blight. On the other hand, the bell pepper dataset comprises two categories, which include Healthy and Bacterial Spot categories. The tomato dataset incorporates ten categories of diseases (see Table 4) and Healthy Leaves.

PlantVillage dataset was selected based on the following attributes, namely, its huge amount of labeled images, rich category types, and its use as a standard benchmark dataset for assessing plant disease classification models based on deep learning algorithms. The use of disease categories labeled by experts will facilitate supervised learning and performance comparison of light-weight CNN models.

3.2 Image Preprocessing and Data Augmentation

A process of image pre-processing was carried out for the purpose of data normalization and efficient feature extraction. The images used in the training set were resized to dimensions of 224×224 pixels, which represents the standard input size that should be used for training models based on MobileNetV2 and EfficientNet-B0 architecture. Moreover, pixel values were normalized to [0,1] range to ensure stable model training. In order to prevent overfitting and ensure the generalization capabilities of the created models, a data augmentation step was carried out on the training set. This involved performing random rotations and random flips along the horizontal and vertical directions, as well as changing image brightness.

3.3 Transfer Learning-Based Feature Extraction

Transfer Learning was implemented in the project due to its ability to simplify the training process through the use of pretrained models capable of extracting features from the data. MobileNetV2 and EfficientNet-B0 pretrained models on ImageNet were used as backbones for feature extraction. The classification layers from the two models were first stripped off before introducing new task-oriented fully-connected layers followed by the Softmax activation layer. The pretrained convolutional layers allow hierarchical feature extraction starting from low-level features like textures and edges to disease-specific higher-

level features. Afterward, fine-tuning of the pretrained layers is implemented in order to allow the models to specialize in detecting disease symptoms on crops efficiently.

3.4 Model Training and Optimization

The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio. The MobileNetV2 and EfficientNet-B0 models were trained using the Adam optimizer with a learning rate of 1×10^{-4} and the Categorical Cross-Entropy loss function. Mini-batch training was employed to improve computational efficiency. To enhance model generalization and prevent overfitting, early stopping and model checkpointing techniques were applied during training. The network parameters were iteratively optimized based on the minimization of the loss function.

3.5 Disease Classification

Once the optimization was completed, the developed classifiers were used to classify plant leaf diseases based on image recognition. Classification of leaf diseases was done independently for three different datasets – potato, bell pepper, and tomato. In the inference step, the deep features extracted from each image were fed to the classifier network and then the Softmax function calculated the output probability values for each category. Based on the probability value, the disease category was classified.

3.6 Edge Deployment

To facilitate deployment on resource-constrained platforms, the transfer learning-based MobileNetV2 and EfficientNet-B0 models, which were pretrained on ImageNet and subsequently fine-tuned on the PlantVillage dataset, were converted into TensorFlow Lite (.tflite) format using TensorFlow Lite. This conversion enables efficient inference with reduced memory consumption and computational overhead, making the models suitable for edge-based smart agriculture applications. Using the converted model, a streamlit application was implemented to perform disease detection via inference. The developed streamlit application includes a graphical user interface, which allows users to upload a leaf picture. After uploading an image, the system automatically scales down and normalizes the input image data. Next, inference is conducted using the deployed lightweight model. Finally, the disease class together with the probability score is returned to the users by the streamlit app. By utilizing the local inference of the lightweight model, the proposed solution enables almost instantaneous results.

4. Mathematical Formulation

Let the dataset be defined as:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

where x_i represents the i^{th} input leaf image and y_i denotes the corresponding disease label. N is the total number of samples in the dataset.

The CNN learns a mapping function:

$$f(x; \theta) \rightarrow y \quad (2)$$

where θ represents the trainable parameters (weights and biases) of the network.

The Softmax function converts logits z_k into class probabilities:

$$P(y = k | x) = \frac{e^{z_k}}{\sum_{j=1}^C e^{z_j}} \quad (3)$$

where C is the total number of classes.

The Categorical Cross-Entropy Loss function is expressed as:

$$L = -\sum_{k=1}^C y_k \log(P_k) \quad (4)$$

where y_k denotes the ground-truth label (one-hot encoded) for class k and P_k is the predicted probability.

The model parameters are updated using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t + \epsilon}} \quad (5)$$

Where:

- α denotes learning rate,
- m_t represents the first moment estimate,
- v_t represents the second moment estimate,
- ϵ is a small constant to prevent division by zero.

5. Experimental Results and Performance Analysis

The effectiveness of the edge-compatible deep learning model was analyzed using PlantVillage dataset to assess the accuracy of classification between MobileNetV2 and EfficientNet-B0 for plant leaf diseases. The experiment was done for three crops including potato, bell pepper, and tomatoes. Classification performance evaluation of two neural networks models included accuracy, precision, recall, F1-score, confusion matrix, ROC-AUC and learning curves.

Table 1. Performance Comparison of Lightweight CNN Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
MobileNet V2	93.4	92.8	93.1	92.9	0.96
EfficientNet-B0	95.7	95.2	95.4	95.3	0.98

Table 1 shows the comparison of the overall performances of MobileNetV2 and EfficientNet-B0. EfficientNet-B0 produced the best classification performance, with 95.7% accuracy and AUC of 0.98, compared to MobileNetV2 with 93.4% accuracy and AUC of 0.96. Consistent enhancement on the performance in terms of precision, recall, and F1-score suggests that EfficientNet-B0 is better at feature extraction than MobileNetV2, making it more effective for edge-based plant disease detection.

Table 2. Class-wise Performance of EfficientNet-B0 for Potato

Class	Precision	Recall	F1-Score	Support
Healthy	0.96	0.97	0.96	152
Early Blight	0.95	0.94	0.95	1000
Late Blight	0.95	0.96	0.95	1000

The classification scores of the potato diseases showed (Table 2) equal performance in all three categories. The F1-scores varied between 0.95 and 0.96, implying an equal level of prediction accuracy. The category Healthy had the highest value for recall, which was equal to 0.97. At the same time, both Early Blight and Late Blight maintained F1-scores equal to 0.95.

Table 3. Class-wise Performance of EfficientNet-B0 for Pepper

Class	Precision	Recall	F1-Score	Support
Healthy	0.93	0.97	0.96	1478
Bacterial Spot	0.95	0.94	0.95	997

As per Table 3, the F1-score values obtained from EfficientNet-B0 for bell pepper disease classification were 0.96 for the Healthy leaves category and 0.95 for the Bacterial Spot category. Recall values were higher than 0.94 for both categories, showing that the model is capable of recognizing diseases with no class bias.

Table 4. Class-wise Performance of EfficientNet-B0 for Tomato

Class	Precision	Recall	F1-Score	Support
Healthy	0.96	0.97	0.96	1591
Target Spot	0.95	0.94	0.95	1404
Mosaic Virus	0.94	0.96	0.95	373
Yellow Leaf Curl Virus	0.95	0.96	0.95	3209
Bacterial Spot	0.89	0.91	0.89	2127
Early Blight	0.93	0.96	0.95	1000
Late Blight	0.91	0.89	0.90	1909
Leaf Mold	0.95	0.98	0.97	952
Septoria Leaf Spot	0.88	0.91	0.90	1771
Two Spotted Spider Mite	0.95	0.96	0.92	1676

Classification of the tomato is the hardest among all datasets owing to its ten different categories of diseases. As shown in Table 4, most of the categories were able to achieve F1-scores that exceed 0.90, while the highest F1-score was attained by Leaf Mold at 0.97. Yellow Leaf Curl Virus, having the most sample size of 3209, had an F1-score of 0.95. Bacterial Spot and Septoria Leaf Spot had relatively lower F1-scores at 0.89 and 0.90 respectively because of their similar symptoms.

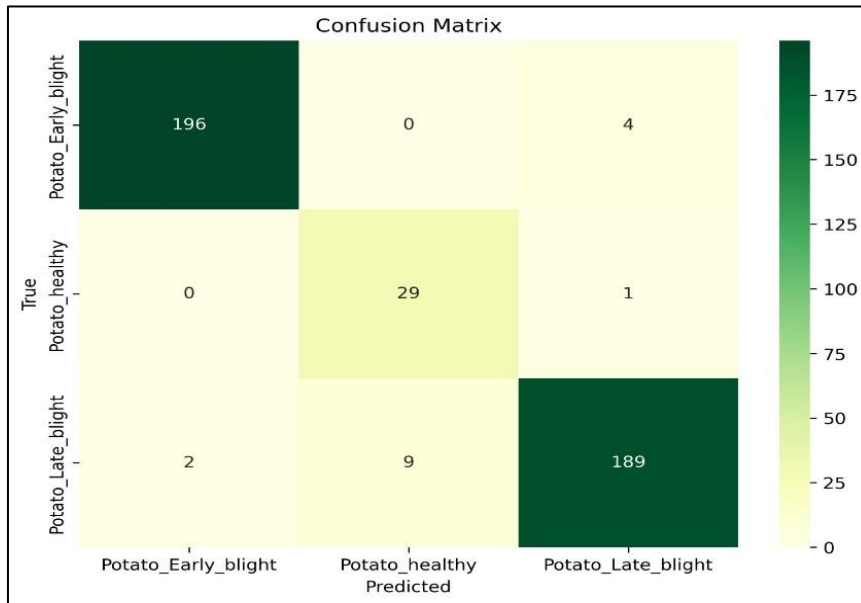


Figure 2. Confusion Matrix for EfficientNet-B0 for Potato

The confusion matrix related to the classification of potato diseases is shown in Figure 2. It can be seen that there were 414 correct classifications in total of 430 test data, which represents around 96.3% accuracy. As most of the predictions are lying on the diagonal, we can say that the predictions and the ground truth labels have high agreement.

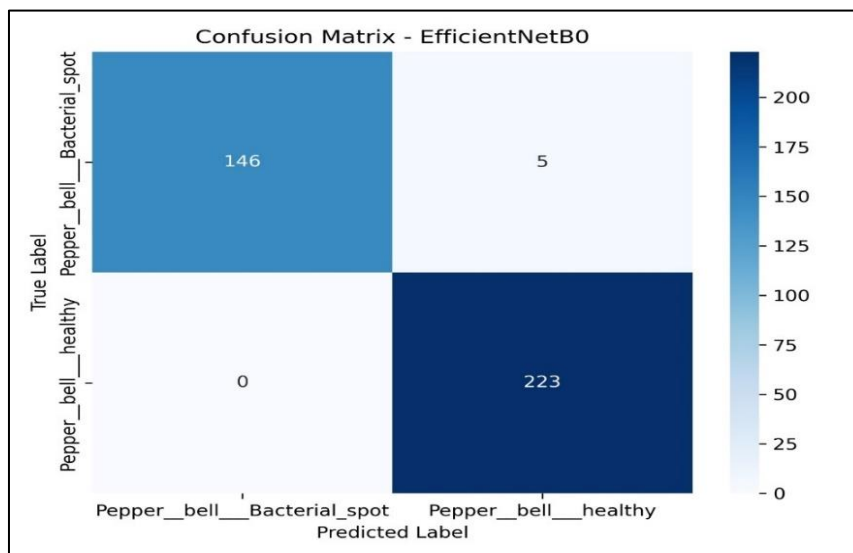


Figure 3. Confusion Matrix for EfficientNet-B0 for Bell Pepper

Confusion Matrix of Bell Pepper (Figure 3) shows impressive accuracy in classifying objects, with 369 out of 374 images classified successfully, thus having 98.7% precision in the process. Misclassifications are confined only to a few images of the Bacterial Spot class, while healthy leaves were classified without errors almost always.

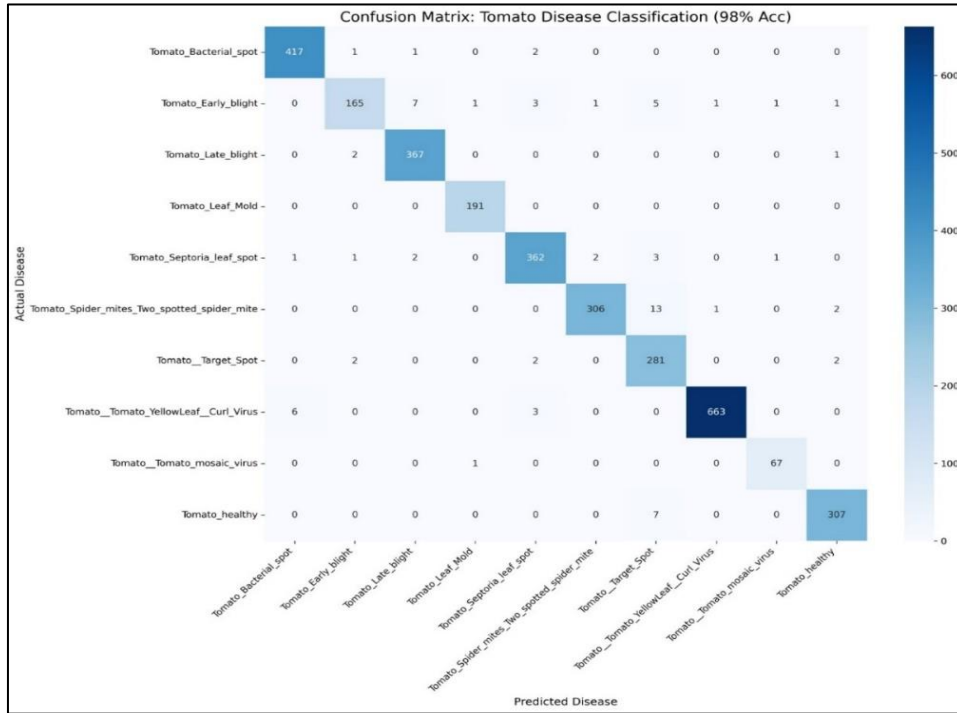


Figure 4. Confusion Matrix for EfficientNet-B0 for Tomato

Confusion matrix for tomato disease classification is shown in Figure 4. High dominance on the diagonal suggests that there has been successful classification of most disease types regardless of the more complicated nature of the dataset. Some confusions have occurred between diseases that share similar appearance, especially when it comes to blight and leaf spot diseases.

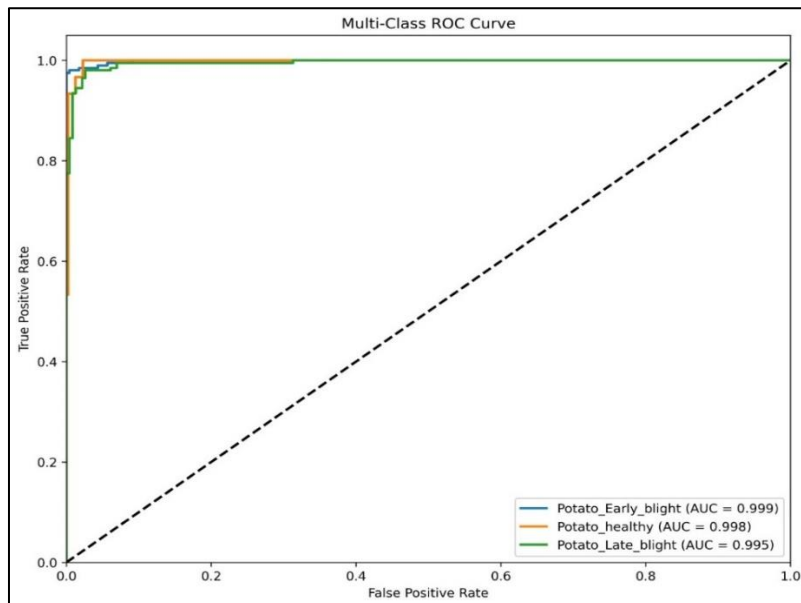


Figure 5. ROC Curve for EfficientNet-B0 for Potato

The ROC plots of the potato diseases (Figure 5) exhibit an outstanding ability to discriminate between classes. All the classes attained an AUC greater than 0.995, with Early Blight attaining an AUC of 0.999. The curves lie near the top left corner, suggesting high sensitivity and specificity.

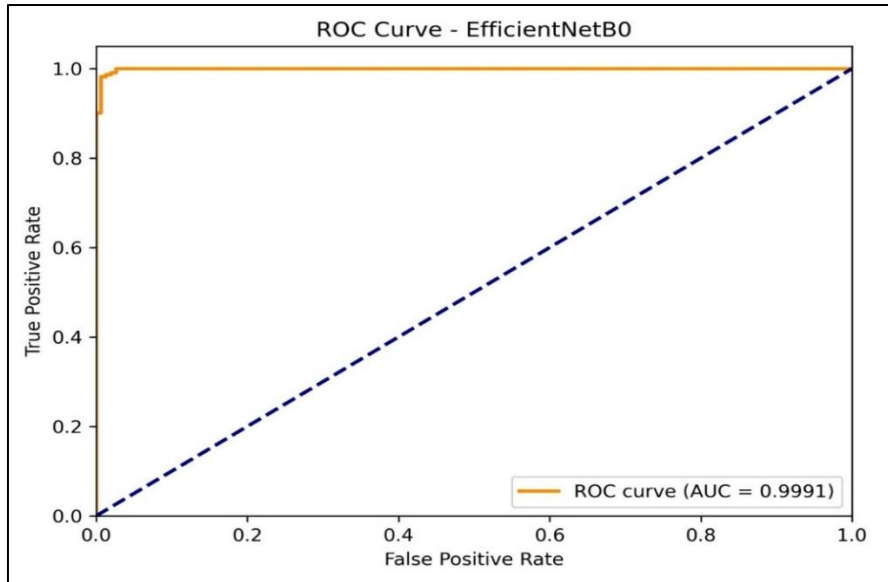


Figure 6. ROC Curve for EfficientNet-B0 for Bell Pepper

The ROC analysis for bell pepper disease detection is illustrated in Figure 6. From the figure, the high area under the ROC curve (AUC = 0.9991) signifies a perfect separability between the two classes. The sharp increase of the ROC curve shows excellent detection ability with minimal false positives.

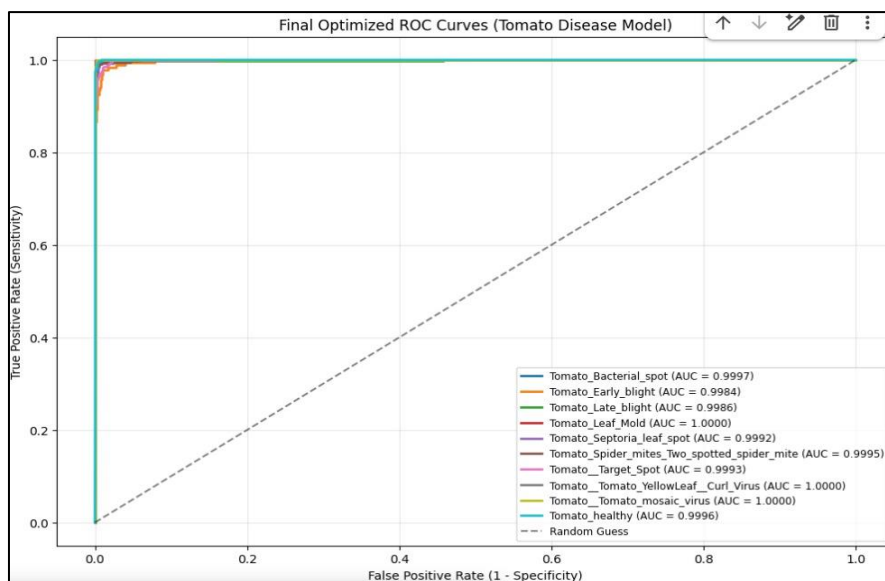


Figure 7. ROC Curve for EfficientNet-B0 for Tomato

From the ROC analysis results (in Figure 7), the AUC values for the classification of tomato diseases range between 0.9984 and 1.0000. It is important to note that certain classes such as Leaf Mold, Yellow Leaf Curl Virus, and Mosaic Virus were able to attain AUC values of 1.0000.

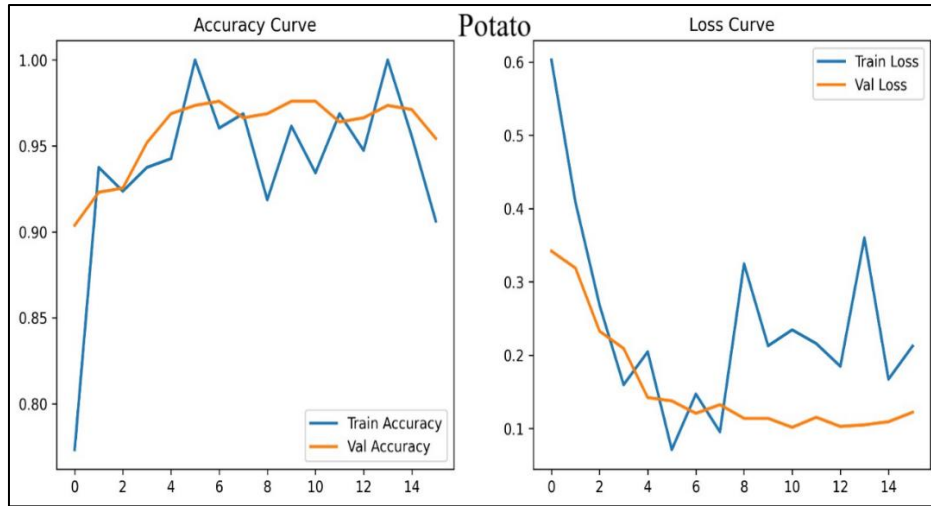


Figure 8. Training Accuracy and Loss Curves for Potato

Figure 8 depicts the training performance of EfficientNet-B0 for potato images trained for 16 epochs. Training accuracy started at about 77% and ended up at nearly 100% during epochs 5 and 13. Validation accuracy was steady at first, rising from 90% to 98% before becoming stable. While training loss went down from 0.61 to below 0.20, validation loss reduced from 0.34 to roughly 0.11. Despite some slight changes seen along the training graph due to the small data size, validation accuracy was stable and high throughout. Validation accuracy being about 96-98% means that there is model convergence without much overfitting.

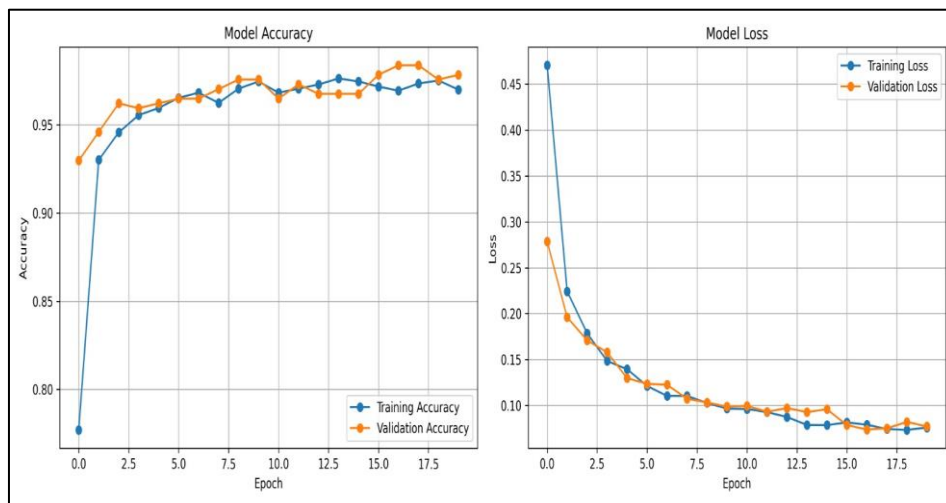


Figure 9. Training Accuracy and Loss Curves for Bell Pepper

Learning curves of the bell pepper dataset are shown in Figure 9. Training accuracy jumped rapidly from 78% to almost 98%, while validation accuracy fluctuated from 96% to 98%. Training loss dropped remarkably from 0.46 to 0.08, whereas the validation loss went down from 0.28 to 0.08. Similarity between training and validation learning curves suggests high generalization performance and robust learning behavior. Lack of significant variation proves that the learning algorithm is capable of recognizing the disease characteristics without overfitting.

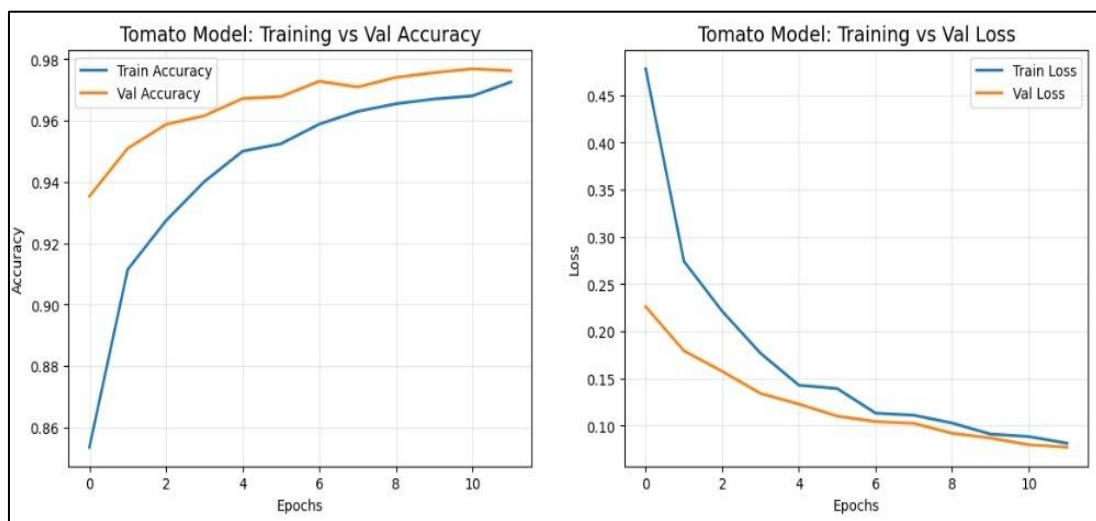


Figure 10. Training Accuracy and Loss Curves for Tomato

The behavior of convergence of EfficientNet-B0 model in terms of tomato diseases is shown in Figure 10. Accuracy was seen to have progressed from around 85% at the beginning to around 97.3% during the last epoch. The increase in validation accuracy has been observed from around 93.5% to around 97.8%. Similarly, the training loss was seen to be decreasing from 0.48 to 0.08. The validation loss was also seen to be decreased from 0.24 to around 0.08. It is clear that there is excellent generalization capacity for EfficientNet-B0 despite increased complexity due to ten classes.

6. Conclusion

This study presented a transfer learning-based framework for multi-class plant disease detection using MobileNetV2 and EfficientNet-B0 models. The proposed framework was based on image preprocessing, transfer learning, use of lightweight deep CNN architectures, as well as deployment of the model through TensorFlow Lite to ensure accurate disease detection while keeping computational expenses low. The proposed models were tested and trained through the

use of PlantVillage datasets featuring images of various diseased potatoes, bell peppers, and tomatoes. From the experimental analysis performed, it is possible to state that both models introduced were efficient tools for detecting diseases in plants. In particular, among all models analyzed, EfficientNet-B0 had the highest accuracy of 95.7. Moreover, from analyzing the confusion matrix and ROC curve of the chosen model, it can be stated that the introduced architecture can efficiently recognize diseases in plants. In summary, the suggested methodology offers a feasible and effective technique for disease detection in plants via smart agriculture. Due to its effectiveness in classifying the images and lightweight nature, the framework is capable of providing timely identification of the disease and helping farmers to make informed decisions concerning their farms. For future studies, the researchers intend to conduct an evaluation of the framework on images obtained from fields and under various environmental conditions.

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