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Pepper Leaf Disease Detection Using Deep Learning Techniques

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Abstract

Early diagnosis of pests and plant diseases is crucial for preventing significant crop losses. With the increasing global population, this issue has become critically important, making effective solutions essential. This study proposes a leaf disease detection system using deep learning techniques, specifically MobileNetV2 integrated with multiple optimization strategies—Adam and learning rate scheduling. Evaluated on the Pepper Plant-Village dataset, the MobileNetV2 model works as a feature extractor, with Soft-Max used for final classification. The model was further validated on a multi-class Apple Plant-Village dataset. Results demonstrate high accuracy: 97.03% for pepper and 94.63% for apple classification. Comparative analysis with Convolutional Neural Network (CNN) architectures shows superior efficiency and faster convergence for our model, outperforming Inception v3 (96.81%) and Visual Geometry Group (VGG-19) (94.93%) on the pepper dataset. When evaluated using additional metrics (F1-score, precision, recall), our proposed model maintains the best performance, achieving F1-scores of 0.97 (pepper) and 0.94 (apple).

1. Introduction

The global population increases daily, driving greater demand for food and nutrition. Each year, pests and diseases destroy vast amounts of crops. Extensive studies have examined diseases affecting various plants such as fig, apple, and grape crops [1-3]. Pepper—an essential ingredient in cuisines worldwide—is particularly vulnerable to bacterial spot disease, which infects pepper plant leaves.

This research suggests a classification and detection model for identifying infected and healthy pepper plants using the MobileNetV2. Deep learning is a branch of artificial intelligence (AI), where it has the ability to process the large data [4-6]. Deep learning has many methods including CNN, Recurrent Neural Network (RNN, Auto-encoder, and ViT [7-11].

The Adam optimizer minimizes model loss by adaptively adjusting learning rates for individual parameters, enhancing convergence toward the global optimum [12]. Learning rate scheduling is an adaptive technique that adjusts the learning rate value during training. This adjustment occurs continuously from the start to the end of the process, working to increase efficiency and accelerate convergence [13].

This study proposes a deep learning model for plant leaf disease classification using MobileNetV2 enhanced with multiple optimization techniques (Adam and Learning schedule). Trained on the Plant-Village dataset to classify pepper leaf diseases, the model employs advanced optimization strategies. For comparative analysis, pre-trained CNN architectures (Inception v3 and VGG-19) were also implemented.

The main contributions of this study are:

- The proposed model was examined using two datasets: a binary classification dataset and a multi-class classification dataset.
- The learning rate schedule is synchronized with the Adam optimizer.
- Testing the model with multiple CNN architectures.

2. Related Works

This section presents the most important studies related to plant leaf disease detection, the methods used to accomplish this task, and the performance of each method.

B. V. Nikith et al. proposed a system for classifying the pests in the leaves of plants. Their dataset comprised eight disease classes, each evaluated separately. The model achieved 96% accuracy for soybean leaf disease. When compared with traditional machine learning approaches—KNN and SVM—which attained 64% and 76% accuracy respectively, the CNN architecture demonstrated superior performance [14].

A. Ghodekar, U. Kingdom, and A. Kumar presented a deep learning model for tomato leaf disease classification. Using a transfer learning approach, they employed NasNet-Mobile – a lightweight architecture. Their preprocessing pipeline included image resizing, augmentation, and brightness adjustment to enhance the dataset. The model was trained on the Plant-Village dataset, achieving accuracies of 93.20% on color images and 83.60% on gray scale images. While computationally efficient, this approach demonstrates a trade-off between training speed and accuracy [15].

Song LIU et al. proposed a model based on MobileNet-V2 to detect the apple leaf disease. In addition to the augmentation, the authors employed GAN network for overcome the scarcity of the data. Furthermore, an attention mechanism was incorporated to refine feature extraction. For comparative analysis, multiple pertained CNN architectures—including Shuffle-Net, Alex-Net, and ResNet-50—were evaluated. The proposed model achieved 96.23% accuracy while maintaining reduced space and time complexity [16].

M. M Khalid and O. Karan proposed a model for classifying the plant leaf diseases. They used multi-class dataset and separated it into two sets; training and testing. The authors used the conventional CNN and Mobile-Net network for achieving this operation, with Explainable AI (XAI) techniques incorporated to enhance model interpretability. The CNN architecture achieved 89% accuracy, while Mobile-Net attained 96%. Evaluation metrics included precision, recall, and F1-score [17].

Wasi Ullah et al. presented an App-ViT model that combines CNN and ViT characteristics for classifying apple leaf diseases. The authors used the Plant Pathology 2021 dataset, which is a multi-class dataset consisting of five classes. The proposed model achieved an accuracy of 96.4%. A limitation of their model is its sensitivity to data scarcity in real-world conditions [18].

M. Chilakalapudi and S. Jayachandran proposed a plant leaf disease detection system integrating transfer learning with the Chronological Flamingo Search Algorithm. The framework employs U-Net++ for leaf segmentation and the Moving Gorilla Remora Algorithm for model optimization. To enhance feature extraction, the authors implemented dimensionality reduction through both color-space transformation and spatial augmentation techniques. The system achieved 95.7% classification accuracy [19].

3. Methodology

This section presents the workflow of the proposed model. The implementation is divided into two sections: the dataset and the proposed model. The former explains and describes the dataset used for training and testing, while the latter provides a detailed explanation of the model architecture.

3.1 Dataset

The Plant-Village dataset [20] has been used to examine the proposed model and test its validity and reliability, specifically the pepper subset. The pepper subset comprises two classes: healthy (1,478 images) and bacterial spot (997 images). Figure 1 (a and b) shows representative images from this dataset.

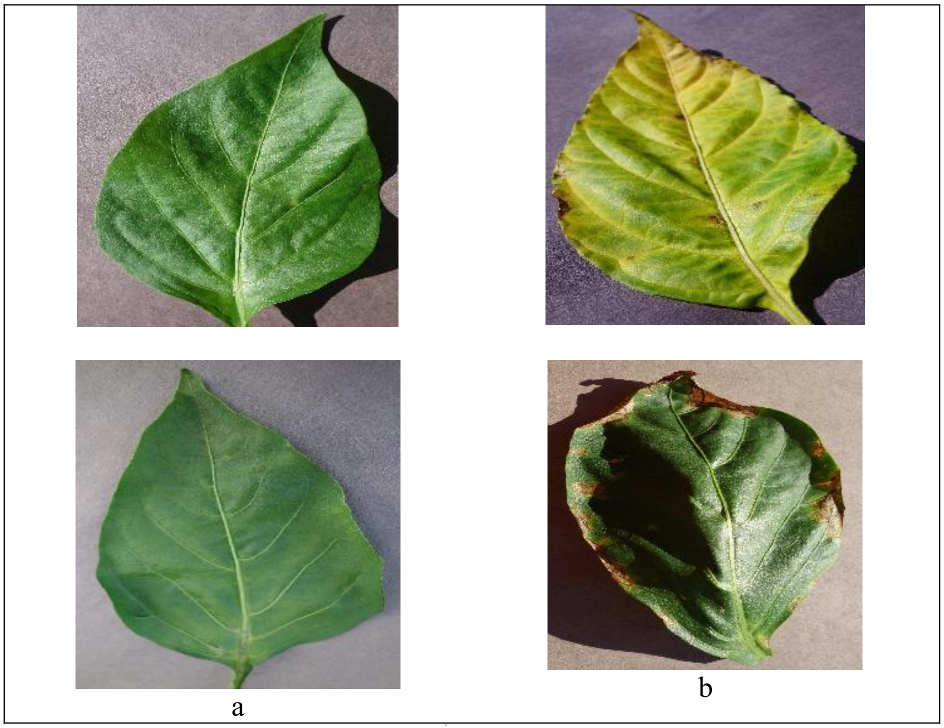

Figure (1): Samples of the Pepper Plant-Village dataset: a) healty b) Bacterial spot.

3.2 The Proposed Model Design

This subsection presents the framework and approach employed for detecting diseases in pepper leaves and provides a detailed explanation of the model architecture.

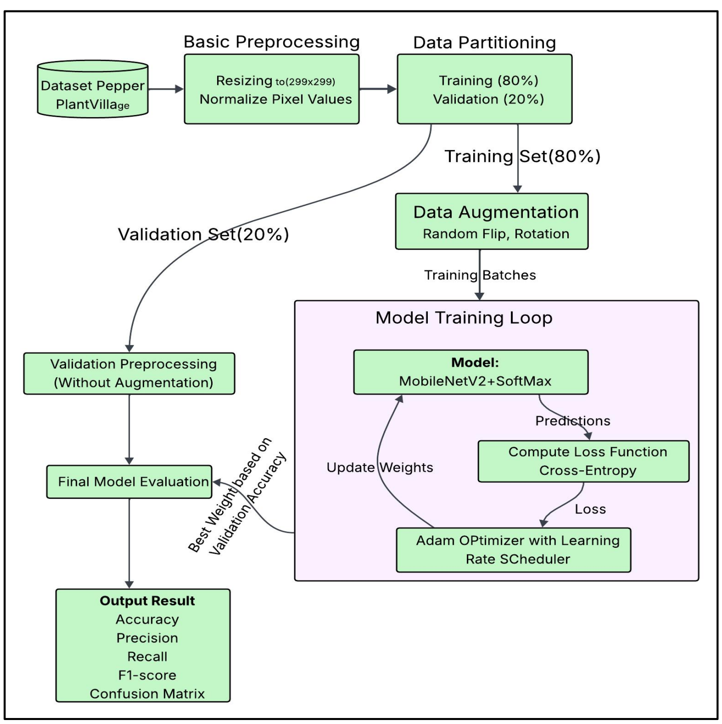

Figure (2): The framework diagram of the proposed model.

The first step is pre-processing, where images' pixels are resized to 299×299; this is the size that MobileNetV2 network accept. Data augmentation is then applied by generating modified versions of each image through random horizontal flips and 10-degree rotations. Finally, pixel values are normalized using Image-Net statistics. In addition, after resizing the images to 229×229, the dataset was further augmented by flipping and rotation each image 10 times.

The second step involves partitioning the data, in which the data is divided into two sets; training and validation, with the rate of 80% and 20% for training and validation, respectively. Both subsets are fed into the MobileNetV2 module, which is work as feature extractor.

The Adam optimizer adjusts model weights. An adaptive learning rate scheduler dynamically adjusts the rate based on validation performance, reducing it by 50% when validation accuracy plateaus for 3 epochs. After training completes 20 epochs, the best-performing weights (based on validation accuracy) are selected. These weights are used in the classification layer (Soft-Max layer), which outputs class probabilities.

Finally, the validity of the model is tested using comprehensive metrics including accuracy, precision, recall, and F1-score, providing a robust assessment of performance.

4. Experimental results and Discussion

This section presents the experimental results of the proposed model and analyzes them to demonstrate both the model's correct implementation and its achievement of the stated objectives. The proposed model employed the Plant-Village dataset, which contains over 50,000 images of multiple plant species—including pepper, tomato, apple, and cherry—where each species includes both healthy images and infected images. The infected images may represent single or multiple disease classes. The apple Plant-Village dataset consists of four classes that include: healthy, apple_scape, cedar_apple_rust, and black_rot.

The model achieves an accuracy of 97.03%, with an F1-score of 0.97, precision of 0.97, and recall of 0.97. Figure 3 shows the validation accuracy, while Figure 4 depicts the confusion matrix.

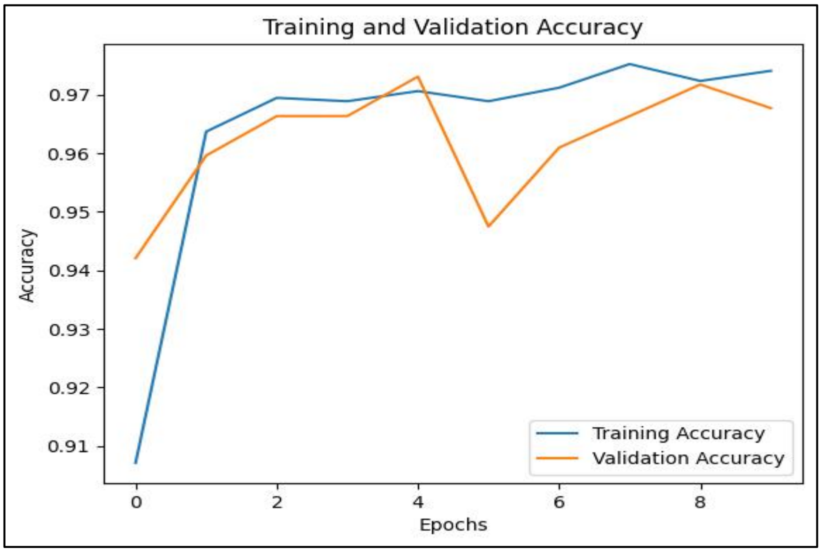

Figure (3): The validation accuracy of the proposed model against Pepper Plant-Village.

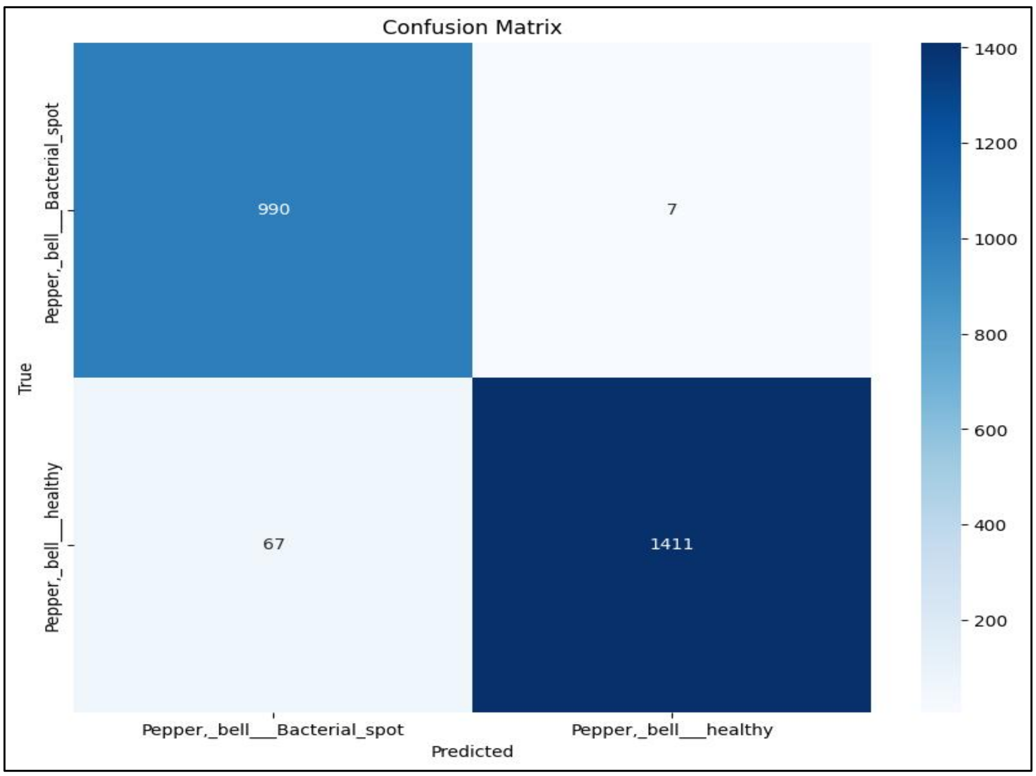

Figure (4): The confusion matrix of the proposed model against Pepper Plant-Village.

The proposed model achieved high performance by integrating the MobileNetV2 architecture with advanced optimization techniques: Adam for weight regularization and adaptive learning rate scheduling to minimize loss. When evaluated on the Apple Plant-Village dataset, which is a multi-class dataset, the model attained 94.63% accuracy. With f1-score of 0.94, precision of 0.95, and recall of 0.95. Figures 5 and 6 show the validation accuracy and confusion matrix respectively for this dataset.

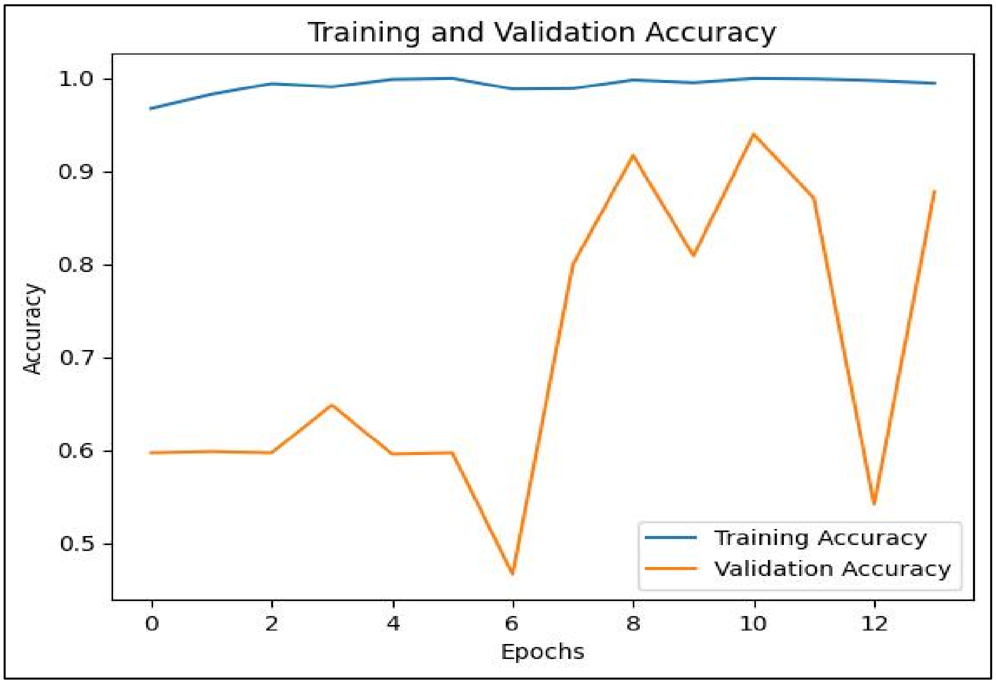

Figure (5): The validation accuracy of the proposed model against Apple Plant-Village.

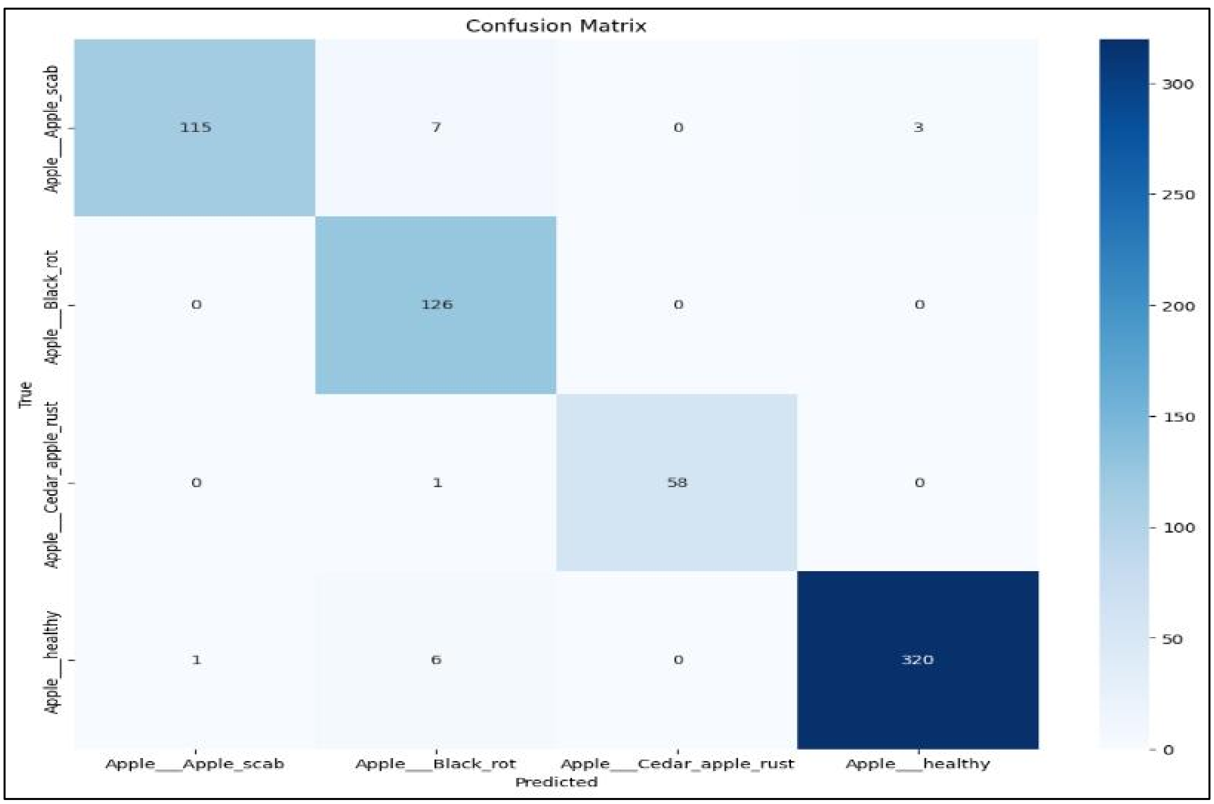

Figure (6): The confusion matrix of the proposed model against Apple Plant-Village.

The proposed MobileNetV2 model outperforms CNN architectures, achieving higher accuracy on the same dataset. Table 1 compares the accuracy of our model with Inception v3 and VGG19 on the Pepper Plant-Village dataset.

Table (1): The accuracy of Inception v3, VGG 19, and our proposed model on Pepper Plant-Village.

The model	Accuracy value
Inceptionv3	**96.81%**
VGG19	**94.93%**
The proposed model	**97.03%**

5. Conclusions

The global population is increasing daily, driving greater demand for food and nutrition. However, pests and diseases destroy huge amounts of crops every year. This study presents a model for plant leaf disease classification using MobileNetV2 architecture. The model employs the latest optimizers, including Adam and a learning rate schedule, to enhance classification and reduce loss. Experiments utilize the Pepper Plant-Village dataset; the proposed model is also tested against the Apple Plant-Village dataset. The model achieves accuracies of 97.03% and 94.63% on the pepper and apple datasets, respectively. Performance is further evaluated using F1-score, precision, and recall. For pepper, these values are 0.97 for each one of F1-score, precision, and recall. For apple, the values are 0.94 for F1-score, while both precision and recall are achieved 0.95. A comparison with Inception v3 and VGG 19 demonstrates that the proposed model achieves higher accuracy.

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