



Transforming Agriculture: Plant Disease Detection with Transfer Learning and Deep Neural Network

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Abstract. Plant leaf disease detection plays a critical role in ensuring healthy crop yields and preventing severe damage caused by plant diseases. Traditional diagnostic methods, however, are often time-consuming and complex, requiring laboratory practices. In contrast, Artificial Intelligence (AI), particularly Deep Learning (DL) and Machine Learning (ML) techniques, have emerged as a boon to the agricultural industry. Recently, ML and DL approaches have been increasingly applied for diagnosing plant diseases. For this study, the Plant Village dataset was obtained from Kaggle and augmented to enhance model training. The proposed method improves detection accuracy without requiring extensive labeled data by leveraging pre-trained deep learning models for feature extraction from plant leaf images. This methodology encompasses data collection, pre-processing, model selection, and evaluation. The performance of the model was assessed using accuracy, precision, recall, and F1 score metrics. The results demonstrated that transfer learning significantly enhanced the model's ability to classify both healthy and damaged leaves with high accuracy and a low probability of false positives. Additionally, the model's adaptability was tested by evaluating its generalization ability across different plant species and types of infections. This paper presents a Convolutional Neural Network (CNN) augmented with pre-trained models to identify and categorize plant leaf diseases. On the PlantVillage dataset, the proposed approach achieved a training accuracy of 99.81% and a validation accuracy of 99.68%.

Keywords: Plant Disease Detection, Transfer learning, Deep learning, Convolutional Neural Network (CNN), Agriculture Technology.

1 Introduction

The identification of plant leaf diseases is a fundamental area of scientific study in agriculture, as these tasks become vital in disease control and in reducing losses to crops. Plant leaf diseases are caused by various viral, pathogen, pest, or environmental conditions. If farmers neglect these diseases, they could lead to economic loss due to decreased productivity or crop death. To support plant health insurance properly, the symptoms of diseases need to be properly diagnosed without remedy delay. India's economy and growth are based primarily on agricultural production, underscoring the importance of agriculture in the nation's development initiatives. In order to increase the accuracy of disease detection across the system, the

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S. Bhalerao et al. (eds.), *Proceedings of the International Conference on Recent Advancement and Modernization in Sustainable Intelligent Technologies & Applications (RAMSITA-2025)*, Advances in Intelligent Systems Research 192,

https://doi.org/10.2991/978-94-6463-716-8_38

study uses a pre-trained architecture to evaluate the quality of several classes of plant leaf diseases [1].

The diagnosis of plant leaf diseases remains a significant challenge in the agriculture sector. Historically, experts were relied upon to identify these diseases, but remote farmers often struggle to access specialized assistance. Furthermore, climate change and ongoing environmental shifts are major contributors to the increased prevalence of plant diseases. Without timely diagnosis and intervention, crop production can suffer severe declines. Early detection is crucial to prevent widespread damage and ensure that infections are managed before they cause substantial yield losses.

To get around this, a lot of deep learning (DL), image processing, and machine learning (ML) approaches have been researched that allow images of plant leaves to be used for the diagnosis of disease in plants. The recent advancements in deep learning technology, which has gained attention for its ability to automatically extract features from images and classify plant diseases. This technology reduces the reliance on manual feature extraction and classifier design, streamlining the identification process [2]. To get diverse and good quality datasets, the first stage is collecting and preprocessing plant leaf images. Photographs of healthy and sick leaves alongside the leaves of several species will be gathered. The second goal will be to find the best model architecture, after which pre-Trained deep learning models will then be selected and further optimized for the task of classifying plant leaf diseases. The third step is to train and fine-tune the chosen model or models in order to obtain a high F1 score, recall, accuracy, and precision in disease categorization. The final step is to put the whole system to substantive tests to analyze its efficacy in differentiating between healthy and sick leaves and to evaluate its performance for different plant species and diseases.

The main aim of our initiative can thus be summed up as follows;

The main goal of the proposed paper is to apply Deep Learning and Transfer Learning approaches for the detection of plant leaf diseases and represent the results to the user in the graphical user interface based on the Mobile application for the system. This is a conventional paper structure depicted in following manner: Part 2 deals with related work. Part 3 Methodology. Part 4 states the Experiment and Results. Part 5 discusses & the concluding portion finishes the paper.

2 Related Work

Various research works have been done in the image classification and identification. CNN algorithm was proposed by S. Pawar et al. [3] that identifies diseases from leaf pictures and provides pesticide recommendations based on findings associated with the disease. This study aims to identify the probable class of appearance on a plant leaf. An uncontrolled method called Neural Network is employed for this kind of estimation. Convolution Neural Networks (CNNs) are used in this research to identify plant illnesses. CNN has fifteen layers in the suggested strategy. In addition to providing the identity of the pesticide provider for each location, the proposed system will additionally give further details regarding the plant disease affecting the leaves in the affected area, including the illness's name, full accuracy, timing, and weather prediction details. Ten plant species are included in the dataset: rice, corn, apple,

sugarcane, cucumber, soyabean, tomato, potato, and pepper. The system employs Gaussian dimensions, restriction, and selection to pre-scan the picture and segregate the leaf area. The suggested system with filtering technique is useful to identify the type of leaf disease with up to 93% efficiency. The Convolution Neural Network offers exceptional accuracy in disease diagnosis when all the contributing components are included. The suggested system gives farmers access to weather prediction data, which can assist them in daily decision-making such as determining which fertilizer is best for a certain weather situation.

K. Shivaprasad et al. [4] developed a deep learning-based system to detect plant leaf disease. The goal of the research was to contrast three deep learning models (CNN, VGG16, and VGG19) for the purpose of detecting plant diseases. A straightforward forward-propagating neural network, the CNN architecture is frequently used for image categorization tasks. On the other hand, VGG16 and VGG19 are deep convolutional neural networks that have demonstrated remarkable performance across a range of computer vision applications. A dataset with 9,127 images of plants labeled with illness labels was utilized to train and assess the models employing recall, precision, F1 score, and accuracy as evaluation criteria. CNN emerged as the top performer overall in the classification challenge, achieving an F1 score of 0.95 and an accuracy of 0.97. It is clear from the results that all three deep learning models can do exceptionally well on the specified classification work.

The diagnosis of plant diseases is essential for maintaining healthy crop production and preventing major crop damage due to these diseases. On the other hand, Traditional methods might be difficult and time-consuming to diagnose. K. Harshavardhan et al.[5] developed a deep learning techniques such as ResNet 34 have been identified as a possible approach for automating the diagnosis of plant leaves. ResNet 34 is capable of accurately classifying plant leaf pictures based on trend and attribute information. Using a large dataset of annotated plant leaf pictures, a ResNet 34 model can be trained to accurately detect various leaf ailments. The reason for this is its ability to handle vanishing gradients effectively and create hierarchical visualizations of input data. ResNet-34 can be trained to consistently recognize and categorize several illnesses of plant leaves with minimal data by using large-scale datasets and transfer learning techniques. The ResNet-34 Model having an accuracy of 98.7.

Y. H. Bhosale et al. [6] identified several types of plant diseases, underlying climate variation, and habitat migration. The study presents the automated recognition and categorization of illnesses of plant leaves utilizing an imaging segmentation method. Furthermore, it summarizes how various illness classification techniques can be used to identify diseases of plants. This research study offers an overview of several plant illnesses and several deep machine learning categorizing methods used to identify abnormalities in a variety of plant leaves. CNN is well known for its capability to continuously retrieve attributes based on the initial photos. Neural network and machine learning techniques are widely used because of their ability to provide accurate depictions. As a result, a stacked sequencing of CNN maximizes the benefits of acquiring comprehensive knowledge for optimal simulation outcomes. In machine learning, features are a key component that affects the classifier in a major way. The study focuses on methods for classifying plant leaf diseases that rely on image processing. The morphological characteristics of the spot attributes are extracted

using the length and proportion of the principal axes, the center of gravity, the position, the corresponding diameter, the deviation, the solidity, the area, the hydrodynamic radius, the degree of difficulty, and the coefficient of Euler number. The model having an accuracy of 93%.

Identifying plant diseases is an important task in agriculture. Early diagnosis of plant diseases is crucial because it can prevent further damage to the plants. Early recognition and treatment of plant diseases that can have a substantial influence on crop well-being and yield is made possible by the early recognition of leaf-related illnesses. Some of the state-of-the-art techniques for identifying plant leaf diseases include visual examination, spectrum analysis, DNA-based, IOT-based, and computerized image analytics. Varun Katoch et al. [7] developed an IOT based plant leaf diseases detection system using SVM model having an accuracy of 94.65 %.

Bincy Chellapandi et al. [8] for plant leaf diseases, they proposed a model which uses CNN and get the accuracy of 87%. On the other hand, they uses pre trained model InceptionV3, InceptionResnetV2, ResNet50, VGG16, VGG19 ,MobileNet, MobileNetV2, DenseNet that are applied on the plant village dataset models achieved accuracy of 97.56%, 97.33%, 93.33%, 98.95%, and 98.52%,97.42%,94.36%,98.95% respectively. D. Yaswanth et al. [9] uses a pertained model ResNet-50 having an accuracy of 91%,on the other hand they uses a Deep convolutional neural network having an accuracy of 99.35 %.

3 Methodology

The various image deep learning and transfer learning techniques can be used to detect plant leaf disease. The methods make use of various aspects of study of plant leaf disease detection using transfer learning. This consists of some steps as shown in Figure 1, which and, it is important for any research. The research methods have been outlined below.

3.1 Datasets

We are using the Plant Village dataset from Kaggle. It contains both healthy and diseased plant leaves. All images in the project are colored since colored images are more accurate than gray scale images. A training and test dataset is randomly selected from the training dataset. These specific setups usually divide the data between 20 and 80 percent. Documentation for the training dataset needs to increase its number of effective results; i.e., when the size of training setups increases, the expected performances of the classifiers stand increased. 20% of the data set is used for system testing, while the remaining 80% is used to train a model.

3.2 Pre-processing & Resizing

Pre-processing helps mitigate unwanted noise in the data and increases the potential of the model to learn salient features. It would come with a regenerate package that aims to apply standard preprocessing transformations like normalization. Using a pre trained model and optimizing it for particular dataset is known as transfer learning.

3.3 Transfer Learning and Model Selection

There is a number of already trained deep learning models like, CNN, ResNet50, Efficient B3, and Generic Model with Average Pooling are considered. The model size, computational power, and specific characteristics of the plant leaf dataset determine the model architecture choice. The common approach is to apply a transfer learning technique to adjust the pre-trained network which was trained on the large dataset like the ImageNet.

3.4 Training of Model

After selecting the transfer learning method, the training process involves adapting the pre-trained model to the given dataset. Usually, the dataset is separated into test, validation, and training sets. During training, the model's performance is tracked on the validation set.

3.5 Evaluation

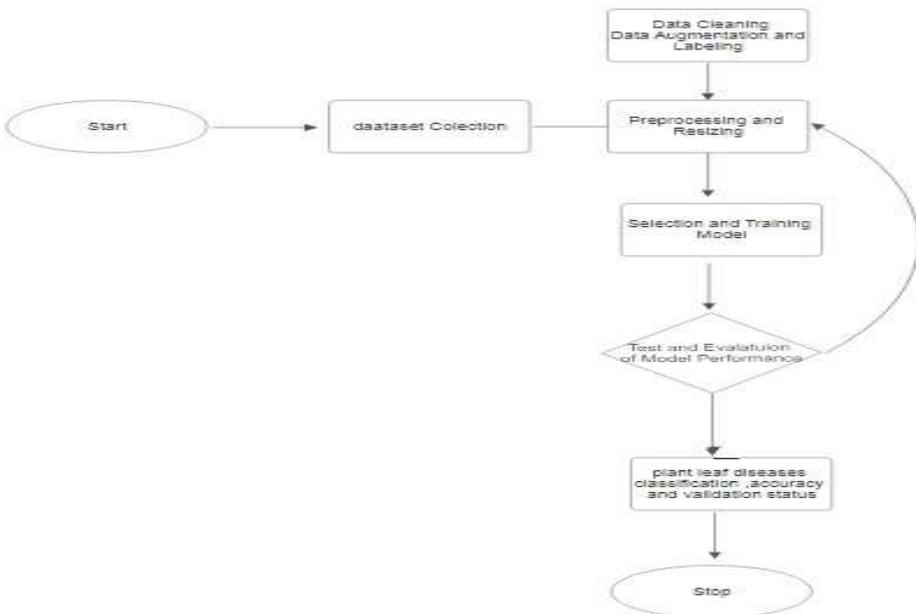


Fig. 1. The Proposed Model

Measures such as recall, accuracy, and precision can be used to assess the model's performance on the validation set. It is necessary to store the trained model in a deployable format, like a.pt or.h5 file. These measures give indication on how well the model can differentiate healthy and diseased leaves as well as minimize on false positives and false negatives.

4 Experiment and Result

4.1 CNN Model in Deep Learning

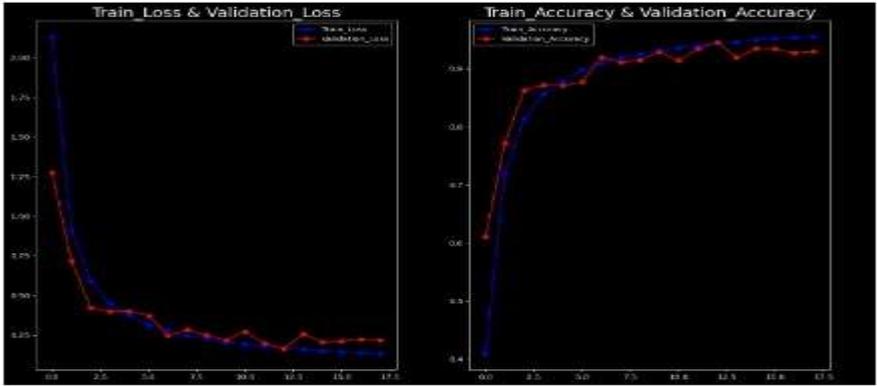


Fig.2 Performance Metric CNN

Classification Report is :

		precision	recall	f1-score	support
Apple___Apple_scab	0.91	0.84	0.85	0.83	63
Apple___Black_rot	0.98	0.69	0.81	0.72	62
Apple___Cedar_apple_rust	0.90	1.00	0.95	0.97	27
Apple___healthy	0.95	0.89	0.91	0.91	163
Blueberry___healthy	0.97	0.99	0.95	0.96	150
Cherry_(including_sour)___Powdery_mildew	0.94	0.97	0.95	0.95	105
Cherry_(including_sour)___healthy	0.90	0.95	0.94	0.92	85
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot	0.78	0.82	0.80	0.81	51
Corn_(maize)___Common_rust	1.00	1.00	1.00	1.00	120
Corn_(maize)___Northern_leaf_blight	0.89	0.85	0.87	0.86	92
Corn_(maize)___healthy	0.98	0.97	0.97	0.97	116
Grape___Black_rot	0.90	0.94	0.92	0.92	118
Grape___Esca_(Black_Measles)	0.99	0.94	0.96	0.95	139
Grape___leaf_blight_(Isariopsis_Leaf_Spot)	0.90	0.95	0.95	0.95	100
Grape___healthy	0.93	0.95	0.95	0.94	42
Orange___Huanglongbing_(Citrus_greening)	0.98	0.99	0.99	0.99	351
Peach___Bacterial_spot	0.94	0.95	0.95	0.95	230
Peach___healthy	1.00	0.87	0.88	0.88	38
Pepper_bell___Bacterial_spot	0.87	0.91	0.89	0.89	99
Pepper_bell___healthy	0.95	0.95	0.95	0.95	148
Potato___Early_blight	0.97	0.96	0.96	0.96	100
Potato___Late_blight	0.83	0.77	0.80	0.80	100
Potato___healthy	0.87	0.27	0.35	0.31	13
Raspberry___healthy	0.82	0.80	0.73	0.77	37
Soybean___healthy	0.98	0.98	0.98	0.98	309
Squash___Powdery_mildew	0.99	0.95	0.97	0.96	184
Strawberry___leaf_scorch	0.97	0.94	0.95	0.95	111
Strawberry___healthy	0.90	0.90	0.92	0.91	45
Tomato___Bacterial_spot	0.93	0.92	0.93	0.93	213
Tomato___Early_blight	0.85	0.69	0.76	0.76	100
Tomato___Late_blight	0.85	0.90	0.87	0.87	191
Tomato___Leaf_Mold	0.76	0.80	0.85	0.81	95
Tomato___Septoria_leaf_spot	0.89	0.89	0.89	0.89	175
Tomato___Spider_mites_Two-spotted_spider_mite	0.86	0.94	0.90	0.90	168
Tomato___Target_Spot	0.90	0.79	0.85	0.82	141
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.95	1.00	0.98	0.98	336
Tomato___Tomato_mosaic_virus	1.00	0.81	0.90	0.87	37
Tomato___healthy	1.00	0.96	0.95	0.95	159
accuracy			0.93	0.93	5431
macro avg	0.91	0.89	0.90	0.90	5431
weighted avg	0.94	0.93	0.93	0.93	5431

Fig. 3 The CNN Model

Our self-built model constructed and trained using a convolution neural network for plant leaf disease detection. During the training phase, this model was refined using a

batch size of 32 and went through 15 iterative learning epochs. The experimental results (shown in Fig. 2) of diagnosing plant leaf disease using CNN model for the plantvillage-dataset are displayed in Fig. 3. Additionally, Fig. 4 displays the model's testing interface. Thorough testing on Plant Village dataset model demonstrated an impressive testing accuracy 93.96% and validation accuracy of 93.24%, in the stage devoted to disease diagnosis and subsequent model evaluation.

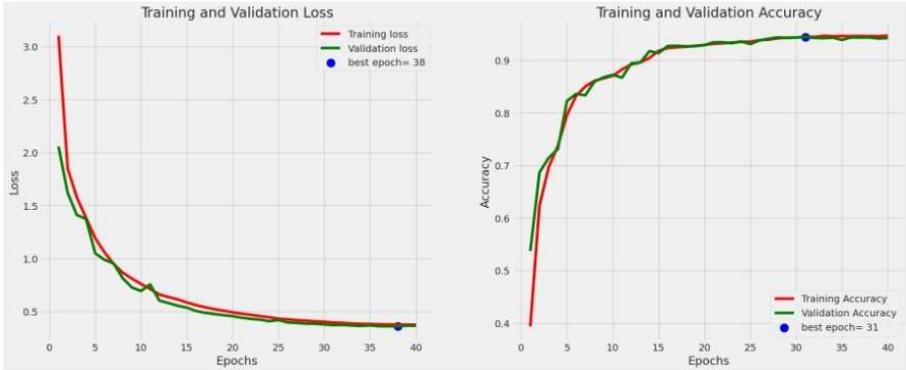


Fig. 4 Training and Validation Accuracy and Loss Graphs

4.2 ResNet-50

The pre-trained ResNet-50 model was utilized for the transfer learning stage to detect plant leaf illnesses. During the training phase, the model was fine-tuned using a batch size of 32 over 40 epochs. The experimental results of diagnosing plant leaf diseases using ResNet-50 on the Plant Village dataset are presented in Figure 4, while Figure 5 showcases the model's testing interface.

Thorough testing on the Plant Village dataset demonstrated commendable performance, achieving a testing accuracy of 94.33% and a validation accuracy of 94.31% (shown in Fig. 5). These results emphasize the model's capability in disease diagnosis and evaluation.

4.3 Generic Model(Xception with Average Pooling)

The pre-trained Generic Model (Xception with Average Pooling) was employed to predict

plant leaf illnesses. During the training phase, the model was fine-tuned using a batch size of 32 over 4 epochs. The experimental results of diagnosing plant leaf diseases using this model on the Plant Village dataset are presented in Figure 6, while Figure 7 showcases the model's testing interface.

Extensive testing on the Plant Village dataset demonstrated remarkable performance, achieving a testing accuracy of 99.66% and a validation accuracy of 99.68%. These results highlight the model's effectiveness in disease diagnosis and evaluation.

	precision	recall	f1-score	support
Apple___Apple_scab	0.50	0.99	0.67	126
Apple___Black_rot	0.00	0.00	0.00	124
Apple___Cedar_apple_rust	1.00	1.00	1.00	55
Apple___healthy	1.00	1.00	1.00	329
Blueberry___healthy	1.00	1.00	1.00	300
Cherry_(including_sour)___Powdery_mildew	1.00	1.00	1.00	211
Cherry_(including_sour)___healthy	0.99	0.99	0.99	171
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot	0.95	0.94	0.95	103
Corn_(maize)___Common_rust	1.00	1.00	1.00	239
Corn_(maize)___Northern_Leaf_Blight	0.96	0.97	0.97	197
Corn_(maize)___healthy	1.00	1.00	1.00	232
Grape___Black_rot	0.00	0.00	0.00	236
Grape___Esca_(Black_Measles)	0.38	1.00	0.55	277
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	0.00	0.00	0.00	215
Grape___healthy	1.00	1.00	1.00	84
Orange___Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	1101
Peach___Bacterial_spot	1.00	1.00	1.00	400
Peach___healthy	0.99	1.00	0.99	72
Pepper,_bell___Bacterial_spot	0.99	1.00	1.00	199
Pepper,_bell___healthy	1.00	0.99	1.00	295
Potato___Early_blight	1.00	1.00	1.00	200
Potato___Late_blight	1.00	0.99	1.00	200
Potato___healthy	1.00	1.00	1.00	31
Raspberry___healthy	1.00	0.99	0.99	74
Soybean___healthy	1.00	1.00	1.00	1018
Squash___Powdery_mildew	1.00	1.00	1.00	367
Strawberry___Leaf_scorch	1.00	0.96	0.98	222
Strawberry___healthy	1.00	0.99	0.99	91
Tomato___Bacterial_spot	1.00	1.00	1.00	425
Tomato___Early_blight	0.99	0.98	0.99	200
Tomato___Late_blight	0.99	0.99	0.99	382
Tomato___Leaf_Mold	1.00	1.00	1.00	190
Tomato___Septoria_leaf_spot	1.00	1.00	1.00	354
Tomato___Spider_mites_Two-spotted_spider_mite	0.99	1.00	0.99	335
Tomato___Target_Spot	1.00	0.99	0.99	281
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	1072
Tomato___Tomato_mosaic_virus	1.00	1.00	1.00	75
Tomato___healthy	1.00	1.00	1.00	318
accuracy			0.94	10861
macro avg	0.89	0.92	0.90	10861
weighted avg	0.92	0.94	0.93	10861

Fig.5. The Model Classification Report

	precision	recall	f1-score	support
Apple__Apple_scab	1.00	0.97	0.99	119
Apple__Black_rot	1.00	1.00	1.00	123
Apple__Cedar_apple_rust	1.00	1.00	1.00	48
Apple__healthy	1.00	1.00	1.00	305
Blueberry__healthy	1.00	0.99	1.00	324
Cherry_(including_sour)__Powdery_mildew	0.99	1.00	1.00	213
Cherry_(including_sour)__healthy	1.00	0.99	1.00	166
Corn_(maize)__Cercospora_leaf_spot_Gray_leaf_spot	0.96	0.87	0.92	111
Corn_(maize)__Common_rust	1.00	0.99	1.00	240
Corn_(maize)__Northern_Leaf_Blight	0.92	0.98	0.95	198
Corn_(maize)__healthy	1.00	1.00	1.00	234
Grape__Black_rot	0.96	1.00	0.98	237
Grape__Esca_(Black_Measles)	1.00	0.97	0.98	269
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00	214
Grape__healthy	1.00	1.00	1.00	89
Orange__Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	1149
Peach__Bacterial_spot	0.98	0.99	0.99	490
Peach__healthy	0.94	1.00	0.97	63
Pepper,_bell__Bacterial_spot	1.00	0.94	0.97	203
Pepper,_bell__healthy	0.99	1.00	0.99	301
Potato__Early_blight	1.00	1.00	1.00	201
Potato__Late_blight	0.98	0.98	0.98	197
Potato__healthy	1.00	0.93	0.96	29
Raspberry__healthy	1.00	0.99	0.99	83
Soybean__healthy	1.00	1.00	1.00	989
Squash__Powdery_mildew	1.00	1.00	1.00	381
Strawberry__Leaf_scorch	1.00	1.00	1.00	206
Strawberry__healthy	1.00	1.00	1.00	102
Tomato__Bacterial_spot	1.00	0.95	0.97	429
Tomato__Early_blight	0.97	0.94	0.95	188
Tomato__Late_blight	0.98	1.00	0.99	391
Tomato__Leaf_Mold	0.98	1.00	0.99	184
Tomato__Septoria_leaf_spot	0.98	0.98	0.98	360
Tomato__Spider_mites_Two-spotted_spider_mite	1.00	0.97	0.99	306
Tomato__Target_Spot	0.92	1.00	0.96	284
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	1033
Tomato__Tomato_mosaic_virus	1.00	0.99	0.99	74
Tomato__healthy	1.00	1.00	1.00	328
accuracy			0.99	10861
macro avg	0.99	0.99	0.99	10861
weighted avg	0.99	0.99	0.99	10861

Fig. 6 The Plant Village Dataset

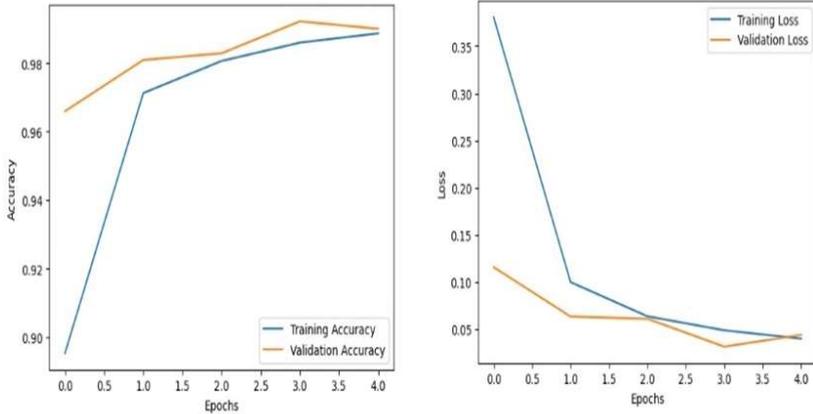


Fig. 7. The Model’s Testing Interface

4.4 EfficientNet-B3

The pre-trained EfficientNet-B3 model was utilized for detecting plant leaf illnesses. During the training phase, the model was fine-tuned with a batch size of 32 over 10 epochs. The experimental results, as illustrated in Figure 8, demonstrate the model's effectiveness in diagnosing plant leaf diseases using the Plant Village dataset. Furthermore, Figure 9 showcases the testing interface of the model. Extensive testing on the Plant Village dataset revealed exceptional performance, achieving a testing accuracy of 99.81% and a validation accuracy of 99.53%. These results in table 1 underline the model's robustness in the disease diagnosis and evaluation stages.

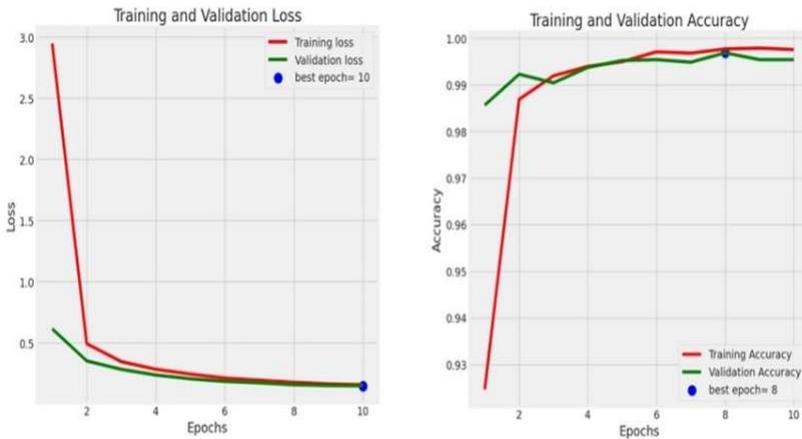


Fig. 8 Experimental Results of Training and Validation Accuracy and Loss

	precision	recall	f1-score	support
Apple__Apple_scab	1.00	1.00	1.00	63
Apple__Black_rot	1.00	1.00	1.00	62
Apple__Cedar_apple_rust	1.00	1.00	1.00	27
Apple__healthy	1.00	1.00	1.00	165
Blueberry__healthy	1.00	1.00	1.00	150
Cherry_(including_sour)__Powdery_mildew	1.00	1.00	1.00	105
Cherry_(including_sour)__healthy	1.00	1.00	1.00	85
Corn_(maize)__Cercospora_leaf_spot_Gray_leaf_spot	0.98	0.91	0.95	51
Corn_(maize)__Common_rust	1.00	1.00	1.00	119
Corn_(maize)__Northern_Leaf_Blight	0.96	0.99	0.97	98
Corn_(maize)__healthy	1.00	1.00	1.00	116
Grape__Black_rot	0.98	1.00	0.99	118
Grape__Esca_(Black_Measles)	1.00	0.91	0.99	139
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	1.00	1.00	108
Grape__healthy	1.00	1.00	1.00	42
Orange__Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	551
Peach__Bacterial_spot	1.00	1.00	1.00	230
Peach__healthy	1.00	1.00	1.00	36
Pepper,_bell__Bacterial_spot	0.99	1.00	1.00	100
Pepper,_bell__healthy	1.00	0.99	1.00	148
Potato__Early_blight	1.00	1.00	1.00	100
Potato__Late_blight	1.00	1.00	1.00	100
Potato__healthy	1.00	1.00	1.00	15
Raspberry__healthy	1.00	1.00	1.00	37
Soybean__healthy	1.00	1.00	1.00	509
Squash__Powdery_mildew	1.00	1.00	1.00	104
Strawberry__Leaf_scorch	1.00	1.00	1.00	111
Strawberry__healthy	1.00	1.00	1.00	45
Tomato__Bacterial_spot	1.00	1.00	1.00	213
Tomato__Early_blight	1.00	1.00	1.00	100
Tomato__Late_blight	1.00	0.99	1.00	191
Tomato__Leaf_Mold	1.00	1.00	1.00	95
Tomato__Septoria_leaf_spot	1.00	1.00	1.00	177
Tomato__Spider_mites_Two-spotted_spider_mite	1.00	1.00	1.00	168
Tomato__Target_Spot	1.00	1.00	1.00	141
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	536
Tomato__Tomato_mosaic_virus	1.00	1.00	1.00	37
Tomato__healthy	0.99	1.00	1.00	159
accuracy			1.00	5431
micro avg	1.00	1.00	1.00	5431
weighted avg	1.00	1.00	1.00	5431

Fig. 9 The testing interface of the model

Table 1. Performance of Different Model

METHOD	TRAINING ACCURACY	VALIDATION ACCURACY
CNN	94.68	93.24
RESNET 50	94.6	94.31

GENERIC MODEL(XCEPTION AVERAGE POOLING)	WITH	99.81	99.68
EFFICIENT B3		99.92	99.53

5 Conclusion and Future Work

Our economy is heavily reliant on agriculture, and we deal with a number of plant leaf disease and agricultural concerns. This research paper shows how well deep learning & transfer learning work for classifying and detecting plant leaf diseases. Utilizing the PlantVillage dataset, this study investigated the use of deep learning approaches for plant leaf disease prediction. The study illustrated the capability of classifiers including CNN, ResNet-50, a Generic Model, and EfficientNet-B3 to precisely detect and categorize plant illnesses. To guarantee a thorough grasp of each classifier's efficacy, essential performance indicators such as precision, accuracy, F1-score, recall, and support were used to assess each one. CNN model provided valuable baseline comparisons, highlighting the advantages of more advanced architectures. ResNet-50 highlighting its stability and robustness in learning. EfficientNet-B3 and the Generic Model both perform exceptionally well, with high training and validation accuracies and minimal over fitting gaps. The findings support that model ability to offer a dependable, quick, and affordable substitute for conventional diagnostic techniques.

Using the Plant Village dataset, we were able to detect a variety of plant leaf diseases with excellent accuracy by utilizing the proposed generic model. The findings support that model ability to offer a dependable, quick, and affordable substitute for conventional diagnostic techniques. The integration of these models into agricultural systems can significantly aid farmers by enabling early disease detection, reducing crop losses, and enhancing yield quality. Despite the promising results, certain challenges persist. Real-world conditions such as varying lighting, complex backgrounds, and environmental factors may impact model performance. This technology can be further extended into mobile or IoT-enabled platforms, making it accessible for real-time disease monitoring in diverse farming environments. By expanding the number of disease kinds, this topic can be further investigated.

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