# An Approach for Classification of Diseases on Leaves

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***Abstract*—In recent years, significant advancements have been made in the realm of plant disease classification, with a particular focus on leveraging the capabilities of deep learning techniques. This study delves into the utilization of renowned Convolutional Neural Network (CNN) models, including EfficientNetB5, MobileNet, ResNet50, InceptionV3, and VGG16, for the purpose of plant disease classification. The core methodology involves employing transfer learning, wherein these established CNN models are employed as a foundation and subsequently fine-tuned using a publicly accessible plant disease dataset. The study also compared the results with some deep learning models and with state-of-the-art. Among the tested CNNs, EfficientNetB5 has shown the best performance. EfficientNetB5 has outperformed another model and obtained 99.2% classification accuracy.**

***Keywords*—Classification of diseases on leaves; transfer learning; fine-tuning; image classification; deep learning**

## I. Introduction

Plant diseases are a pervasive and complex aspect of agriculture and horticulture, exerting significant impacts on global food production and ecosystem health. Plant diseases can manifest in various ways, from visible symptoms like wilting, discoloration, and lesions to more subtle signs of stunted growth and reduced yield. The management of plant diseases necessitates a multifaceted approach, combining practices such as crop rotation, the use of disease-resistant cultivars, proper sanitation, and judicious application of pesticides. As the world grapples with the challenge of feeding a growing population, understanding and mitigating plant diseases is of paramount importance to ensure sustainable agricultural systems and safeguard global food security [1].

Hence, numerous studies in this field have been conducted, deploying various methods such as classical machine learning models and state-of-the-art deep learning techniques [2] [3] [4] [5]. Authors have also employed data preprocessing methods to enhance model accuracy. Besides, there have been studies focusing on feature extraction using traditional techniques like SURF [6], HOG [7], etc.

In this study, we used a CNN [8] model, including EfficientNetB5, MobileNet, ResNet50, InceptionV3, and VGG16, to classify plant diseases within an existing dataset. Additionally, the study compared the results with other deep learning models and state-of-the-art methods. The obtained results were highly satisfactory, achieving an accuracy and F1-score of 99.2% and 99.22%, respectively.

This article is divided into five sections. The first section is the introduction. In the subsequent Section II, we present related works. Moving forward, Section III is the proposed methodology. The experimental procedures and outcomes are discussed in Section IV. Lastly, the conclusion wraps up the article.

## II. Related Works

Numerous research have been conducted in recent years to address the issue of plant disease. Researchers are continuously finding new, creative ways to increase their accuracy.

In the article [9], the author proposed a deep learning-based method for tomato disease detection that utilizes the Conditional Generative Adversarial Network (C-GAN) to generate synthetic images of tomato plant leaves. Then, a DenseNet121 model is trained on synthetic and real images using transfer learning to classify the tomato leaves images into ten categories of diseases. The results obtained accuracy of 99.51%, 98.65%, and 97.11% for tomato leaf image classification into five classes, 7 classes, and 10 classes, respectively.

In [10], a comprehensive four-step procedure is presented for enhancing the accuracy of plant disease detection and classification in images. The process commences with preprocessing, employing a Wiener filter to mitigate background noise. Disease spots are subsequently identified using the hue histogram in the HIS model, followed by precise segmentation through the K-means algorithm and highest hue value calculation in the HSV color model. Afterward, seventeen color and texture features are extracted from the disease-affected regions and input into a forward-propagation deep neural network (FPDNN) classifier. To improve results, the Bayesian regularization back propagation algorithm is applied. Impressively, the FPDNN was subjected to testing with varying hidden layers, achieving its peak accuracy of 97.18% with 19 hidden layers. This underscores the effectiveness of this methodology in accurate plant disease identification and classification.

In [11], the authors concentrated their efforts on crafting an integrated model for the precise detection of tomato diseases through the utilization of image data. To achieve this, they rigorously assessed the performance of seven distinct neural network architectures, including renowned ones like VGG16, ResNet50, and various EfficientNet variants, all fine-tuned through transfer learning methodologies. After a thorough evaluation, the most proficient models were selected, and a weighted average ensemble technique was applied to amalgamate them. This amalgamation resulted in the proposal of a final model boasting an impressive accuracy rate of 98.1%.

This study [12], the identified diseases were categorized into three distinct groups: bacterial, viral, and fungal infections. The research delved into a thorough exploration of these aspects and employed a range of machine learning (ML) and deep learning (DL) techniques. The ML methods employed in the study encompassed SVM, KNN, RF (Random Forest), and LR (Logistic Regression), while the DL approach featured the use of Convolutional Neural Networks (CNN) for disease prediction in plants. Among the machine learning classifiers, the RF (Random Forest) yielded the highest accuracy, achieving an impressive rate of 97.12%. However, the CNN classifier, representing the deep learning model, outshone them all with an even higher accuracy of 98.43%.

In the study [13] conducted by Nagamani H S and Sarojadevi H, the focus was directed towards the detection and classification of diseases that impact tomato leaves, employing a range of machine learning techniques. This comprehensive investigation encompassed the utilization of FuzzySVM, Convolutional Neural Network (CNN), and Region-based Convolutional Neural Network (R-CNN) models. The researchers executed an array of sophisticated image processing and feature extraction methodologies to enhance the predictive capabilities of their models. Remarkably, their findings unveiled that the R-CNN model emerged as the standout performer, achieving an impressive accuracy rate of 96.735% in the classification of various disease types afflicting tomato plants.

In research [14] of Nishant Garg and colleagues , the model was meticulously trained on a substantial dataset consisting of 8,000 images across the relevant classes and rigorously tested on a separate test set comprising 2,000 images. The hybrid methodology employed a fusion of Convolutional Neural Network (CNN) for effective feature extraction from input data and a finely tuned Support Vector Machine (SVM) classifier for precise classification. This synergistic combination proved to be highly effective, achieving an impressive accuracy rate of 92.6%. The authors, in [15], used a Convolutional Neural Network (CNN), specifically the VGG model, to detect Multi-Crops Leaf Disease (MCLD) by classifying diseased and healthy crop leaves. They achieved impressive results with an accuracy of 98.40% for grapes and 95.71% for tomatoes.

In their research paper [16], the authors conducted a comprehensive assessment of deep learning techniques, leveraging pre-trained CNN models within the PyTorch framework for the classification of tomato plant diseases. They evaluated various models, such as EfficientNetB0, ResNext-50-32x4d, and MobileNet-V2, with ResNext-50-32x4d emerging as the top performer, achieving an impressive accuracy rate of 90.14%. In the paper cited as [17], the authors introduce a novel approach for classifying seven distinct types of tomato diseases employing Deep Learning models. Their models were trained on an extensive dataset comprising 10,448 images, and the results were striking. The trained models exhibited remarkable accuracy, with the highest testing precision achieving an impressive 95.71%.

This article [18] used deep learning for crop disease detection. They employed a Convolutional Neural Network (CNN) with two convolutional and two pooling layers in the model. The results are quite promising, as the proposed CNN model outperformed well-known pre-trained models like InceptionV3, ResNet 152, and VGG19. The CNN achieved an impressive 98% training accuracy and maintained a strong 88.17% testing accuracy. This paper [19] focuses on the identification of tomato plant diseases, utilizing a transfer learning approach with the EfficientNetB3 model. The dataset comprises 11 distinct types of leaves and is sourced from an online database. The EfficientNetB3 model undergoes 15 training iterations with a batch size of 32, employing two optimizers, Adamax and Adam. Notably, the use of the Adam optimizer resulted in an accuracy of 94%.

In this research [20], a prediction model for Tomato Early Blight Disease (TEBD) was developed using image-based data. The TEBD dataset was improved through various image processing techniques such as Background Removal, Augmentation, Resizing, Noise Removal, and Segmentation. Subsequently, a Convolutional Neural Network (CNN) was employed to train the model on the enhanced dataset. The model's performance was exceptional, achieving a remarkable mean accuracy of 98.10%, demonstrating its capacity to accurately predict TEBD with a batch size of 64 and 15 training epochs.

In the study described in [21], the researchers employed established CNN architectures like AlexNet, ResNet50, and VGG16 for feature extraction. Subsequently, they applied the minimum redundancy maximum relevance feature selection algorithm to refine these features for optimal performance. These selected features were then combined through concatenation. To classify the concatenated features, the researchers utilized well-known machine learning classification algorithms. Remarkably, their proposed approach achieved outstanding results, boasting an impressive accuracy of 98.3% for tomato leaf disease detection and 96.3% for the Taiwan dataset.

In this study [22], an innovative approach was introduced by fusing two pre-trained models, namely EfficientNetB3 and MobileNet, collectively referred to as the EffiMob-Net model, for highly precise tomato leaf disease detection. The researchers conducted thorough hyperparameter tuning to meticulously select the ideal settings for constructing the most suitable model. The performance of this hybrid model was rigorously assessed, focusing on accuracy metrics specifically chosen for disease detection. Impressively, the proposed EffiMob-Net model achieved an exceptional success rate of 99.92%. In reference [23], the research leveraged pre-trained CNN models, namely Inception V3 and Inception ResNet V2, to effectively classify images of tomato leaves as healthy or unhealthy. Remarkably, their approach yielded outstanding results, boasting a remarkable accuracy rate of 99.22%. Additionally, they managed to keep the loss to an impressively low 0.03. This achievement was made possible through strategic use of dropout rates, with 50% for one model and 15% for the other.

In [24], authors employed a dataset comprising tomato leaves, encompassing six distinct disease types along with a class for healthy tomato leaves. This dataset, consisting of 6,594 tomato leaf images, was sourced from Plant Village. In addtional, approach of study, utilizing the ResNet-50 model, delivered a remarkable outcome, achieving a substantial accuracy rate of 96.35% when tested on a balanced dataset split, with 50% used for training and the remaining 50% for testing. In this study [25], Sanjeela Sagar and Jaswinder Singh conducted an experimental and comparative analysis of tomato leaf disease classification, employing both traditional machine learning algorithms such as random forest (RF), support vector machines (SVM), and naïve bayes (NB), as well as a deep learning convolutional neural network (CNN) algorithm. Notably, our findings revealed that the CNN, specifically when integrated with a pre-trained Inception v3 model, outperformed traditional methods. This advanced approach achieved an impressive accuracy rate of over 95%.

In [26], Irene Sultana and her team have introduced a substantial dataset consisting of 14,529 tomato leaf images encompassing ten distinct infections. In their study, they harnessed the power of deep learning by employing InceptionV3 and ResNet-50 as the learning algorithms, capitalizing on transfer learning techniques for classifier training. Their innovative deep learning model delivered commendable outcomes, achieving an accuracy rate of 85.52% for InceptionV3 and an even more impressive 95.41% for ResNet-50. In this research paper [27], authors focus on the crucial task of cassava plant disease detection, recognizing that deep learning models surpass traditional machine learning methods, as observed in prior research. In additional, Prashant Giridhar Shambharkar and Saurabh Sharma employ the EfficientNet-B0 architecture in conjunction with k-fold cross-validation to develop a highly effective disease detection model. EfficientNet's reputation for superior classification, speed, and scalability across various dimensions makes it an ideal choice. Result attains an impressive 96.68% accuracy when evaluated on a collect Kaggle dataset.

The common challenge for researchers is the difficulty in increase accuracy to classification of plant diseases on leaves. Therefore, in this study, we have conducted several experiments on several Machine Learning models (including pre-trained Deep Learning models) to validate their better performance in the scenario.

## III. Background

### A. Image Classification

One of the most pivotal and burgeoning research domains in contemporary times is image classification, particularly within the realm of medical imaging analysis. Image classification, also referred to as image categorization, plays a critical role in determining the presence of diseases by generating a classification output based on input images. Its primary objective is to assign a specific label to an image, which proves instrumental in various applications.

Image classification extends its relevance to numerous real-world sectors and industries, encompassing environmental studies, agriculture, remote sensing, urban planning, surveillance systems, geographic mapping, disaster management, and item identification. This versatile and transformative technology not only aids in medical diagnoses but also finds widespread utility in addressing a multitude of challenges and opportunities across diverse fields.

### B. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) stand as a cornerstone in the domain of deep learning, particularly in the realm of image analysis and recognition [8]. CNNs leverage a distinctive mathematical technique known as convolution, which involves performing an operation on two functions to derive a third function, illustrating the transformation of one function by the other. In CNN architecture, convolution plays a pivotal role in extracting hierarchical features from input images, enabling the network to progressively discern complex patterns. CNNs are composed of multiple layers of artificial neurons, which function as mathematical units responsible for aggregating input information and generating activation values, closely mirroring the information processing capabilities of human neurons, as they assimilate sensory inputs and produce corresponding responses. This structural and functional alignment with biological neural systems contributes to CNNs' extraordinary efficacy in tackling intricate image-based tasks and solidifies their status as a cornerstone technology in modern deep learning.

Kernel convolution [8] serves as a foundational element not only in Convolutional Neural Networks (CNNs) but also in various Computer Vision methodologies. This technique involves the application of a small matrix, referred to as the kernel or filter, to modify an image based on the filter's values. In the context of the mathematical representation, the input image is symbolized as $g$ and the kernel is represented as $p$. The process can be expressed using the following formula, which is instrumental in generating subsequent feature map values. The indices for the rows and columns of the resulting matrix are typically denoted as $a$ and $b$, respectively, as indicated in equation (Eq. 1). This fundamental operation forms the basis for extracting important visual information and features from images, underpinning a wide range of computer vision applications.

$$G[a,b] = (g * p)[a,b] = \sum_i \sum_j p[i,j]g[a-i,b-j] \tag{1}$$

Within the Convolutional Neural Network (CNN) architecture, the first layer is the convolutional layer, tasked with the process of disentangling diverse features from the input images. In this layer, a $NxN$ sized filter is employed in tandem with the input image to execute the convolution operation. The forward propagation through this layer unfolds in two phases. Initially, the first step is to determine the intermediate value $X$, which is produced when the input data from the previous layer is convolutioned with the $Y$ tensor (which contains filters), and then bias $d$ is added. The next involves using our intermediate value as the input for a non-linear activation function (our activation is denoted by $h$). For the fans of matrix equations, the subsequent formulas, encapsulated as Eq. (2) and (3).

$$X^{[l]} = Y^[l].C^[l-1] + d^[l] \tag{2}$$

$$C^{[l]} = h^{[l]}(X^[l]) \tag{3}$$

### C. ResNet50 Model

ResNet [28] represents a distinctive variant of a convolutional neural network (CNN) that was first presented in the research paper titled "Deep Residual Learning for Image Recognition" in 2015. This concept is introduced by He Kaiming, Zhang Xiangyu, Ren Shaoqing, and Sun Jian. ResNet-50 is a convolutional neural network that is 50 layers deep, including

48 convolutional layers, one MaxPool layer, and one average pool layer. Residual neural networks are a type of artificial neural network (ANN) that constructs networks by assembling residual blocks [29].

### *D. MobileNet Model*

MobileNet [30] is a simple but efficient and not very computationally intensive convolutional neural networks for mobile vision applications. MobileNet is widely used in many real-world applications which includes object detection, fine-grained classifications, face attributes, and localization. In this lecture, I will explain you the overview of MobileNet and how exactly it becomes the most efficient and lightweight neural network. MobileNet uses depthwise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.

### *E. VGG16 Model*

VGG16 [31] is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" [32]. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous model submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

### *F. InceptionV3 Model*

InceptionV3 [33] is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. It has a total of 42 layers and a lower error rate than its predecessors. Additional, it is introduced on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy, et. al. [34].

### *G. EfficientNetB5 Model*

EfficientNetB5 [35] is part of a family of eight DCNN models called EfficientNet, introduced by Google AI [36]. The eight models of EfficientNet range from B0 to B7 where the largest is B7. EfficientNets showed higher accuracy and better efficiency in comparison to existing CNNs. The EfficientNet architectures are based on a scaling approach that uses a compound coefficient to consistently scale the three dimensions (resolution, depth, and width). This results in higher performance and greater accuracy of the models.

## IV. PROPOSED ARCHITECTURE

Fig. 1 shows our proposed approach. The goal of this process is to increase the amount of data large enough for deep learning models to bring high efficiency to the model. Then, the data will be divided into three parts: training set, validating set and testing set. Next, pretrain models with the ImageNet dataset are used without the output layer. We reuse all the trained weights from the ImageNet dataset. After input layer, we create an additional layer called AugmentedLayer, this layer is responsible for enhancing data from the input dataset with different techniques such as: flip, rotation, zoom and contract. After that, we proceed to add layers in turn: Dense with 256 hidden units, followed by activation layer with ReLu, Batch Normalization layer, dropout layer with value 0.3, dense layer and final is output layer.

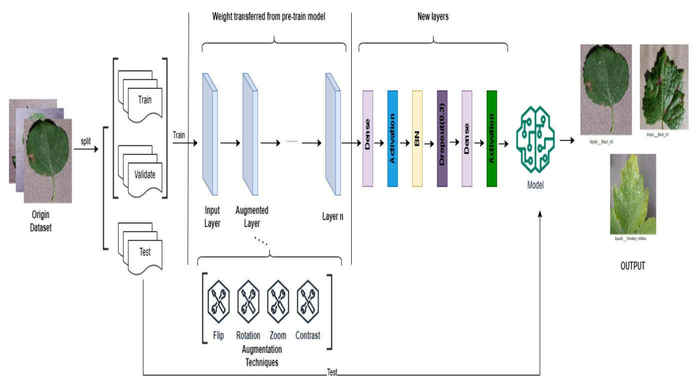


Fig. 1. Our proposed architecture.

The details of the input and output of each layer and the number of parameters of the proposed architecture are shown in Table I.

TABLE I. SUMMARY OF PROPOSED MODELS

| Layer (type) | Output Shape | Param # |
|---|---|---|
| ——————————————————————— | | |
| inputLayer (InputLayer) | [(None, 224, 224, 3)] | 0 |
| AugmentationLayer (Sequential) | (None, 224, 224, 3) | 0 |
| efficientnetb5 (Functional) | (None, 2048) | 28513527 |
| dense_3 (Dense) | (None, 256) | 524544 |
| activation_1 (Activation) | (None, 256) | 0 |
| batch_normalization_1 (BatchNormalization) | (None, 256) | 1024 |
| dropout_1 (Dropout) | (None, 256) | 0 |
| dense_4 (Dense) | (None, 38) | 9766 |
| activationLayer (Activation) | (None, 38) | 0 |
| ... | | |
| **Trainable params: 534,822** | | |
| **Non-trainable params: 28,514,039** | | |

## V. EXPERIMENTS

### *A. Dataset and Experimental Environment*

The dataset [37] used contained 87,867 images of fruits and vegetables belonging to 38 different categories. The pre-split data consists of three sets: training, validation and testing. The training set includes 70,295 images. The validation set has 15,814 images. The test set contains 1,758 images. Each photo will contain a plant-diseases of leaves. Fig. 2 shows the distribution of data of the training set.

In this experimental, we train the data with the proposed model. The experiment was performed on a computer with the following configuration: Core i5 12400F, 32GB RAM, and Geforce RTX 3060 12VRAM graphics card.

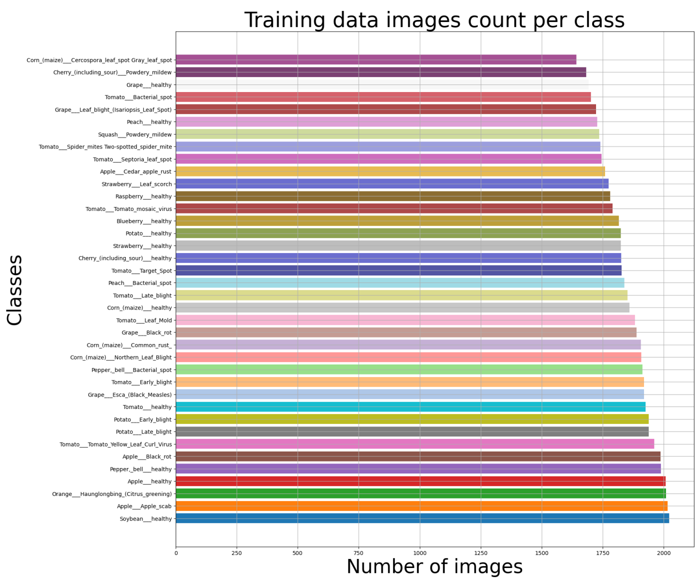


Fig. 2. Data distribution.

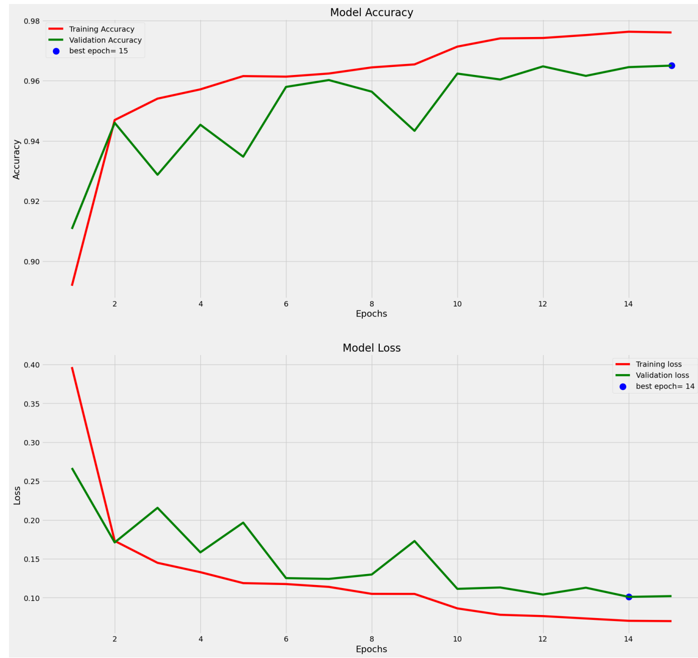


Fig. 3. Accuracy and loss during training.

### *B. Experiment 1: Evaluation of the Proposed Model*

In this experiment, we performed on the hyperparameter set with the specified values as follows: batch_size=32, epoch=15, learning_rate=0.00001, and optimizer=Adam. The Table II compares the results between some deep learning models based on our approach. In which, (1) is train loss, (2) is train accuracy, (3) is validation loss, (4) is validation accuracy, (5) is test loss, (6) is test accuracy and final is F1-Score.

TABLE II. Comparison Between the Proposed Model and Some other Models

| **Models** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** |
|---|---|---|---|---|---|---|---|
| **EfficientNetB5** | **0.22** | **0.92** | **0.14** | **0.95** | **0.02** | **0.992** | **0.992** |
| InceptionV3 | 1.70 | 0.50 | 1.92 | 0.45 | 1.35 | 0.587 | 0.585 |
| MobileNet | 0.65 | 0.79 | 0.67 | 0.78 | 0.57 | 0.82 | 0.82 |
| ResNet50 | 0.06 | 0.97 | 0.10 | 0.96 | 0.03 | 0.9898 | 0.9898 |
| VGG16 | 0.24 | 0.91 | 0.21 | 0.92 | 0.06 | 0.9829 | 0.9829 |

From the comparison table above, we can see that the fine-tune EfficientNetB5 model achieves a performance of 99.2 with both accuracy and F1 measure. Fig. 3 shows the accuracy and loss in training data of it.

And the confusion matrix of the fine-tune EfficientNetB5 model is shown in Fig. 4.

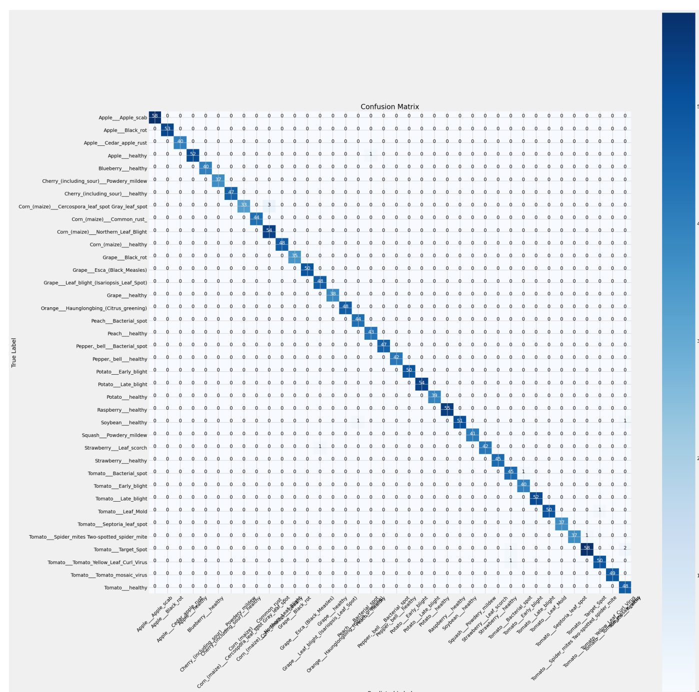


Fig. 4. Confusion matrix of fine-tuned efficientNetB5 model.

### *C. Experiment 2: Compare the Results with Some other Deep Learning Models and State-of-the-Art*

In Experiment 2, to have a basis for evaluating the effectiveness of the proposed approach, we also compare the results of the proposed model (*fine-tuned EfficientNetB5 model with highest accuracy in Experiment 1*) with the state-of-the-arts. The results are shown in the Table III.

From the results in Table II and Table III, we can see that our approach is quite simple but achieves high effectiveness in the applied classification problem. With a large amount of image data (87,867 images) combined with augmented layer, this study demonstrates superiority over most other models. However, in some cases, it is not as effective as [22] and [23].

## VI. Conclusion

The problem of plant disease classification based on images plays a significant role in real-life scenarios, particularly in contributing to addressing issues related to the quality and quantity of agricultural produce. The results of research on leaf

TABLE III. COMPARISON WITH STATE-OF-THE-ARTS

| Refs | Dataset | No. Classes | No. Images | Accuracy |
|---|---|---|---|---|
| [9] | tomato plantvillage | 5 | 16,012 | 0.971 - 0.995 |
| [22] | Plantvillage | 11 | 32,535 | 0.9992 |
| [10] | plant village | 19 | 75 | 0.9718 |
| [11] | plant village tomato leaf | 10 | 14500 | 0.981 |
| [12] | plant village | 30 | 53200 | 0.9843 |
| [16] | plantvillage | 38 | 163,000 | 0.9014 |
| [13] | tomato leaf disease | 7 | 735 | 0.96735 |
| [17] | Plantvillage | 7 | 11,165 | 0.9571 |
| [18] | Plantvillage | 14 | 3,000 | 0.98 |
| [23] | Plantvillage | 14 | 54,305 | 0.9922 |
| [24] | Plantvillage | 6 | 6,594 | 0.9635 |
| [14] | tomato leaf disease | 8 | 10000 | 0.926 |
| [15] | plantvillage | 38 | 54,303 | 0.984 |
| [25] | Plantvillage | 5 | 11,123 | 0.95 |
| [26] | Plantvillage | 10 | 14,529 | 0.9541 |
| [27] | Cassava disease leaf | 5 | 22,031 | 0.9668 |
| **Ours** | **Plant Disease** | **38** | **87,867** | **0.992** |

disease classification also aid in more accurate identification of various diseases affecting plants. In the realm of plant disease classification, numerous studies have explored various methodologies, including classical machine learning models, deep learning models, transfer learning, and fine-tuning techniques. However, the results have not yet been obtained really high such as: the number of plant disease leaves in the data set is small or the accuracy achieved is not high. Because of that, this study has proposed an approach through building a CNN model that is relatively simple but helps bring about high accuracy. The study tested on a data set of 38 classes of plant disease leaves. The results are very satisfactory with the accuracy and F1-Score of 99.2% and 99.22%, respectively. In the future, we will build new models or combine from many different models to further improve the accuracy of this problem.

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