

Ensemble of Deep Learning Models for Multi-plant Disease Classification in Smart Farming

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Abstract—Plant disease identification at an early stage plays a crucial role in ensuring efficient management of the diseases and crop protection. The occurrence of plant ailments can result in substantial reductions in both crop yield and quality, which may cause financial setbacks for farmers and lead to food shortages for consumers. Traditional methods of disease detection rely on visual observation, which can consume a significant amount of time, be a labor-intensive, and often be inaccurate. Automated disease detection systems, based on techniques for machine learning have the potential to greatly improve the precision and speed of disease detection. This article presents a model for classifying plant diseases that combines the output of two transfer learning models, EfficientNetB0 and MobileNetV2, to improve disease classification accuracy. The PlantVillage Dataset was used to train and test the model under consideration, which contains 54,305 photos of 38 different plant disease classes, achieving an accuracy rate of 99.77% in disease classification. The use of an ensemble of deep learning models in this study shows promising results, indicating that the technique can enhance the accuracy of plant disease classification. Besides, this study contributes to the development of accurate and reliable automated disease detection systems, thereby supporting sustainable agriculture and global food security.

Keywords—Ensemble learning; automated disease detection systems; transfer learning models; plant diseases

I. INTRODUCTION

Plants are susceptible to a variety of diseases, and this is particularly true in the Mekong Delta region of Vietnam and across the world. There are numerous factors that contribute to the development and spread of plant diseases, including weather conditions, soil health, and the presence of pests and pathogens [3]. The Mekong Delta, situated in the southwest of Vietnam, is also referred to as the Western Region, the humid and warm climate provides ideal conditions for the growth of many plant diseases, which can have significant economic and environmental impacts on local farmers and communities [41]. Similarly, in other parts of the world, plant diseases can be a major challenge for agriculture and food security, affecting yields and quality of crops. Therefore, it is crucial to monitor and manage plant diseases to prevent their spread and minimize their impact on plant health and food production. In recent times, there has been a growing interest in using machine learning (ML) and deep learning (DL) techniques to improve the early diagnosis of plant diseases. This involves developing algorithms that can analyze large datasets of plant images and detect early signs of disease, such as changes in leaf color or texture. These algorithms can be trained using labeled datasets of healthy and diseased plants, allowing them to identify

patterns and make accurate predictions about the health of a plant. By using these advanced techniques, researchers hope to enhance the precision and quickness of disease diagnosis, which could help farmers to take preventive measures and minimize crop losses. The study's primary contribution is to introduce a model for classifying plant diseases that combines the output of two transfer learning models, EfficientNetB0 and MobileNetV2, to improve disease classification accuracy.

II. RELATED WORKS

Numerous research studies have investigated the use of both traditional classification algorithms and advanced deep learning models in classifying plant leaf diseases. This indicates that there is an ongoing effort to develop more accurate and efficient methods for identifying and diagnosing diseases that affect plant leaves. The article [30] proposes ANN and SVM classifiers to identify and classify fungal diseases with an accuracy of 87% and 91.16%, respectively. This study [14] utilizes the Support Vector Machine (SVM) classifier for disease recognition, achieving an accuracy rate exceeding 90%. In the research [28] employs the SVM classification technique and involves the extraction of color and texture features, resulting in a classification accuracy of 88.89%. Through the extraction of features such as color, shape, and texture from images of healthy and unhealthy tomato plants and feeding them to a classification tree, the study [36] achieved a classification accuracy of 97.3% for six types of tomato images. The study [20] combines convolution neural networks (CNNs) and SVM method to extract features and classify rice leaf disease images, respectively. The research achieves a classification accuracy of 96.8%. The study [12] presents a fresh model for identifying plant leaf diseases, which employs a Deep CNN trained with an open dataset comprising 39 classes of images of plant leaves and their backgrounds. The research attains a classification accuracy of 96.46%. The paper [44] discusses the practicality of using CNN for classifying plant diseases in leaf images, resulting in an accuracy rate of 99.32%. The study [25] introduces a new approach to identifying rice diseases that utilizes deep CNN techniques, achieving an accuracy rate of 95.48%. The paper [48] presents a novel approach to classifying tomato leaf diseases using a deep CNN that incorporates an attention mechanism, achieving an accuracy rate of 99.24% on the tomato leaf diseases dataset. A compact CNN is suggested in this research [27] for the Tomato Disease identification task, achieving an F1 score of 99.70%. [43] The tomato diseases are accurately defined and classified using Convolutional Neural Network (CNN), achieving a success rate of 98.49%. In recent times,

transfer learning has gained widespread popularity and has been successful in solving several problems with significant achievements. Agriculture imaging tasks [32], [5], [26], [33], [31]; Medical imaging tasks [34], [2], [47], etc. To utilize the pretrained model for identifying plant diseases, this paper [49] presents the identification of apple leaf diseases with an accuracy of 93.71% using DenseNet-121. The study [16], the VGG16 deep learning model has been employed to achieve a 90% accuracy in identifying diseases in tea leaves. In this paper [45] employs the VGG16 model to identify diseased apple leaves with an accuracy of 90.4%. The identification of haploid and diploid maize seeds is achieved with an accuracy of 94.22% in this study [1] using the VGG-19 model. The classification of Tomato crop diseases is achieved in this paper [35] with an accuracy of 97.29% using VGG16 and 97.49% using AlexNet. The study [21] employed transfer learning with the plant village dataset to retrain the EfficientNet B7 deep architecture. Subsequently, down-sampling of collected features was performed using a Logistic Regression technique, which achieved a 98.7% accuracy. The research [13] involved tomato leaf disease detection, which was performed using Densenet-Xception, resulting in an accuracy of 97.10%. In this study [39], CNN models were employed to categorize diseases found in tomato plants, achieving an accuracy of 98.6% across 10 different disease classes. In the study [42], the success rate for tomato leaf disease recognition using VGG16, InceptionV3, and Resnet50 models were 99.62%, 99.75%, and 99.5%, respectively. The goal of this study [37] was for the purpose of diagnosing diseases present in tomato leaves by categorizing healthy and unhealthy tomato leaf photos using two pretrained CNNs, namely InceptionV3 and Inception ResNetV2. The study [22] achieved an accuracy of 99.22%. In this work, three CNN-based models (VGG-16, ResNet-152, and EfficientNet-B4) were proposed for the classification of tomato leaf diseases. The study found that the models reached accuracies of 93.75%, 97.27%, and 98%, respectively. With the utilization of a DenseNet model, the paper [6] achieved a classification accuracy of 99.9% in identifying tomato diseases. By leveraging MobileNetV2, the research [24] created an enhanced algorithm for recognizing apple leaf diseases and achieved an accuracy rate of 96.23%. In the research [4], the detection of tomato leaf diseases was performed using several models, with MobileNet achieving an accuracy rate of 94%, Xception at 95.32%, VGG16 at 93.35%, ResNet50 at 96.03%, DenseNet121 at 96.3%, and EfficientNetB5 at 99.07%.

III. TRANSFER LEARNING MODELS AND ENSEMBLE LEARNING

A. Transfer Learning Models

Transfer learning (TL) [29] is a technique in machine learning that improves the learning process by leveraging a pre-trained model for a new task. TL models are neural networks that have undergone training on a large dataset, typically used for tasks such as image recognition or natural language processing. These models are then adjusted and fine-tuned for a new task using a smaller dataset. The core principle behind transfer learning is based on the idea that a model capable of recognizing specific features in one domain can be repurposed to identify similar features in another domain. In recent times, various Deep Learning models, including EfficientNet, MobileNet, VGG, DenseNet, Xception, ResNet,

among others, have emerged victorious in the ILSVRC competitions. The ImageNet database, containing more than 1.4 million images for 1000 different classes, is the most widely utilized dataset for these competitions. The present research involves the combination of EfficientNetB0 and MobileNetV2 models for the classification of plant diseases.

B. Ensemble Learning

Ensemble learning (EL) [11] is a method that involves merging multiple separate models to achieve improved overall performance in terms of generalization. There are several types of ensemble models that can be used for this purpose, each with its own unique approach and set of advantages and disadvantages. One of the most common types of ensemble models is bagging [8], which stands for bootstrap aggregating. The Bagging technique consists of training multiple models on distinct subsets of data, followed by the amalgamation of their predictions through averaging or majority voting. This approach can diminish the variance of the models and enhance their general stability. Another popular ensemble method is boosting [10] [9], which involves sequentially training weak models and adjusting the weights of the training examples to focus on the most difficult cases. Boosting can be effective for improving the accuracy of the models and reducing bias. Stacking [46] is a more complex type of EL that involves training several models and then using another model, called a meta-model or a blender, to combine their predictions. Finally, decision fusion strategies based on deep ensemble models use deep learning methods to combine the results of several models, either in a hierarchical or parallel manner, to achieve better performance.

In our approach, we utilized two transfer Learning models (EfficientNetB0 [40] and MobileNetV2 [15] [38]) for the purpose of extracting deep features from the data provided. These deep features were then integrated together to form a single, high-dimensional feature vector. These features were then fed into a few dense layers for further processing and feature transformation. Finally, the resulting features were used to perform classification. This allowed us to leverage the complementary strengths of different deep networks and capture a richer representation of the input data compared to using a single deep network or traditional feature extraction methods. The outcomes demonstrate the proficiency of our method in leveraging the power of TL models for multi-plant disease classification.

IV. METHODOLOGY

A. Dataset and Data Preparation

The data set utilized in this research is PlantVillage dataset was first introduced at [17], [18]. The PlantVillage dataset comprises 54,305 images of leaves, both healthy and diseased, which have been categorized into 38 different groups based on their species and type of disease. The images include 14 types of crops and consist of 38 categories can be found in Table III. To train and evaluate the effectiveness of the suggested model, the dataset was divided into three separate groups, namely the training set, testing set, and validation set, in the proportion of 60:20:20. The distribution of the data set can be discovered in Fig. 1 and examples of plant disease

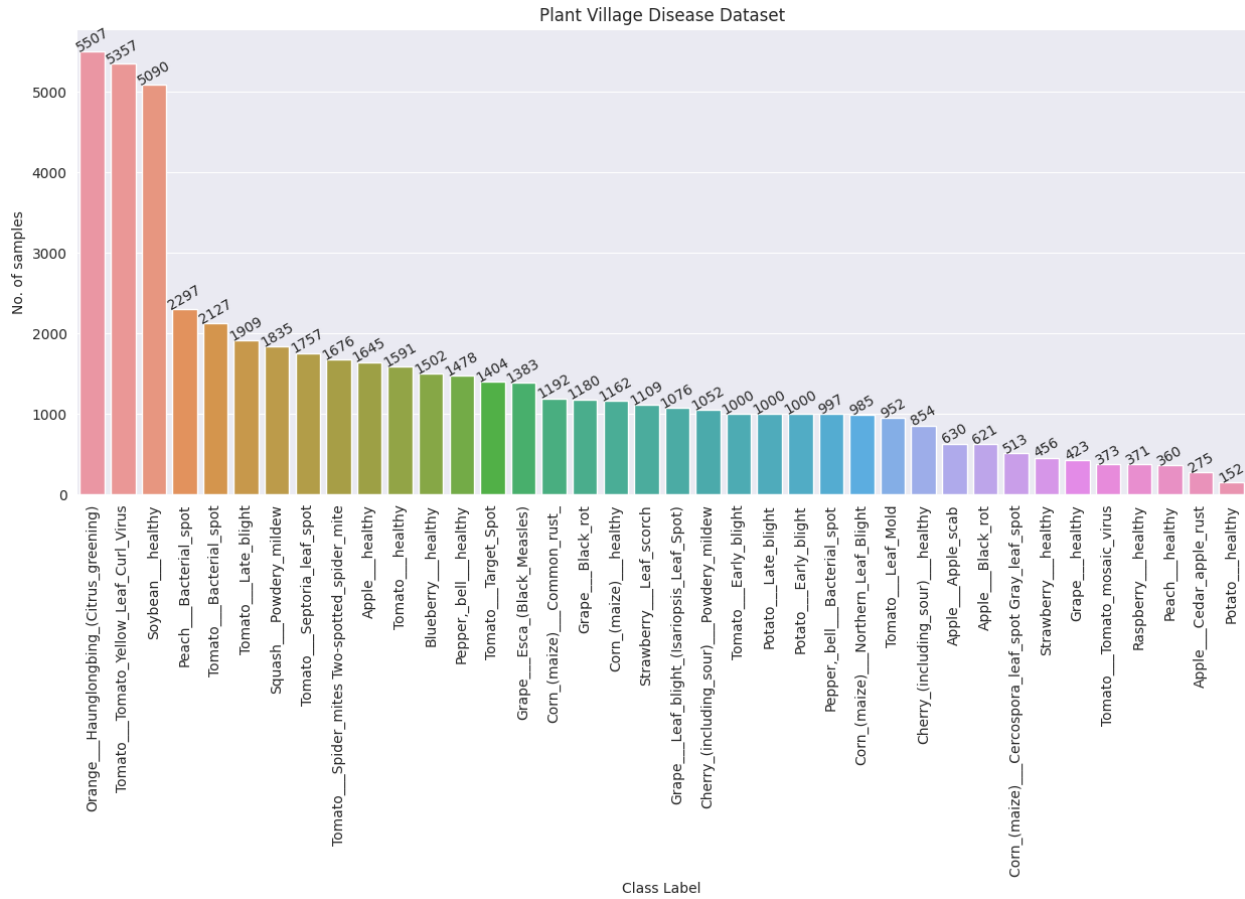


Fig. 1. A dataset distribution.

pictures from The PlantVillage dataset can be presented Fig. 2. Before the model training and evaluation, the datasets for training, validation, and testing will go through preprocessing techniques. These techniques consist of resizing the images to 224x224 and applying the image preprocessing function.

B. Proposed Model

In this research, we utilized two transfer Learning models (EfficientNetB0 [40] and MobileNetV2 [15] [38]) to extract deep features from the input data. These deep features were then concatenated together to create a feature vector. Then, these features were fed into a few dense layers for further processing and feature transformation. Finally, the resulting features were used to perform classification. The suggested model for plant disease classification can be seen in Fig. 3. The model has two main backbone networks, “EfficientNetB0” and “MobileNetV2,” both of which produce an output shape of (None, 1280). These output tensors are then processed by two separate batch normalization layers, and their outputs are concatenated together to form a (None, 2560) tensor. This concatenated tensor is then fed into a dense layer comprising of 256 units, followed by a dropout layer with a dropout rate of 0.5 to prevent overfitting. Finally, the output of the dropout layer is passed through another dense layer with 38 units, which produces the final output of the model. The overall count of parameters within the model is 6,983,177,

with 6,901,922 of them being trainable and the remaining 81,255 being non-trainable. The Architecture and Proposed model can be displayed in Fig. 4 and Table 1 showcases the representation of various information including layers of the model, the shape of each layer’s output, the count of trainable parameters in every layer, and the overall count of trainable parameters within the model. The proposed model also utilizes the technique of learning rate scheduling [23] during its training process. Learning rate scheduling is a technique that adjusts the learning rate, which controls the step size of the gradient descent optimization algorithm, during training. The purpose of this technique is to improve the convergence of the model by gradually reducing the learning rate over time. In this model, after two epochs, the learning rate has decreased by a factor of 0.5 to wait to adjust the learning rate if training accuracy does not improve. In order to address potential overfitting in the model, the regularization techniques used in this architecture assisting in avoiding overfitting and improve the model’s overall performance, which is important for many applications in the real world.

C. Model Evaluation Metrics

This study examined the effectiveness of DL models using a range of metrics, including Precision, Recall, F1-score, and Accuracy. Accuracy was employed to assess the overall performance of the models in predicting the target

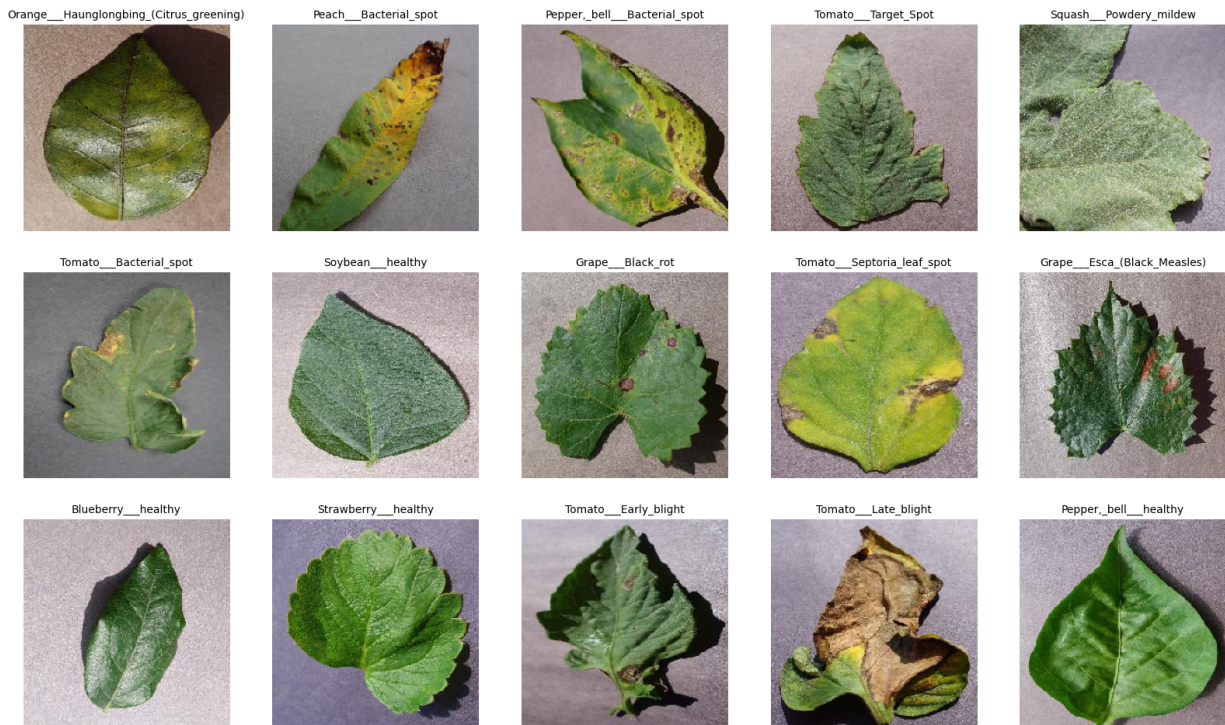


Fig. 2. Sample plant disease in plantVillage dataset.

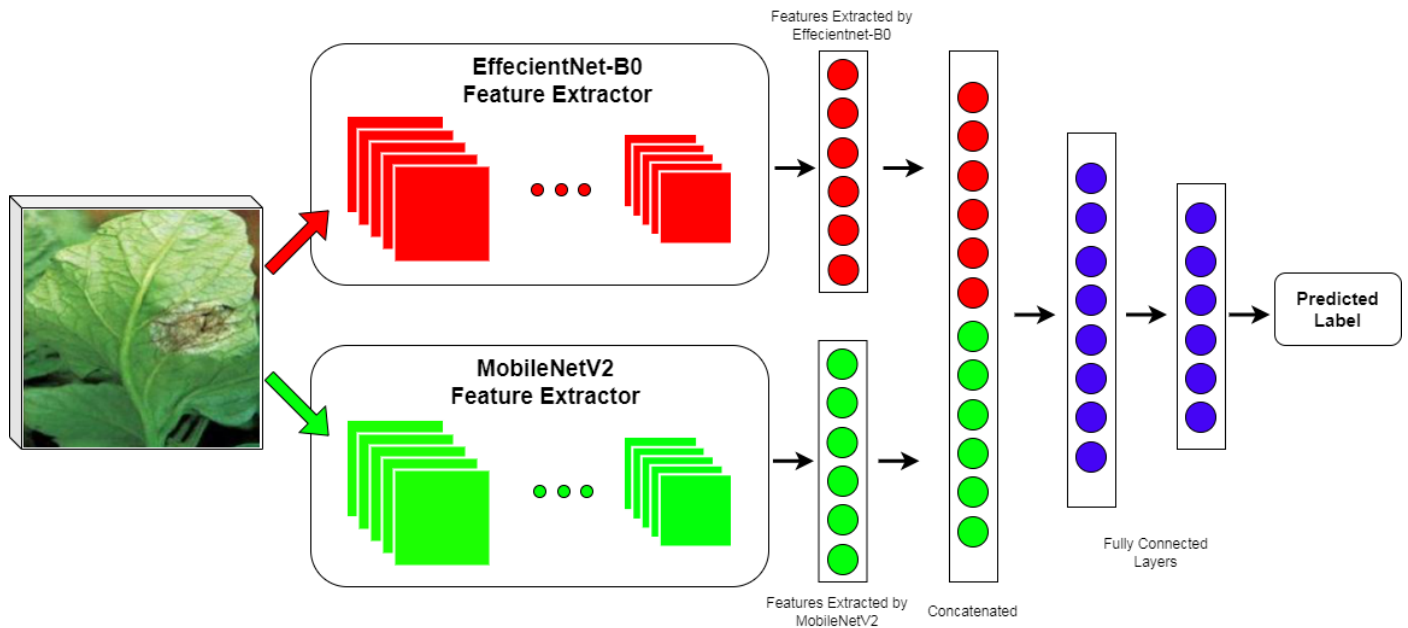


Fig. 3. Proposed model for plant disease classification.

variable. Precision measured the ratio of true positive results to all positive predictions, while recall measured the ratio of true positive predictions to all actual positive instances in the dataset. F1-score, which combines precision and recall, provided a balanced perspective on the model's performance, particularly in scenarios with imbalanced classes. By employing multiple evaluation metrics, we gained a comprehensive understanding of the model's performance and made well-

informed judgments regarding its effectiveness.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

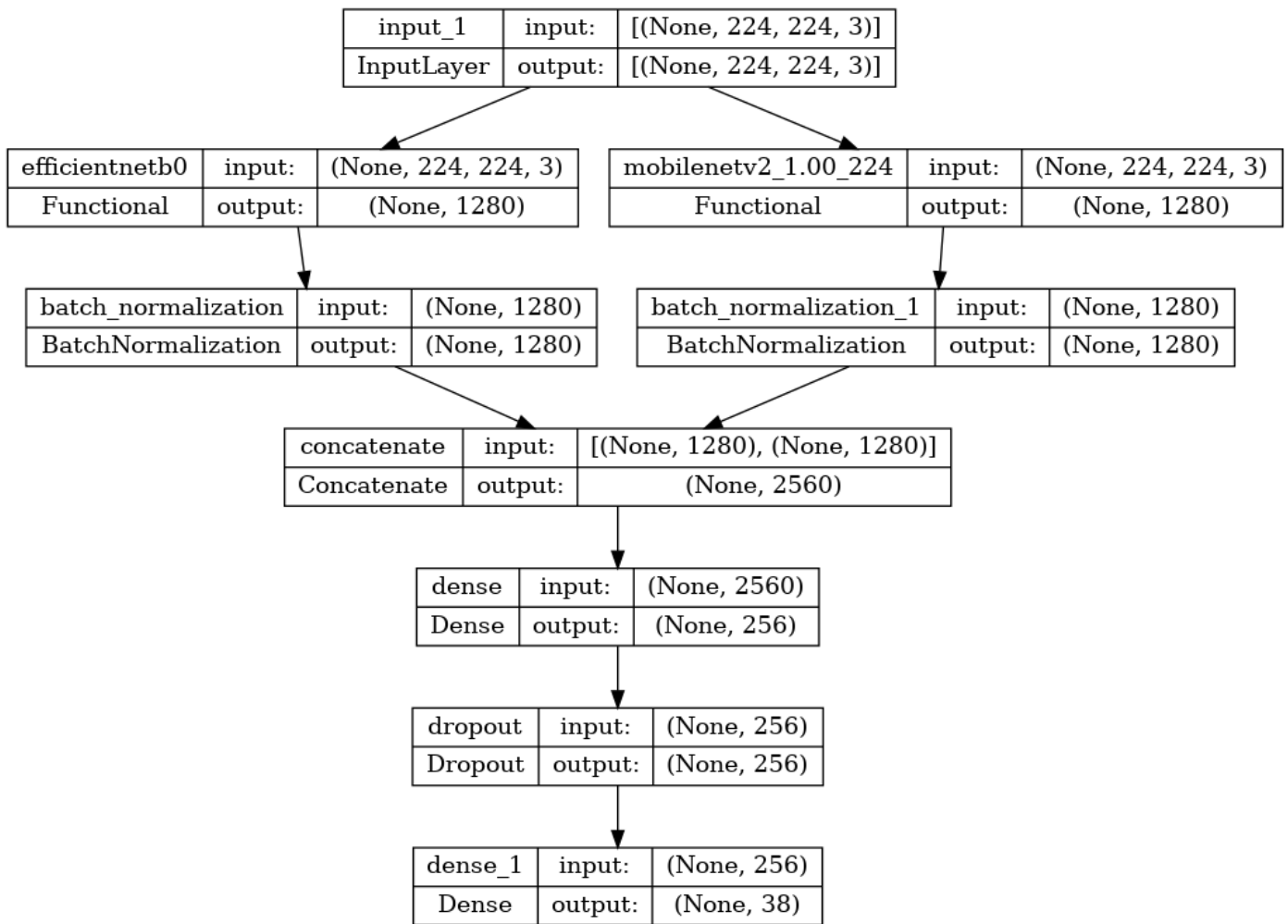


Fig. 4. The architecture of the suggested model is used in this study.

TABLE I. THE LAYERS OF PROPOSED MODEL

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
efficientnetb0 (Functional)	(None, 1280)	4049571
mobilenetv2_1.00_224 (Functional)	(None, 1280)	2257984
batch_normalization (BatchNormalization)	(None, 1280)	5120
batch_normalization_1 (BatchNormalization)	(None, 1280)	5120
concatenate (Concatenate)	(None, 2560)	0
dense (Dense)	(None, 256)	655616
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 38)	9766
Total params: 6,983,177		
Trainable params: 6,901,922		
Non-trainable params: 81,255		

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F_1 - Score = \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

In which, TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative.

D. Results

Table II presents a comparative examination of the suggested model with modern methods on similar problems. The table includes the name of the plant, the quantity of categories, the number of pictures in the dataset, and the method used for detection along with the accuracy rate achieved. The PlantVillage dataset was used for both training and testing the recommended model, containing 54,305 photos of 38 different plant disease classes. According to the findings, the model that was suggested, which combines the output of two transfer learning models, EfficientNetB0, and MobileNetV2, achieved an accuracy rate of 99.77%, which outperformed all other methods listed in the table. According to the results, the suggested approach has the potential to substantially enhance the precision of plant disease classification and provide more reliable automated disease detection systems. The classification report presents the evaluation metrics for each class of plant disease, along with the support values for each class presented in Table III. The report shows that the model performs excellently, with most classes achieving perfect scores for evaluation metrics. The report provides useful insights into the model's capacity to identify and categorize various types of plant diseases. The confusion matrix of the suggested

model results is displayed in Fig. 5 and Fig. 6 presents the metrics that measure the proposed model's performance during both training and validation phases, which include loss and accuracy.

V. CONCLUSION

The presented study highlights the importance of timely identification of diseases that affect plants and the significant losses that can result from their unchecked spread. Traditional methods of disease detection are often inaccurate, time-consuming, and labor-intensive, making it difficult for farmers to efficiently manage their crops. The use of automated disease detection systems based on machine learning algorithms offers an excellent opportunity to improve the accuracy and speed of disease detection. The model for classifying plant diseases that have been suggested, which combines the outputs of two transfer learning models, EfficientNetB0 and MobileNetV2, has demonstrated an accuracy rate of 99.77% in disease classification, indicating its potential to provide more reliable automated disease detection systems.

Furthermore, this study's results offer promising indications that the use of an ensemble of DL models can significantly enhance the accuracy of plant disease classification. The development of more accurate and reliable automated disease detection systems is vital to support sustainable agriculture and global food security, making this study a valuable contribution to this field of research.

VI. FUTURE WORKS

There are several future works that can be pursued based on the findings of this study. First, the model can be tested on different datasets containing images of plant diseases to assess its robustness and generalizability. This will help to determine if the model can be applied to other crops and environments. Second, the model can be integrated into a real-time monitoring system to enable early detection and timely intervention. This will require the design of an easy-to-use interface that can be used by farmers and other stakeholders.

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TABLE II. COMPARE OUR PROPOSED MODEL WITH MODERN METHODS ON SIMILAR PROBLEM

The study	Dataset / Plant Name	The number of classes	The number of images	Method of Use	Accuracy
[12]	Plant Leaf Diseases	39	61,486	CNN model	96.46%
[44]	Soybean Diseases	4	12,673	CNN model	99.32%
[25]	Rice Diseases Dataset	10	500	CNN model	95.48%
[48]	The Tomato Plant	10	4,585	CNN model	99.24%
[27]	PlantVillage's Tomato Crop Dataset	10	18,160	CNN model	99.70%
[43]	PlantVillage's Tomato Crop Dataset	10	3,000	CNN model	98.49%
[49]	Apple Leaf Disease	6	2,462	DenseNet-121	93.71%
[45]	PlantVillage's Apple Crop Dataset	4	2,086	VGG16	90.40%
[35]	PlantVillage' Tomato Leaves Dataset	7	13,262	AlexNet VGG16	97.49% 97.23%
[21]	Grape Leaf Diseases Dataset	4	9,027	EfficientNet B7	98.70%
[13]	The Tomato Plant	9	-	Densenet_Xception	97.10%
[39]	The Tomato Plant	10	17,929	CNN model	98.60%
[42]	The Tomato Plant	10	19,553	VGG19 Inception-V3 Resnet50	99.62% 99.75% 99.50%
[37]	Tomato Plant (PlantVillage and Field)	3	5,225	Inception V3 Inception ResNet V2	99.22% 99.22%
[22]	The Tomato Plant	10	5,524	ResNet-152 EfficientNet-B4 VGG-16	93.75% 97.27% 98.00%
[6]	Tomato Leaf Disease	10	7,301	DenseNet	99.80%
[24]	Apple Leaf Disease	9	11,100	MobileNetV2	96.23%
[4]	Tomato Leaf Diseases	10	11,000	EfficientNetB5 MobileNet Xception VGG16 ResNet50 DenseNet121	99.07% 94.00% 95.32% 93.35% 96.03% 96.30%
[19]	Grape Leaf Diseases	4	3,885	GoogleNet	94.05%
[7]	Tomato Leaves Diseases	9	14,828	GoogleNet AlexNet	99.18% 98.66%
This study	PlantVillage Dataset	38	54,305	EfficientNetB0 + MobileNetV2	99.77%

TABLE III. CLASSIFICATION REPORT

#	Type	Class	Precision	Recall	F1-Score	Accuracy	Support
C1	Apple	Scab	1.00	1.00	1.00	100%	126
C2	Apple	Black Rot	1.00	1.00	1.00	100%	124
C3	Apple	Cedar Apple Rust	1.00	1.00	1.00	100%	55
C4	Apple	Healthy	1.00	1.00	1.00	100%	329
C5	Blueberry	Healthy	1.00	1.00	1.00	100%	300
C6	Cherry (including sour)	Powdery Mildew	1.00	1.00	1.00	100%	211
C7	Cherry (including sour)	Healthy	1.00	0.99	1.00	99.42%	171
C8	Corn (maize)	Cercospora Leaf Spot Gray Leaf Spot	0.95	0.97	0.96	97.09%	103
C9	Corn (maize)	Common Rust	1.00	1.00	1.00	100%	239
C10	Corn (maize)	Northern Leaf Blight	0.98	0.97	0.98	97.46%	197
C11	Corn (maize)	Healthy	1.00	1.00	1.00	100%	232
C12	Grape	Black Rot	1.00	1.00	1.00	100%	236
C13	Grape	Esca (Black Measles)	1.00	1.00	1.00	100%	277
C14	Grape	Leaf Blight (Isariopsis Leaf Spot)	1.00	1.00	1.00	100%	215
C15	Grape	Healthy	1.00	1.00	1.00	100%	84
C16	Orange	Haunglongbing (Citrus Greening)	1.00	1.00	1.00	100%	1101
C17	Peach	Bacterial Spot	1.00	1.00	1.00	100%	460
C18	Peach	Healthy	1.00	0.99	0.99	98.61%	72
C19	Pepper, Bell	Bacterial Spot	1.00	1.00	1.00	100%	199
C20	Pepper, Bell	Healthy	1.00	1.00	1.00	100%	295
C21	Potato	Early Blight	1.00	1.00	1.00	100%	200
C22	Potato	Late Blight	1.00	1.00	1.00	100%	200
C23	Potato	Healthy	1.00	1.00	1.00	100%	31
C24	Raspberry	Healthy	1.00	1.00	1.00	100%	74
C25	Soybean	Healthy	1.00	1.00	1.00	99.9%	1018
C26	Squash	Powdery Mildew	1.00	1.00	1.00	100%	367
C27	Strawberry	Leaf Scorch	1.00	1.00	1.00	100%	222
C28	Strawberry	Healthy	1.00	1.00	1.00	100%	91
C29	Tomato	Bacterial Spot	1.00	1.00	1.00	99.76%	425
C30	Tomato	Early Blight	0.99	0.99	0.99	99.5%	200
C31	Tomato	Late Blight	1.00	0.98	0.99	98.43%	382
C32	Tomato	Leaf Mold	1.00	1.00	1.00	100%	190
C33	Tomato	Septoria Leaf Spot	1.00	1.00	1.00	100%	354
C34	Tomato	Spider Mites Two-spotted Spider Mite	1.00	1.00	1.00	100%	335
C35	Tomato	Target Spot	1.00	1.00	1.00	99.64%	281
C36	Tomato	Tomato Yellow Leaf Curl Virus	1.00	1.00	1.00	99.91%	1072
C37	Tomato	Tomato Mosaic Virus	1.00	1.00	1.00	100%	75
C38	Tomato	Healthy	0.99	1.00	1.00	100%	318

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