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Automation for Tomato Leaf Disease Diagnosis via Transfer Learning and Soft Voting (ToLDD-TLSV)

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The research work describes an enhanced automation system for diagnosing the leaf diseases of tomato crop through transfer learning and soft voting ensemble technique termed as ToLDD-TLSV. While using six preexisting deep learning convolution neural networks like VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet, the method provided an accuracy of 99. 2%. These models are elaborately fine-tuned for the tasks of diagnosing multiple types of diseases affecting tomato plants in a much more precise manner. Adding to this, the use of the soft voting system combined the advantages of these multiple models in the ensemble method and considerably boosted total diagnostic accuracy. Thus, the results confirm the solidity, reliability, and performance of this ensemble technique as a major leap forward in precision agriculture and crops vitality assessment. The concept used in this method also boosts the disease diagnosis accuracy compared to the traditional methods while providing a practical and efficient solution for agricultural purposes on a vast scale, enabling all-round crop management and increased yield. Therefore to conclude this study formulates the basis to build on and improve future automated plant disease diagnosis methods and advancements in agricultural technology. With this prospect, this research stands to enhance precision agriculture on the following grounds: It can enhance disease management and decrease crop loss increasing the security of the food.

Keywords: Ensemble Learning, Tomato Leaf Disease, Soft Voting, Transfer Learning, ToLDD-TLSV.

1. Introduction

The use of artificial intelligence in the specific area of agriculture has however been increasing and CNNs have turned out to be indispensable in plant pathology. The intended and named research paper is titled "Innovative Approach to Tomato Leaf Disease Diagnosis via Transfer Learning and Soft Voting (ToLDD-TLSV)" and its domain is related to crop leaf disease detection. The given strategy is based on the principle of transfer learning and ensemble learning in order to optimize the disease classification task that plays a vital role in the early detection of diseases and disease management in crops. Transfer learning simply borders that, after training some of the earlier models such as VGG16, Inception Net, ResNet, Mobile Net, Efficient Net, and Dense Net using gigantic and more diversified data sets, Some of these pre-trained models are capable of training on large amounts of data and identifying intricate features that can be transferred to work on a few data as wanted. In our work, we incorporate the use of these existing pre-trained models to boost CNN's efficiency in the differentiation of healthy and diseased tomato leaves. Therefore, given the fact that Rich features are learned by these models, the goal shall be to obtain high accuracy and reliability of classification.

In addition to, transfer learning, we employ ensemble learning especially soft voting in order to improve the classification results. Ensemble learning is applicable to the idea of generating different varieties of CNNs and getting improved diagnostic outcomes from the results obtained from all the different varieties. The majority voting strategy which stands as the nucleus of the proposed ensemble approach receives the benefits from the individual models while being the least affected by their bias at the same time. This method brings a brilliant improvement in diagnostic accuracy because of the multi-weakness and multi-strength features of the various CNN structures that improve the capability of identifying tomato leaf diseases.

Therefore, the results of the present study support ensemble learning for agricultural diagnostics and show a massive improvement in disease detection rates compared with unique CNN techniques. This study therefore makes a significant input to both the improvement of food security and improving on sustainable practices in agriculture through assimilating and applying progressive AI techniques to conventional agricultural practices. It underscores the possibilities AI solutions present for the enhancement of crop management practices, thus promoting the durability of the worldwide food supply system in the context of agriculture's volatility. With this in mind, the suggested strategy may help to create a pro-active basis for early disease diagnosis and efficient crop protection, which are obligatory for sustainable agriculture and the health of the global food chain.

Applications of the convolutional neural network are many and they include MRI image classification[1], video shot boundary detection[2] and Object detection[3]. On its part, the research conducted by Hase A. K. et. al. and Algani et al. In [4], [5] examine deep learning technologies for plant disease identification and discuss the modern trends and uses of diagnosis in the agricultural field. A combine innovative method concerning deep learning for the identification of tomato leaf diseases and its classification is designed and established by Trivedi N. K et al. in [6] using more than one neural network approaches. Thus, the ToLeD model is introduced that utilizes CNN to detect tomato leaf diseases and indicates an effective use of deep learning to improve agricultural disease control M Agarwal, et al. [7]. This paper affirms that applied deep learning by Amara, J. et al. Banana leaf diseases and other plant diseases can easily be diagnosed in real farming areas and this has been made possible by the application of neural networks and this is very useful in increasing the yield of banana production [8]. In the research work [9], Barbedo, J. G. A discussed different factors affecting utilization of deep learning for crop disease diagnosis facilities namely data quality, model structures, and environmental parameters.

A system is implemented using deep learning for the detection of tomato leaf diseases and the identification of the symptoms that may be present, which establishes the approach's efficiency for revealing comprehensive characteristics of diseases [10]. This is proved effectively by Chen J. et al. in [11] who experimented with the CNNs and transfer learning for crop disease detection where they seen that transfer learning has a major improvement on the model performance even where training data is very limited. Other researchers[12] have also proposed an integration of the bacterial scavenging technique in a convolutional neural network for enhancing the model's performance on plant leaf disease identification. Deep Neural Network based models for detecting diseases in millet crops were studied by several researchers[13], who used transfer learning to enhance the accuracy and efficiency of the diagnoses [2013]. Research studies, for instance, on DCNN for the prognosis of crop leaf ailments are critiqued to establish and demonstrate the advantages and pitfalls of differing CNN configurations and their usage in plant pathology [14].

Analyzing different models of deep learning for crop disease detection, it is noted that they demonstrate high accuracy and can significantly transform the agriculture industry through the introduction of new reliable methods of diseases identification [15]. The researchers illustrated the application of Deep Learning in tomato crop diseases, pest' detection, and demonstrated the practical feasibility of employing the techniques for monitoring and managing crop surveillance[16] [17]. Annotated image diagnostic methods of plant health disorders were created and introduced including a number of media processing algorithms using a range of AI methodologies to increase the reliability of the diagnosis [18], [19], [20]. Some recent studies comparing different algorithmic procedures of neural networks for plant leaf disease classification have pointed the advantages and the disadvantages of each of these methods[21], [22]. A research work [23] provides an outline of the model, multiple Convolutional Neural Networks in the identification of grape leaf diseases, and the significance of using multiple neural networks for better results.

A comprehensive survey of the applications of DL in farming [24], highlighting its effectiveness in areas such as crop and soil management, disease detection, and precision farming is published. A deep convolutional neural network with an attention mechanism is used by the researchers [25] for the Identification of Apple Leaf Diseases which has given satisfactory accuracy. Much research work [26], [27], [28] is done on utilizing deep CNN for rice disease identification, demonstrating the potential of CNNs in accurately diagnosing plant diseases. Research work was done and explored real-time plant disease recognition using transfer learning, showcasing the practical application of AI in real-time agricultural monitoring [29], [30]. Machine Learning is used to measure the cases of crop disease &the percentage of infection from the images of leaves, offering valuable insights into automated plant health assessment [31], [32]. The system uses the diseased and healthy images for training and CNN fetches the various features during training and learns. The learned algorithm achieves very high accuracy.

2. Method

This section contains a detailed introduction to the dataset, the proposed model, and the application of ensemble using soft voting.

2.1 Dataset

The Plant Village dataset is an extensive image collection intended for crop disease identification and classification. This study concentrates on tomato imagery, although it covers a wide range of crops, including tomatoes, potatoes, grapes, apples, corn, blueberries, raspberries, soybeans, squash, and strawberries. Several classifications covering both disease-affected and healthy plants are included in the dataset. The dataset specifically covers diseases including tomato Bacterial Spot, tomato Mosaic Virus, tomato Spider Mites, tomato Bacterial Spot, tomato Early Blight, tomato Late Blight, tomato Leaf Mold, and tomato Septoria Leaf Spot. There are 1500 photos in each disease category, many of which are used in experiments and analysis.

2.2 ToLDD-TLSV - Proposed Model

The design of the ToLDD-TLSV system, which combines ensemble soft voting and transfer learning to enhance crop leaf disease detection, especially with regard to tomato leaves, is illustrated in Figure 1. The image dataset—specifically, the tomato leaf dataset—comes from Plant Village. In order to get ready for machine learning model training, raw image data must go through necessary changes including scaling, normalization, and noise reduction during the image preprocessing stage. Furthermore, image augmentation techniques are used to improve model robustness by increasing dataset variety through zooms, flips, translations, and rotations. After that, the dataset is divided into training and validation sets, as well as a test set for assessment.Pre-trained CNN models, such as VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet, are used for the image classification task during the model learning phase. The tomato leaf disease dataset is used to refine these models once they have been pre-trained on sizable datasets. Every model gains proficiency in classifying diverse crop leaf diseases, enhancing its capacity to recognize and differentiate between diverse conditions impacting tomato plants. Weights that have been pre-trained on the ImageNet dataset are initialized for each model. Three RGB color channels and 224x224 pixels are the typical for input image sizes.

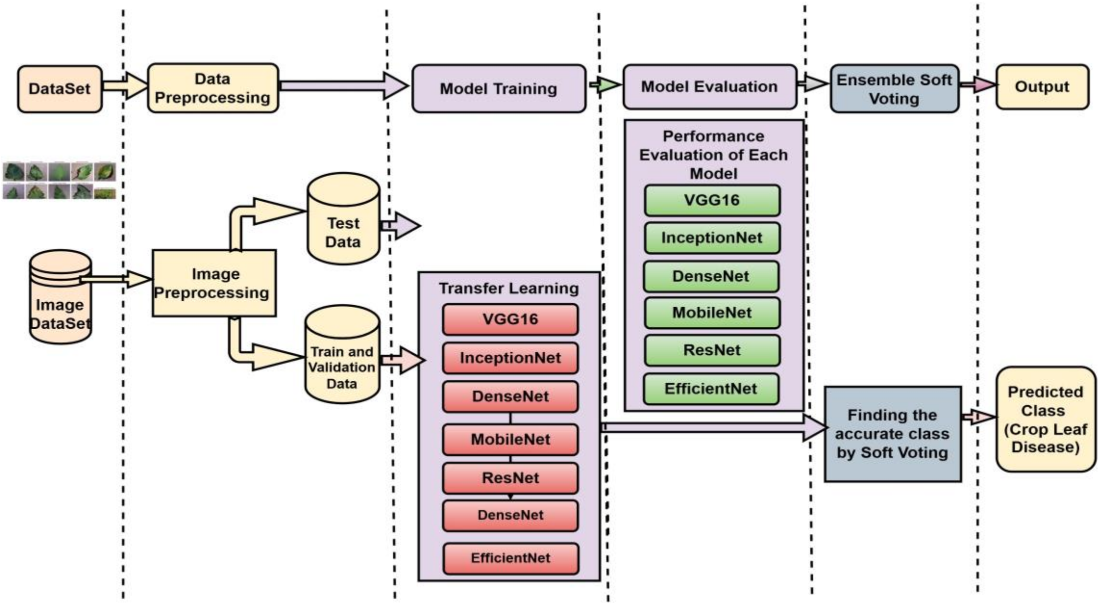


Figure 1: The suggested model's system architecture

A layer of GlobalAveragePooling2D by taking the average of every element in each map, ToLDD-TLSV eliminates the requirement for a completely connected layer, hence reducing the spatial dimensions of feature maps. Understanding complex patterns is made possible by a fully connected layer that comes next, featuring 1024 units and ReLU activation. The final output layer uses a softmax activation function and is designed for the multi-class classification of tomato leaf diseases, which include 10 classes. To minimize loss, the step size during training epochs is determined by the learning rate, which in our model is set at 0.00001. While exact convergence is encouraged by a decreased learning rate, training times may increase. The effectiveness of each pre-trained model—InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet—in identifying agricultural leaf diseases is assessed separately. Transfer Learning is the process of using pre-trained models to improve overall performance in image categorization. The performance of the VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet during training and validation is examined. The networks were trained using data on tomato leaf disease. To be used at a later time, the trained and verified models are preserved on disk.

2.3 Applying Ensembling with Soft Voting for Enhancing Classification Accuracy

In order to increase classification accuracy, ensemble soft voting is employed. Figure 2 below shows how the soft voting system operates. Algorithm 1 is the written and printed version of the Ensemble Learning utilizing Soft Voting (ToLDD-TLSV) algorithm. The method uses six pre-trained image classification models to soft vote to determine the final predicted class name. It displays the pseudo-code for this process.

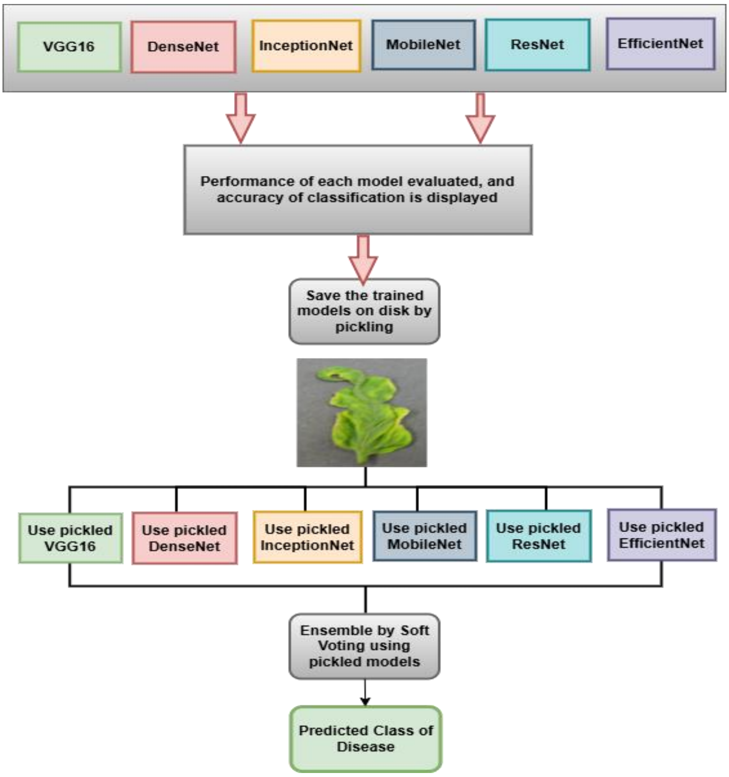


Figure 2: Ensemble Learning using Soft Voting ToLDD-TLSV

Algorithm 1 Ensemble Learning using Soft Voting (ToLDD-TLSV)

Input: Diseased Crop Leaf Instances
Output: $C_{\text{ToLDD-TLSV}}$ Class name of disease
Load the pickled models: VGG16, DenseNet, InceptionNet, MobileNet, ResNet, EfficientNet
Preprocess the input test instance images
Initialize an array A to store predicted probabilities for each model
for each test instance **do**
    Obtain predicted probabilities $P_V, P_I, P_D, P_M, P_R, P_E$
    Store the predicted probabilities in the array A
end for
Calculate $\text{Prob}_{\text{ToLDD-TLSV}}$ average predicted probabilities for each class across the models:
Initialize an array to store average probabilities
for each class **do**
    Calculate the average probability by averaging corresponding probabilities from all models
end for
$C_{\text{ToLDD-TLSV}} = \max(\text{Select label which has the maximum average probability } \text{Prob}_{\text{ToLDD-TLSV}})$
Output $C_{\text{ToLDD-TLSV}}$ the final predicted class name

Using an ensemble approach called "soft voting," the projected probabilities of each model are averaged, and the class with the highest average probability is identified as the final predicted class. Equations (1) and (2) are derived mathematically and are utilized in the ToLDD-TLSV algorithm's implementation.

$$\mathrm{Prob}_{\mathrm{ToLDD-TLSV}} = \frac{(P_V + P_I + P_D + P_M + P_R + P_E)}{6} \qquad (1)$$

Where,

$\mathrm{Prob}_{\mathrm{ToLDD-TLSV}}$ is average of probabilities predicted for each class for soft voting

P_V is predicted probabilities by VGG16

P_I is predicted probabilities by Inception

P_D is predicted probabilities by Densenet

P_M is predicted probabilities by Mobilenet

P_R is predicted probabilities by Resnet

P_E is predicted probabilities by Efficientnet

$$C_{\mathrm{ToLDD-TLSV}} = \max(\mathrm{Prob}_{\mathrm{ToLDD-TLSV}}) \qquad (2)$$

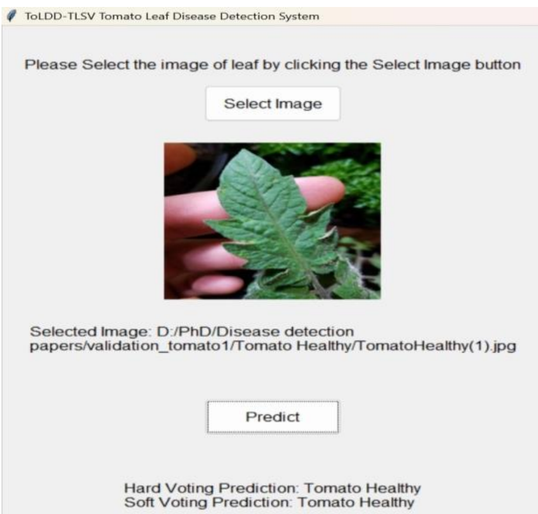
Where,

$\mathrm{Prob}_{\mathrm{ToLDD-TLSV}}$ is average of probabilities predicted for each class for soft voting

$C_{\mathrm{ToLDD-TLSV}}$ is Class predicted by proposed model ToLDD-TLSV

3. Results and Discussion

The trained ensembled model is tested through a desktop application developed which will ask to input the image of a leaf and display the detected class of disease for the leaf. The desktop application screenshot for healthy leaf prediction is shown in Figure 3(a) and the image with disease and the name of disease is shown in Figure 3(b)



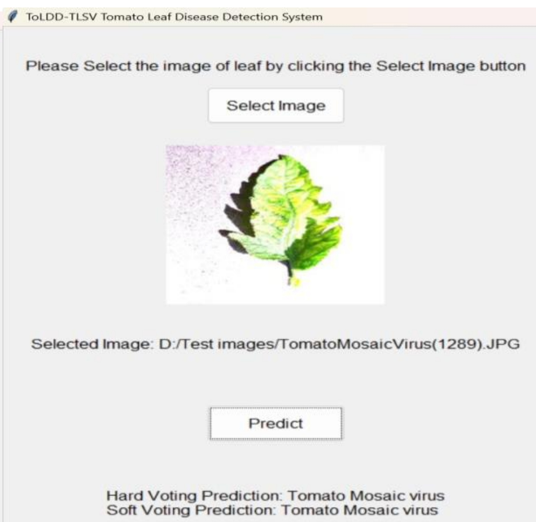


Figure 3(a): Screenshot of desktop application that predicted healthy leaf

Figure 3(b): Screenshot of desktop application that predicted diseased leaf

All the models were trained using a dataset of tomato leaf diseases, and their performance was assessed using accuracy measures throughout all epochs. A sample classification report of VGG16 is shown in Table 1. The accuracy trends over epochs are shown in Figure 4. A consistent rising trajectory in the training accuracy showed that the system was continuously learning from the training set. Simultaneously, the validation accuracy also rose, though sporadically a common occurrence in deep learning training showing strong generalization to previously unseen data. Figure 4 shows how the training loss for InceptionNet, DenseNet, and VGG16 steadily dropped as the epochs went on. This decrease indicates that training was successful in minimizing errors and promoting learning. DenseNet and InceptionNet also exhibit comparable performance metrics, such as training and validation accuracy, as well as training and validation loss.

Table 1. Classification Report of VGG16

Disease	Precision	Recall	F1-Score	Support
Tomato Bacterial spot	0.93	0.97	0.95	301
Tomato Early blight	0.99	0.9	0.94	298
Tomato Healthy	0.96	1	0.98	334
Tomato Late blight	0.88	0.96	0.92	302
Tomato Leaf Mold	0.99	0.8	0.89	272
Tomato Mosaic virus	0.99	0.98	0.99	302
Tomato Septoria leaf spot	0.88	0.93	0.91	294
Tomato Spider mites	0.85	1	0.92	305
Tomato Target Spot	0.85	0.85	0.85	297
Tomato Yellow Leaf Curl Virus	0.98	0.94	0.96	295

Metric	Value
Accuracy	92.6
Macro Average	92.9
Weighted Average	93.1

Notable findings from the classification report include high precision scores for diseases including tomato mosaic virus (0.99), tomato leaf mold (0.99), and tomato early blight (0.99), which show a low rate of false positives. With recall scores of 1.00, Tomato Healthy and Tomato Spider mites were the most successful, indicating that almost all real cases were accurately identified. Precision, recall, and F1-scores for Tomato Bacterial Spot (0.95) and Tomato Yellow Leaf Curl Virus (0.96) were found to be in balance. With a total accuracy of 92.6%, the model was shown to be accurate in classifying 92.6% of tomato diseases.

Pre-trained models such as DenseNet, InceptionNet, MobileNet, ResNet, and EfficientNet were also trained and assessed. With an accuracy of 97.83%, DenseNet was the most accurate, followed by InceptionNet with 95.61%. ResNet (95.12), MobileNet (94.3), and EfficientNet (96.7) are the accuracy values of other pre-trained models. A comparison graph showing these pre-trained models' classification accuracies is shown in Figure 5. The "Training Accuracy and Validation Accuracy" graph illustrates how different deep learning models behave in terms of accuracy on training and validation datasets.

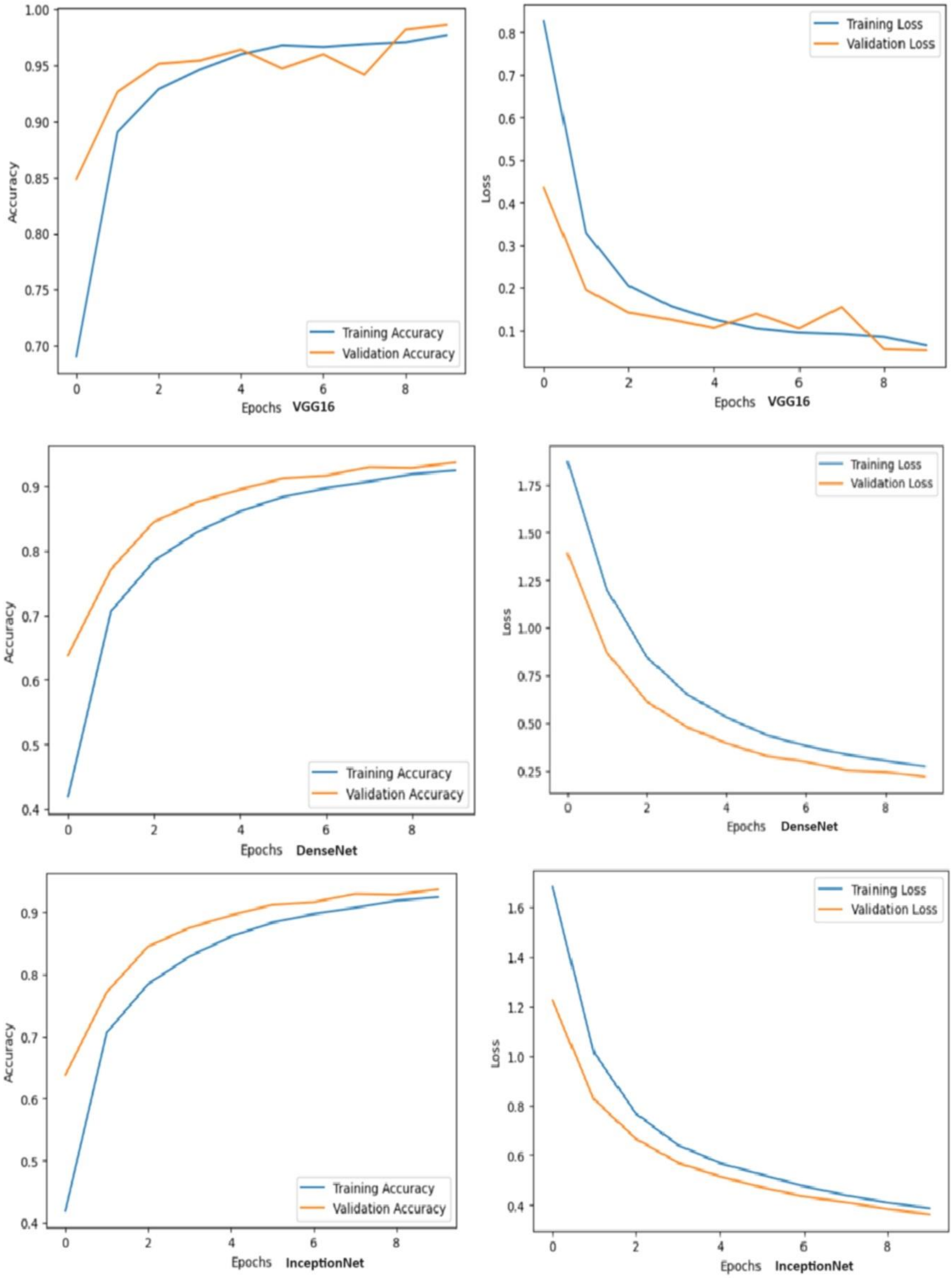


Figure 4: Graph of VGG16, DenseNet, and InceptionNet for Training, Validation Accuracy Vs Number of epochs and Training, Validation Loss Vs Number of epochs

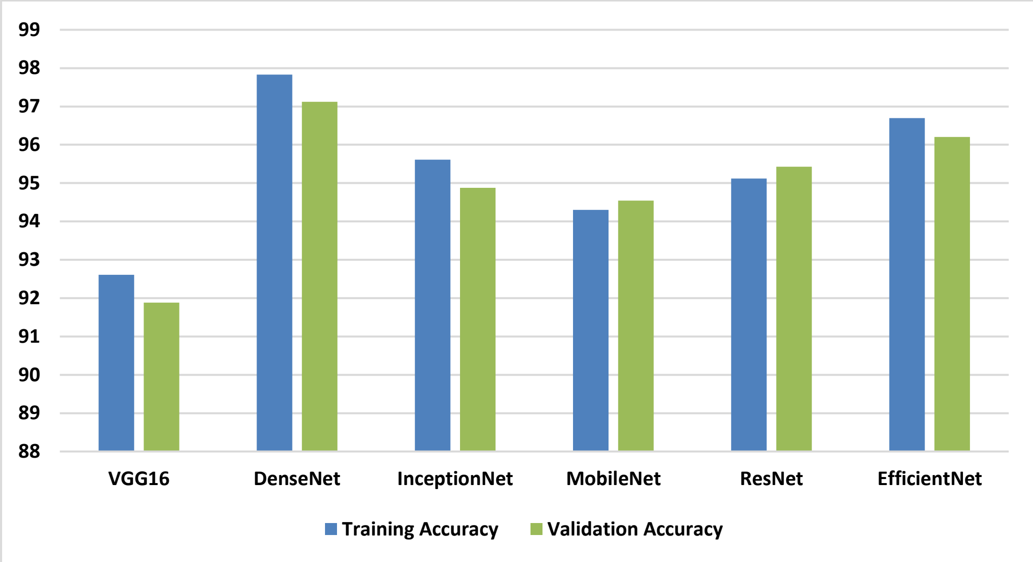


Figure 5: Comparison graph of training and validation accuracy for models VGG16, InceptionNet, ResNet, MobileNet, EfficientNet and DenseNet

Figure 5's graph displays a 92% training accuracy and a 90% validation accuracy for the VGG16. Potential overfitting is indicated by the model's marginally superior performance on training data as opposed to validation data. DenseNet has a 98% training accuracy and a 96% validation accuracy. DenseNet has good performance with only a small amount of overfitting, with very high training accuracy and slightly lower validation accuracy. Comparably, the DenseNet and InceptionNet models, which have respective accuracy percentages of 96% and 95% on training and validation sets, show strong generalization and little overfitting.The validation accuracy was 92% and the training accuracy of MobileNet 94%. The moderate discrepancy in accuracy between training and validation for MobileNet indicates some overfitting but overall strong performance. 94% validation accuracy and 95% training accuracy for ResNet. ResNet exhibits good generalization with a small gap and high accuracy for both training and validation sets. 97% of training and 95% of validation accuracy are achieved with EfficientNet. Additionally, EfficientNet exhibits excellent performance and outstanding generalization with very high training accuracy and somewhat lower validation accuracy with a tiny gap.

To increase the accuracy of tomato leaf disease identification in the experiment, we assembled three pre-trained deep learning models, including VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet. The models were pickled for later use after being independently trained and validated on the 1500 photos for 10 different classes in the tomato leaf disease dataset. Next, we used the ensemble soft voting method. Table 2 prints the classification report for the ToLDD-TLSV model. Table 3 displays the individual model's performance both before and after the ensemble. Soft voting was used to assemble VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet, which increased tomato leaf disease detection accuracy and robustness.

Table 2: The report of for ToLDD-TLSV Model

Disease	Precision	Recall	F1-Score	Support
Tomato Bacterial spot	0.99	0.99	0.99	301
Tomato Early blight	0.992	0.92	0.955	298
Tomato Healthy	1	0.988	0.994	334
Tomato Late blight	0.985	0.98	0.9825	302
Tomato Leaf Mold	0.989	0.985	0.987	272
Tomato Mosaic virus	0.987	0.993	0.99	302
Tomato Septoria leaf spot	0.968	0.983	0.975	294
Tomato Spider mites	0.94	1	0.969	305
Tomato Target Spot	0.96	0.973	0.9665	297
Tomato Yellow Leaf Curl Virus	0.993	0.993	0.993	295
Metric	Value			
Accuracy	-	-	0.9861	3000
Macro Average	0.9872	0.9862	0.9865	3000
Weighted Average	0.9863	0.9864	0.9865	3000

Table 3: Accuracy Values in Various Scenario

Pre-trained Models	Before Ensembling		After Ensembling Accuracy
	Training Accuracy	Validation Accuracy	
VGG16	92.61	91.88	98.61
DenseNet	97.83	97.12	
InceptionNet	95.61	94.88	
MobileNet	94.3	94.54	
ResNet	95.12	95.43	
EfficientNet	96.7	96.2	

The graph in Figure 6 illustrates the slight advantage in validation accuracy between the two techniques: before ensemble and after ensemble using soft voting.

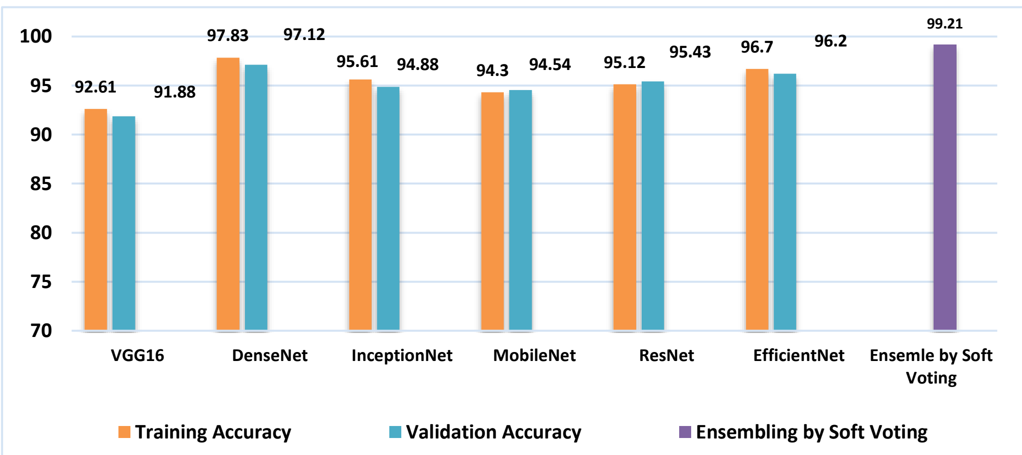


Figure 6: Comparison graph of accuracies before and after Ensemble for models VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet with ToLDD-TLSV

The confusion matrix is printed to find the correctly classified and misclassified instances before ensembling and after ensembling. The confusion matrix after ensembling is shown in below Figure 7. The correctly classified instances are very large i.e. approximately 99% and the misclassified instances are very less or negligible. It is observed that the tomato leaf mold class has less number of correctly classified instances and more misclassified instances.

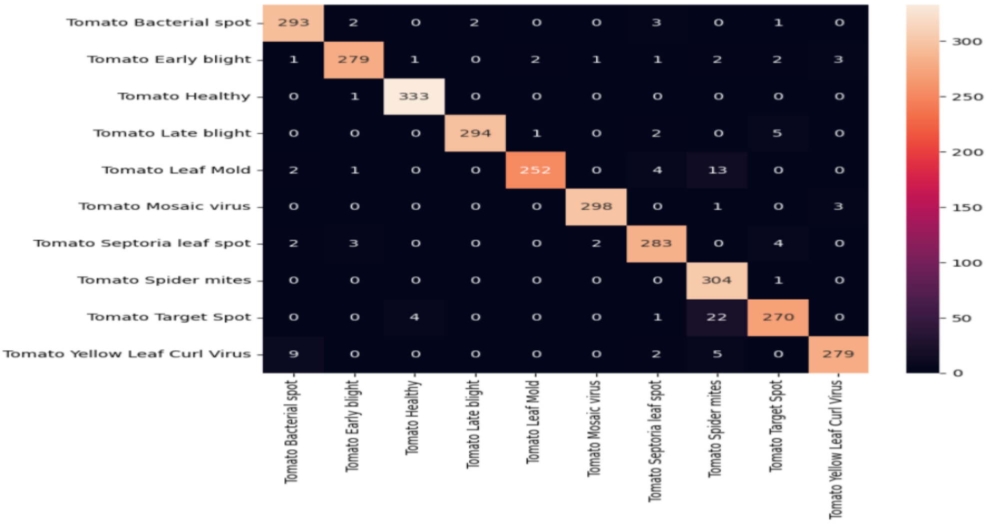


Figure 7: Confusion Matrix showing number of correctly classified and misclassified instances

4. Conclusion

In order to automate the detection of leaf diseases in tomato crops, the research presents a novel model called ToLDD-TLSV that makes use of CNN and transfer learning techniques. The study greatly improves classification accuracy in differentiating between damaged and healthy tomato leaves by utilizing pre-trained models such as VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet. By combining the advantages of distinct models, the suggested model uses ensemble learning via soft voting to increase prediction resilience and reliability. By allowing the CNN models to learn from large datasets like ImageNet, transfer learning plays a critical role in improving the models' capacity to precisely classify leaf diseases. By combining the results of multiple models, this method reduces biases and errors that are common in solo models. With ToLDD-TLSV, classification accuracy increased significantly as evidenced by the findings, which show an astounding 99.2% accuracy through soft voting. High recall and precision rates are shown by VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet for a variety of tomato illnesses. ToLDD-TLSV, a recently created model, has practical implications that include targeted therapies for higher agricultural yield and early disease identification to minimize crop loss. Its capacity to adapt to different crops increases its usefulness in a wider range of agricultural applications and greatly increases agricultural productivity.

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