VotTomNet: Voting-based tomato disease diagnosis with transfer learning

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ABSTRACT

The research presents an advanced automation system, termed VotTomNet, designed for diagnosing tomato leaf diseases using transfer learning, and soft and hard voting ensemble techniques. By leveraging six pre-trained deep learning convolutional neural networks—VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet—the system achieved an impressive accuracy of 99.2%. These models were meticulously fine-tuned to diagnose multiple types of tomato diseases with heightened precision. The integration of a soft and hard voting mechanism further enhanced the overall diagnostic accuracy by combining the strengths of these diverse models into a powerful ensemble. The findings underscore the robustness, reliability, and effectiveness of this ensemble technique, marking a significant advancement in precision agriculture and crop health assessment. By outperforming traditional methods, this approach offers a more practical and efficient solution for large-scale agricultural applications, enabling comprehensive crop management and improved yield. In conclusion, this research lays a strong foundation for future innovations in automated plant disease diagnosis and agricultural technology. Its contributions have the potential to revolutionize disease management, reduce crop losses, and ultimately enhance food security on a global scale.

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1. INTRODUCTION

The use of artificial intelligence in agriculture has seen significant growth, with convolutional neural networks (CNNs) becoming essential in plant pathology. This research paper focuses on detecting crop leaf diseases. The proposed strategy combines transfer learning and ensemble learning to optimize disease classification, a critical aspect of early disease detection and crop management. Transfer learning leverages pre-trained models—such as VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet—that have been trained on large, diverse datasets. These models, capable of learning complex features, can then be adapted to work on smaller, specific datasets. In our research, we utilize these pre-trained models to enhance CNN performance in distinguishing between healthy and diseased tomato leaves. The rich features learned by these models aim to deliver high accuracy and reliable disease classification. In addition to transfer learning, we incorporate ensemble learning, particularly soft and hard voting techniques, to improve classification accuracy. Ensemble learning involves generating various CNN architectures and integrating their outputs to achieve better diagnostic results. The majority voting approach at the core of the proposed ensemble method benefits from the strengths of individual models while minimizing their biases. This technique significantly enhances diagnostic accuracy by harnessing the diverse strengths and weaknesses of multiple CNN structures, improving the model's ability to detect tomato leaf diseases. The findings of this study demonstrate that ensemble learning offers a substantial improvement in agricultural diagnostics, with notably higher disease detection rates compared to using individual CNN techniques. It highlights the potential of AI solutions to enhance crop management practices, reinforcing the stability and sustainability of the global food supply system amid agriculture's inherent uncertainties. In conclusion, the proposed strategy provides a proactive framework for early disease detection and effective crop protection, essential for sustainable agriculture and maintaining a healthy 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, Hase *et. al.* [4] and Algani *et al.* [5] examine deep learning technologies for plant disease identification and discuss the modern trends and uses of diagnosis in the agricultural field. A combined innovative method concerning deep learning for the identification of tomato leaf diseases and their classification is designed and established by Trivedi *et al.* [6] using more than one neural network approach. 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 Agarwal *et al.* [7]. This paper affirms that applied deep learning by Amara *et al*. [8], where 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 which is very useful in increasing the yield of banana production. Barbedo [9] discussed different factors affecting the 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 in revealing comprehensive characteristics of diseases [10]. This is proved effectively by Chen *et al.* [11], who experimented with the CNNs and transfer learning for crop disease detection where they see that transfer learning has a major improvement on the model performance even where training data is very limited. Other researchers [12] have also proposed the 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, who used transfer learning to enhance the accuracy and efficiency of the diagnoses [13]. 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 disease identification [15]. The researchers illustrated the application of deep learning in tomato crop diseases and 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]–[20]. Some recent studies comparing different algorithmic procedures of neural networks for plant leaf disease classification have pointed out the advantages and the disadvantages of each of these methods [21], [22]. Ji *et al.* [23] provide an outline of the model, multiple CNNs 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] highlights its effectiveness in areas such as crop and soil management, disease detection, and precision farming. A deep convolutional neural network with an attention mechanism is used by Wang *et al*. [25] for the identification of apple leaf diseases which has given satisfactory accuracy. Many research works [26]–[28] are utilizing deep CNN for rice disease identification, demonstrating the potential of CNNs in accurately diagnosing plant diseases. The other research works [29], [30] explored real-time plant disease recognition using transfer learning, showcasing the practical application of AI in real-time agricultural monitoring. Machine learning is used to measure the cases of crop disease and 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. From the above study of the literature, the following scientific questions arise. Can transfer learning be used for identifying leaf diseases? Using the majority voting technique, is it possible to improve the accuracy of the classification algorithm? Can we improve the yield of crops by early detection of leaf diseases using transfer learning and soft voting?

2. PROPOSED METHOD

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

2.1. Dataset

The plant village dataset is a comprehensive collection of images designed for the identification and classification of crop diseases. While this study focuses specifically on tomato images, the dataset spans a variety of crops, including potatoes, grapes, apples, corn, blueberries, raspberries, soybeans, squash, and strawberries. It includes classifications for both diseased and healthy plants. For tomatoes, the dataset covers several diseases such as bacterial spots, mosaic viruses, spider mites, early blight, late blight, leaf mold, and septoria leaf spots. Each disease category contains approximately 1,500 images, many of which are utilized for experimentation and analysis in this study.

2.2. VotTomNet: The proposed model

The design of the VotTomNet system, which combines ensemble soft and hard voting with transfer learning to enhance crop leaf disease detection, especially about tomato leaves, is illustrated in Figure 1. The image dataset—specifically, the tomato leaf dataset—comes from Plant Village. 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 typical for input image sizes.

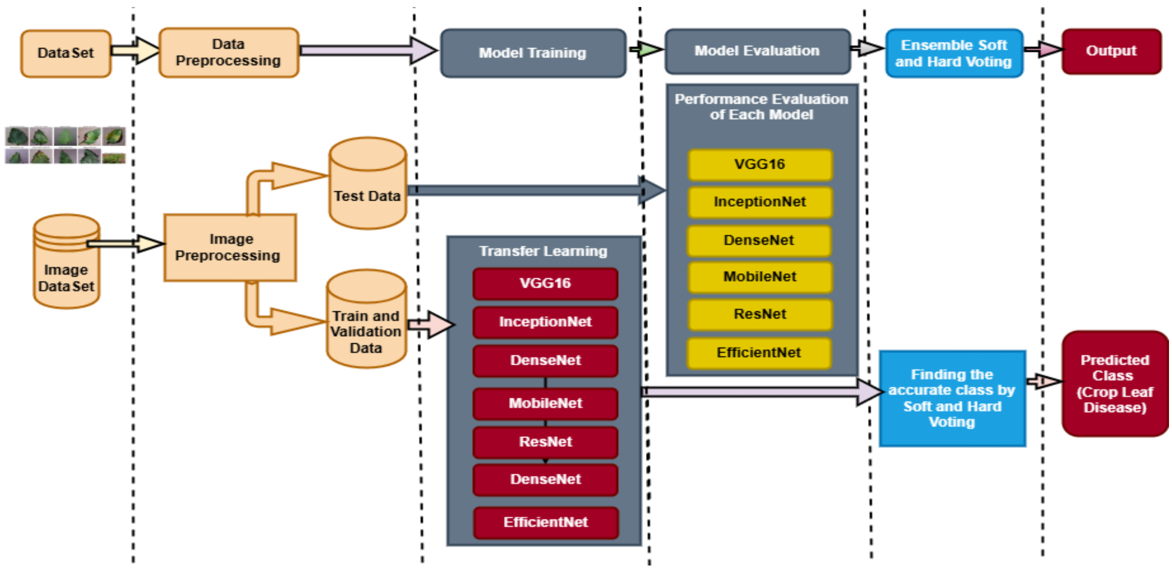


Figure 1. The suggested model's system architecture

A layer of GlobalAveragePooling2D by taking the average of every element in each map, VotTomNet 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 1,024 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 and hard voting for enhancing classification accuracy

In order to increase classification accuracy, ensemble soft voting and hard voting are employed. Algorithm 1 is a written and printed version of the ensemble learning utilizing soft and hard voting (VotTomNet) algorithms. 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.

Algorithm: Ensemble learning using soft and hard voting (VotTomNet)

```
Input: Diseased Crop Leaf Instances
Output: Class name of diseaseC_VotTomNet
1. Load the pickled models: VGG16, DenseNet, InceptionNet, MobileNet, ResNet, EfficientNet
2. Preprocess the input test instance images
3. Initialize an array to store predicted probabilities for each model
4. For each test instancedo:
a. Obtain predicted probabilities from VGG16, DenseNet, InceptionNet, MobileNet, ResNet,
EfficientNet
b. Store the predicted probabilities in the array
End for
5. Calculate average predicted probabilities for each class across the models:
- Initialize an array to store average probabilities
- for each classdo
Calculate the average probability by averaging corresponding probabilities from all models
End for
6. Select the class label which is having maximum average probability as the final predicted
class
7. Output the final predicted class nameC_VotTomNet
```

Using an ensemble approach called soft and hard voting, the projected probabilities of each model are averaged, and the class with the highest average probability is identified as the final predicted class. The VotTomNet algorithm's implementation utilizes (1) and (2), which are derived mathematically.

$$Prob_{VotTomNet} = \frac{(P_V + P_I + P_D + P_M + P_R + P_E)}{6} \quad (1)$$

where
$Prob_{VotTomNet}$ is average of probabilities predicted for each class for soft and hard 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

$$C_{VotTomNet} = max(Prob_{VotTomNet}) \quad (2)$$

where
$Prob_{VotTomNet}$ is average of probabilities predicted for each class for soft voting
$C_{VotTomNet}$ is class predicted by proposed model VotTomNet

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, as shown in Figure 2. The desktop application screenshot for healthy leaf prediction is shown in Figure 2(a) and the image with leaf disease and the name of the disease i.e. tomato mosaic virus is shown in Figure 2(b).

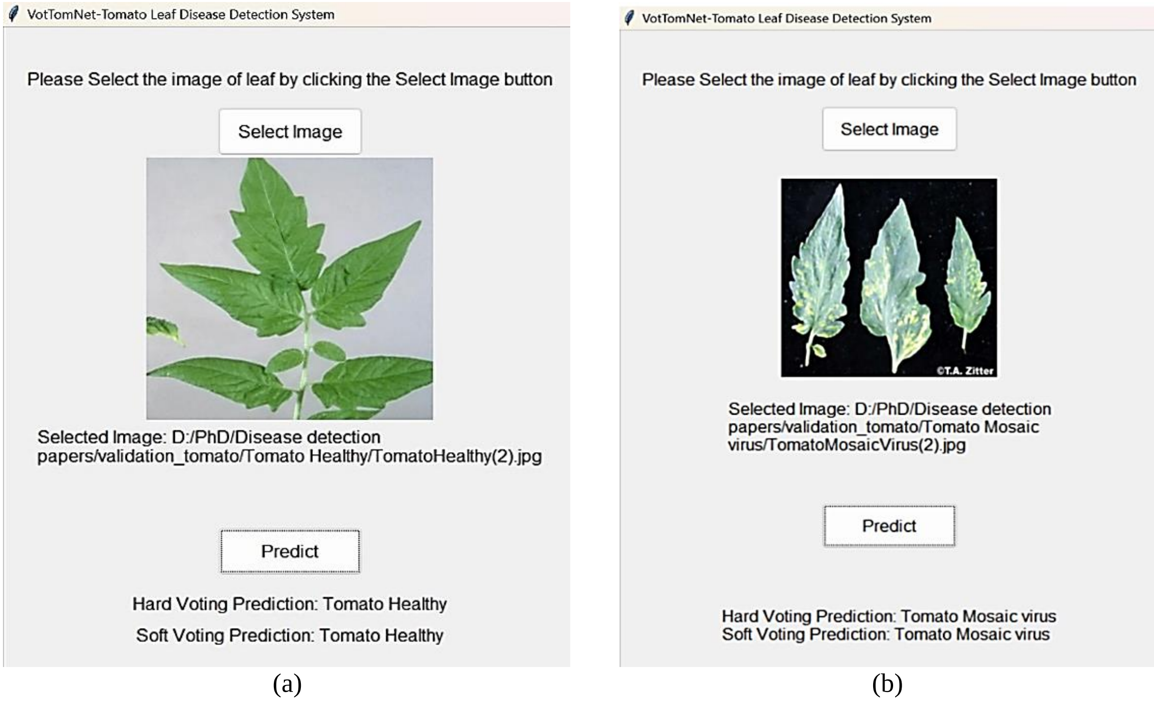


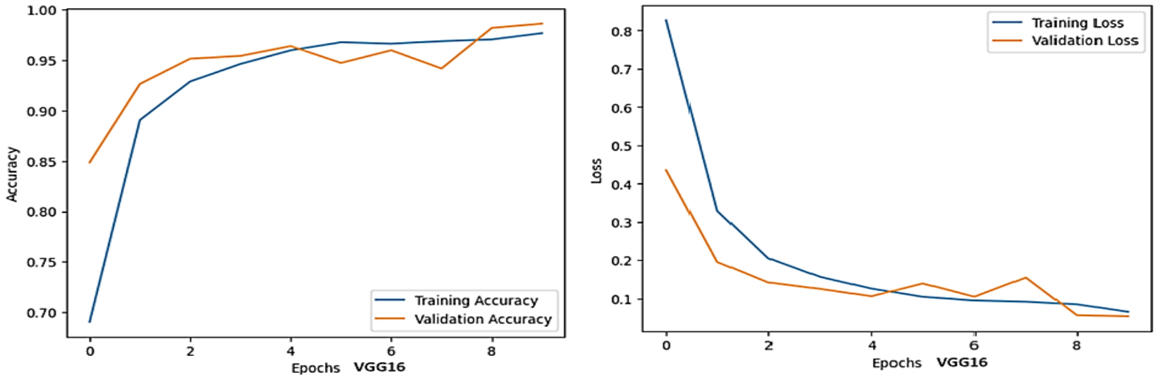
Figure 2. The desktop application screenshot for VotTomNet with (a) healthy and (b) disease leaf prediction

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 3. 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 common occurrence in deep learning training showing strong generalization to previously unseen data. Figure 3 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.



Validation accuracy vs number of epochs and training Validation loss vs number of epochs

Figure 3. Graph of VGG16 for training

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%. The accuracy values of the other pre-trained models: ResNet MobileNet and EfficientNet are 95.12%, 94.3%, and 96.7%, respectively. A comparison graph showing these pre-trained models' classification accuracies is shown in Figure 4. 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 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 was 94%.

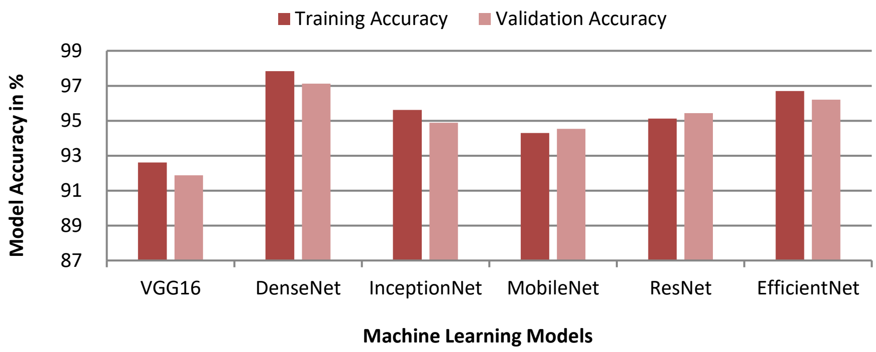


Figure 4. Comparison graph of training and validation accuracy for models VGG16, InceptionNet, ResNet, MobileNet, EfficientNet and DenseNet

The moderate discrepancy in accuracy between training and validation for MobileNet indicates some overfitting but overall strong performance, with a 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. With EfficientNet, 97% of training and 95% of validation accuracy are achieved. 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 ensembled six 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 1,500 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 VotTomNet model. Table 3 displays the individual model's performance both before and after the ensemble. Soft voting was used to ensemble VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet, which increased tomato leaf disease detection accuracy and robustness. The graph in Figure 5 illustrates the slight advantage in validation accuracy between the two techniques: before ensemble and after ensemble using soft and hard voting.

Table 2. The report of for VotTomNet 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 scenarios

Pre-trained Models	Before Ensembling		After Ensembling accuracy
	Training accuracy	Validation accuracy	
VGG16	92.61	91.88	99.21
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	

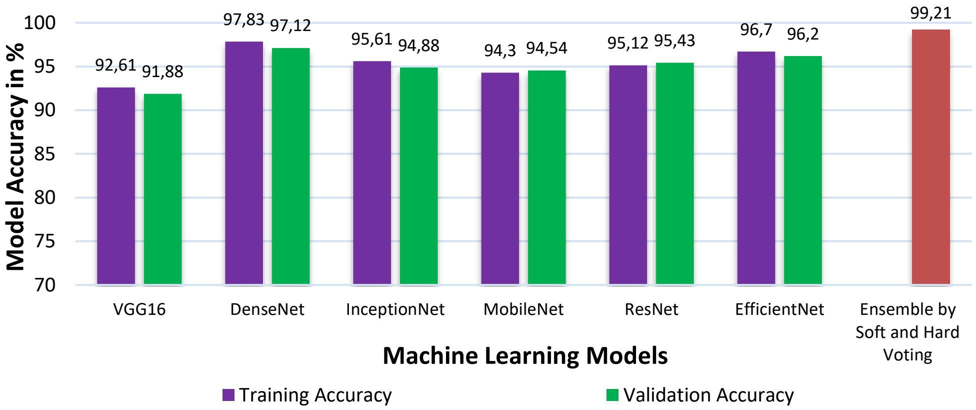


Figure 5. Comparison graph of accuracies before and after ensemble for models VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet with VotTomNet

4. CONCLUSION

In order to automate the detection of leaf diseases in tomato crops, the research presents a novel model called VotTomNet 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 and hard 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 VotTomNet, classification accuracy increased significantly as evidenced by the findings, which show an astounding 99.2% accuracy through soft and hard voting. High recall and precision rates are shown by VGG16, InceptionNet, ResNet, MobileNet, EfficientNet, and DenseNet for a variety of tomato illnesses. VotTomNet, 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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