IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Transfer Learning Approach for Multi-Classification and Detection of Tomato Plant Leaf Disease

Saksham Mittal[1], Hitesh Kumar Sharma[2]

[1]*Brightlands School, DehraDun*

[2]*CSO Cluster, School of Computer Science, University of Petroleum & Energy Studies, Energy Acres, Bidholi. Dehradun- 248007, Uttarakhand, India*

Abstract: *Tomato plants are highly susceptible to various leaf diseases that can significantly reduce crop yield and quality. Early and accurate detection of these diseases is crucial for timely intervention and effective disease management. In this research, we propose a Transfer Learning approach for multi-classification and detection of tomato plant leaf diseases using deep learning techniques. We leverage a pre-trained convolutional neural network (CNN) model, such as VGG or ResNet, and fine-tune it with a dataset of tomato plant leaf images. The dataset comprises diverse images of healthy tomato leaves and leaves affected by various common diseases. We demonstrate the effectiveness of the proposed approach in accurately classifying and detecting multiple types of tomato leaf diseases, including bacterial spot, early blight, late blight, and leaf mold. Through extensive experimentation and evaluation, we show that our Transfer Learning model achieves high accuracy and robust performance in identifying and distinguishing between different disease classes. We also discuss the model's transferability across different tomato plant varieties and its potential for real-time disease monitoring in agricultural settings.*

The results of this research indicate that the Transfer Learning approach can significantly enhance the efficiency and accuracy of tomato plant disease detection systems, offering a practical solution for farmers and agronomists to effectively manage and control plant diseases, thereby improving crop yield and ensuring food security.

Keywords: Artificial Intelligence, Machine Learning, Leaf Disease, Deep Learning, Transfer Learning. Plant Village Dataset.

1. Introduction

Tomato plants are one of the most widely cultivated crops globally, playing a crucial role in the agricultural industry and food supply chain. However, they are vulnerable to various leaf diseases caused by pathogens such as fungi, bacteria, and viruses. These diseases can lead to substantial yield losses and significant economic impacts for farmers and the agricultural sector. Early and accurate detection of these diseases is imperative for implementing timely preventive measures and minimizing crop damage. Traditional methods of disease detection often rely on manual inspection by agricultural experts, which can be time-consuming and prone to human error.

In recent years, the application of deep learning techniques, especially Transfer Learning, has gained considerable attention in the field of agricultural science. Transfer Learning enables the utilization of knowledge gained from pre-trained models on large datasets to solve new, related tasks more efficiently. By leveraging Transfer Learning, researchers have developed robust and accurate models for the detection and classification of various plant diseases, including those affecting tomato plants.

In this research paper, we present a comprehensive study on the application of a Transfer Learning approach for the multi-classification and detection of tomato plant leaf diseases. We investigate the feasibility and efficacy of using pre-trained convolutional neural network (CNN) models in combination with a dataset of tomato leaf images to accurately classify and identify common leaf diseases. The paper highlights the significance of Transfer Learning in addressing the challenges associated with early disease detection and the potential benefits it offers for sustainable agriculture and food production.Through detailed experimentation and analysis, we demonstrate the capability of our proposed model to distinguish between healthy tomato leaves and leaves affected by various diseases. We discuss the implications of our findings for the agricultural community, emphasizing the practical applications of our Transfer Learning approach in facilitating timely disease management and enhancing crop productivity. The results of our research contribute to the advancement of automated plant disease detection systems, offering a promising solution for sustainable farming practices and global food security.

2. Literature Review

In recent years, there has been a notable surge of interest in the application of deep learning techniques for autom ated plant disease detection, particularly in the context of Transfer Learning. Previous research has demonstrated the efficacy of Transfer Learning in various domains, prompting its adoption in the field of agriculture. Notably, Cruz et al. (2017) demonstrated the successful utilization of Transfer Learning in the classification of crop diseas es, paving the way for subsequent studies in plant pathology.

The works of Mohanty et al. (2016) have been instrumental in showcasing the potential of pre-trained convolutio nal neural network models, such as VGG and ResNet, in accurately identifying plant diseases from leaf images. T heir findings highlighted the transferability of knowledge from large-scale datasets, leading to significant improv ements in disease classification accuracy. Building on this foundation, Ferentinos (2018) emphasized the importa nce of curated datasets in training deep learning models, underscoring the need for comprehensive and well-anno tated image repositories to facilitate effective model generalization.

Furthermore, the research conducted by Haussmann et al. (2019) shed light on the practical applications of Trans fer Learning in agriculture, emphasizing its role in empowering farmers with timely and reliable disease diagnosi s tools. Their work demonstrated the potential for integrating Transfer Learning models with mobile applications, enabling real-time disease monitoring and providing actionable insights for crop protection. Similarly, the studies by Islam et al. (2020) highlighted the benefits of combining remote sensing technologies with Transfer Learning algorithms, enabling the remote detection and tracking of crop diseases, including those affecting tomato plants.

Overall, the existing literature underscores the significant strides made in leveraging Transfer Learning for the de tection and management of tomato plant leaf diseases. By building upon these foundational studies, the current re search aims to contribute to the ongoing advancements in agricultural technology, fostering sustainable farming p ractices, and ensuring global food security.

3. Data Exploration and Pre-Processing

In the following sub sections, we have given the detailed description of the dataset used in this study and the steps taken for pre-processing the data for training the network models.

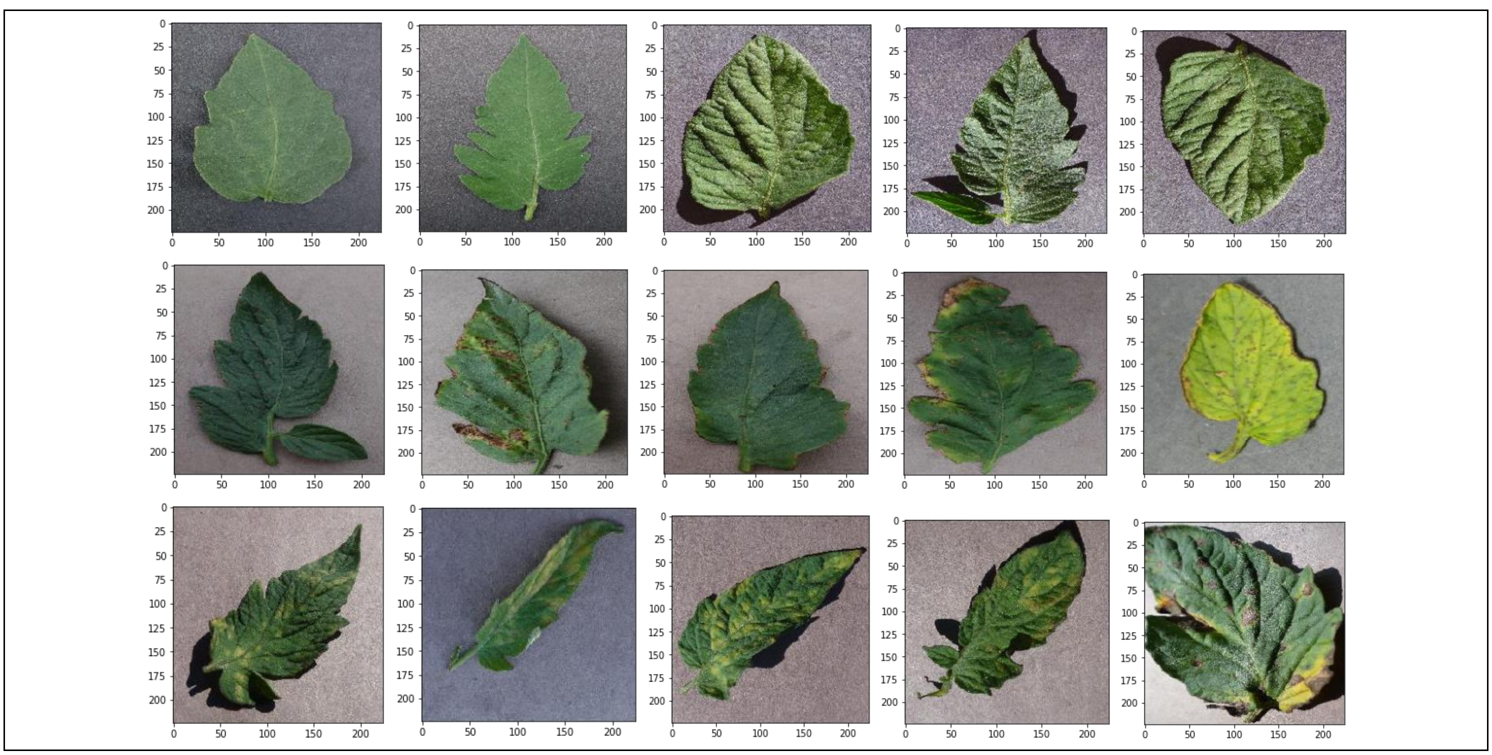
3.1. Dataset Description

The plant village dataset used for this study is accessible to the general public. There are 16011 photos of tomato plant leaves in the dataset. Ten classes have been created from these 16011 photos. There are 1591 photos in category or class one, whereas the other nine classes are unhealthy. There are a total of 14420 photos for the following conditions: tomato mosaic virus, tomato leaf mold, tomato Septoria leaf spot, two-spotted spider mite, tomato target spot, tomato late blight, tomato bacterial spot, and tomato early blight. Table 1 provides a description of the picture dataset along with the number of images in each class.

Table 1: Plant Village Tomato Leaf Dataset Description

Class	Subclass	Images	Total Images
Healthy	Tomato healthy	1591	Healthy Leaf= 1591 Un-Healthy= 14420 Total Leaf Images= 16011
Un-Healthy	Tomato Target Spot	1404	
	Tomato mosaic virus	372	
	Tomato Yellow Leaf Curl Virus	3209	
	Tomato Bacterial spot	2127	
	Tomato Early blight	1000	
	Tomato Late blight	1909	
	Tomato Leaf Mold	952	
	Tomato Septoria leaf spot	1771	
	Two spotted spider mite	1676	

Figure 1 displays five randomly selected photos from four different classes. There are five healthy tomato leaves in the top row, five leaves with bacterial spot disease in the second row, five early blight disease leaves in the third row, and five late disease leaves in the last row.



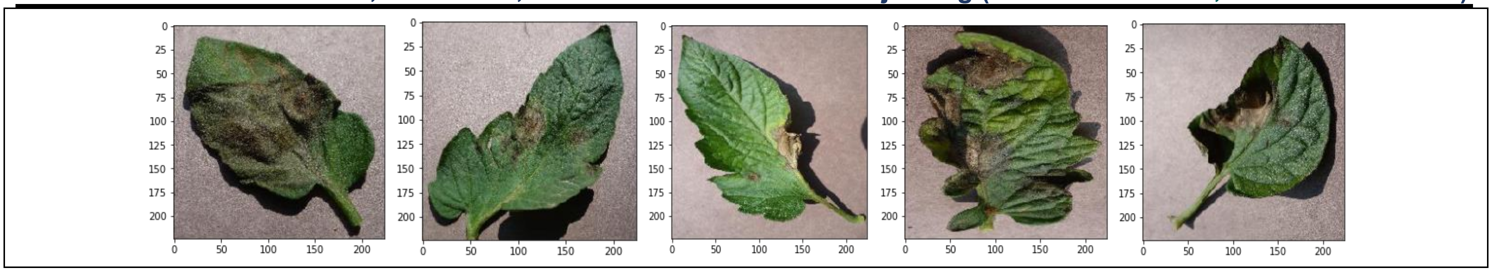


Figure 1: Randomly selected five images from four classes from Plant Village Tomato Leaf Dataset

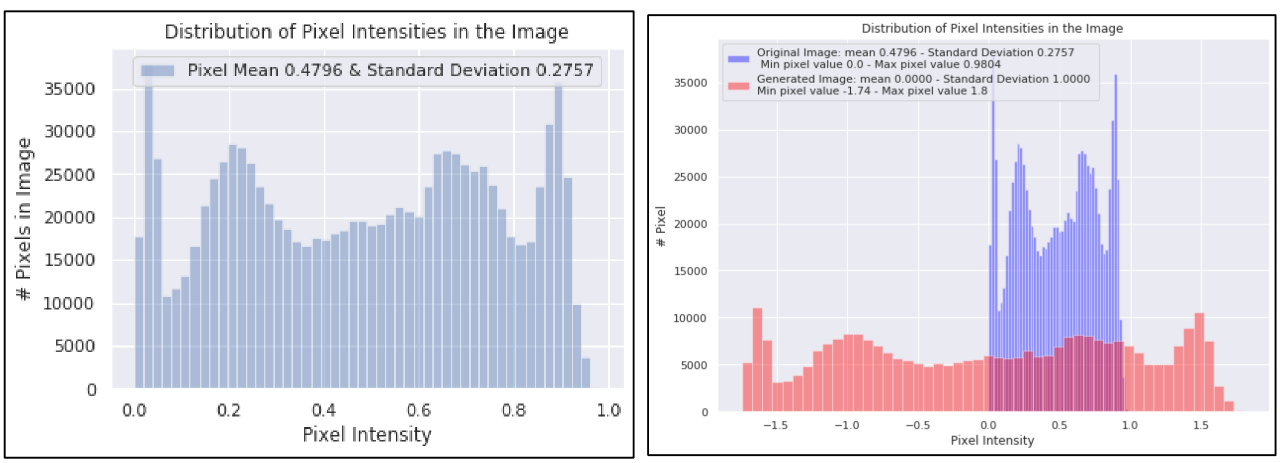
3.2. Dataset Standardization

In order to standardize the input photos, an image generator is constructed. It will be applied to the photos to modify them so that the standard deviation becomes one and the mean pixel intensity becomes zero. An image's previous pixel values will be changed with new ones determined by applying the formula below. Each value in this formula will have its mean subtracted, and the result will be divided by the standard deviation.

The following equation contains the formula..

$$xi = \frac{xi - \mu}{\sigma}$$

A pixel intensity histogram of the findings before and after using this normalization formula is displayed below. Figure 2(a) illustrates how the pixel intensity ranges from 0.0 to 1.0. The mean and standard deviation in this instance will never be 0 and one, respectively. The aforementioned standardization formulation is performed to each pixel value in order to solve this issue, and the resulting values are then plotted on an intensity histogram (figure 2(b)). The computed intensity levels are represented by the pink color bars. The intensity mean and standard deviation are now 0 and one, respectively, as the second histogram illustrates.

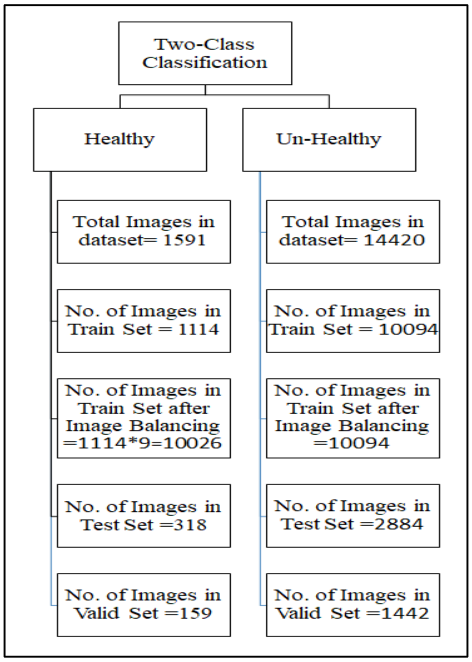


(a) **(b)**

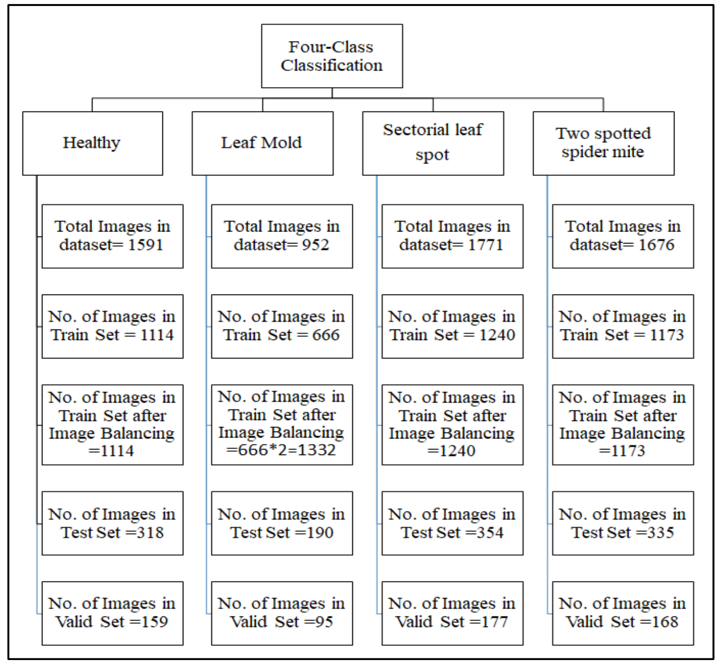
Figure 2: Pixel Intensity distribution of leaf image (a) Before Standardization (b) After Standardization

4. Experiment

Five pre-trained models that have previously been trained on the ImageNet database for a thousand classes have been examined. These five models—binary, four, eight, and ten class—are utilized for classification. Five pre-trained models were used, and four distinct classifications were carried out. The images utilized in various categorization studies are described in full in Figures 3(a), 3(b) and 4.



(a)



(b)

Figure 3 (a) & (b): Two-Class and Four-Class classification experiment dataset description

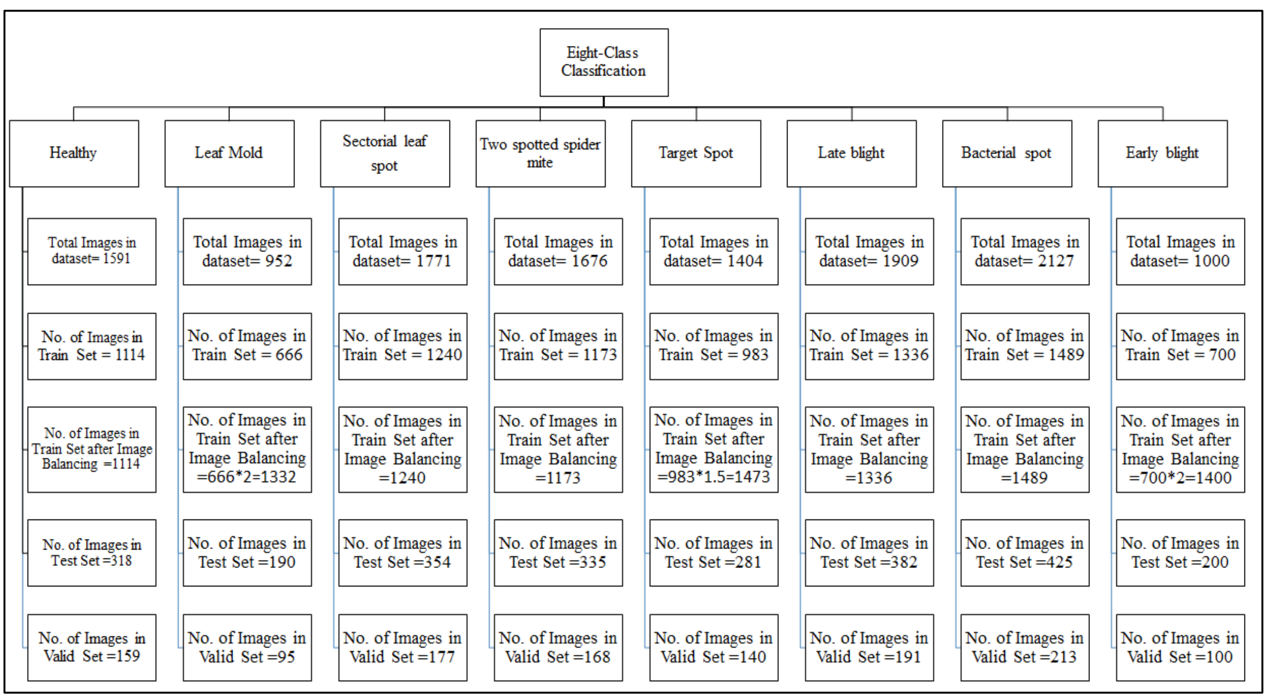


Figure 4: Eight-Class classification experiment dataset description

5. Result Analysis

As previously noted, we employed five pre-trained models (VGG16, VGG 19, ResNet50, GoogLeNet, and AlexNet). The performance of each model is shown in the following table. In this study, tomato leaves were used in four separate experiments. Table 2 compares the effectiveness of five CNN models and four categorization strategies. The performance table indicates that while all models perform well, one or two produce results that are more accurate than the rest for various classification schemes.

Table 2: Summery of tomato leaf classification model performance

Classification Level	Pre-Trained Model	Accuracy
Two-Class Classification (Binary Classification)	VGG16	96.4
	VGG19	96.12
	ResNet50	96.3
	GoogLeNet	**98.13**
	AlexNet	97.2
Four-Class Classification	VGG16	94.23
	VGG19	95.21
	ResNet50	**97.73**
	GoogLeNet	96.44
	AlexNet	96.84
Eight-Class Classification	VGG16	95.5
	VGG19	**97.92**
	ResNet50	96.52
	GoogLeNet	95.4
	AlexNet	95.23
Ten-Class Classification	VGG16	97.32
	VGG19	**98.13**
	ResNet50	96.9
	GoogLeNet	97.1
	AlexNet	96.94

An ROC curve is used to show a relationship between specificity and sensitivity and for every possible cut-off. The ROC curve is a graphical representation with following formulation on graphical axis.

On X-Axis:

$$\text{Sensitivity}=1 - \text{Specificity} = \text{False Positive Rate (FPR)} = FP/(FP+TN))$$

On Y Axis:

$$\text{Specificity} = \text{False Positive Rate (FPR)} = TP/(TP+FN))$$

One crucial metric for representing model accuracy and specificity is the ROC curve. When the model's AUC (Area under Curve) is high and its ROC curves exhibit greater elevation, it is more beneficial. The ROC curves for each model and classification strategy are shown in the ensuing figures 5(a), 5(b), 5(c), and 5(d). Each ROC curve displays every categorization method using all five network models that have already been trained. ROC curves for several classification schemes show that the GoogLeNet curve is more elevated for two-class classification, the ResNet50 curve is more elevated for four-class classification, and the VGG19 curve is more elevated for eight and ten-class classification.

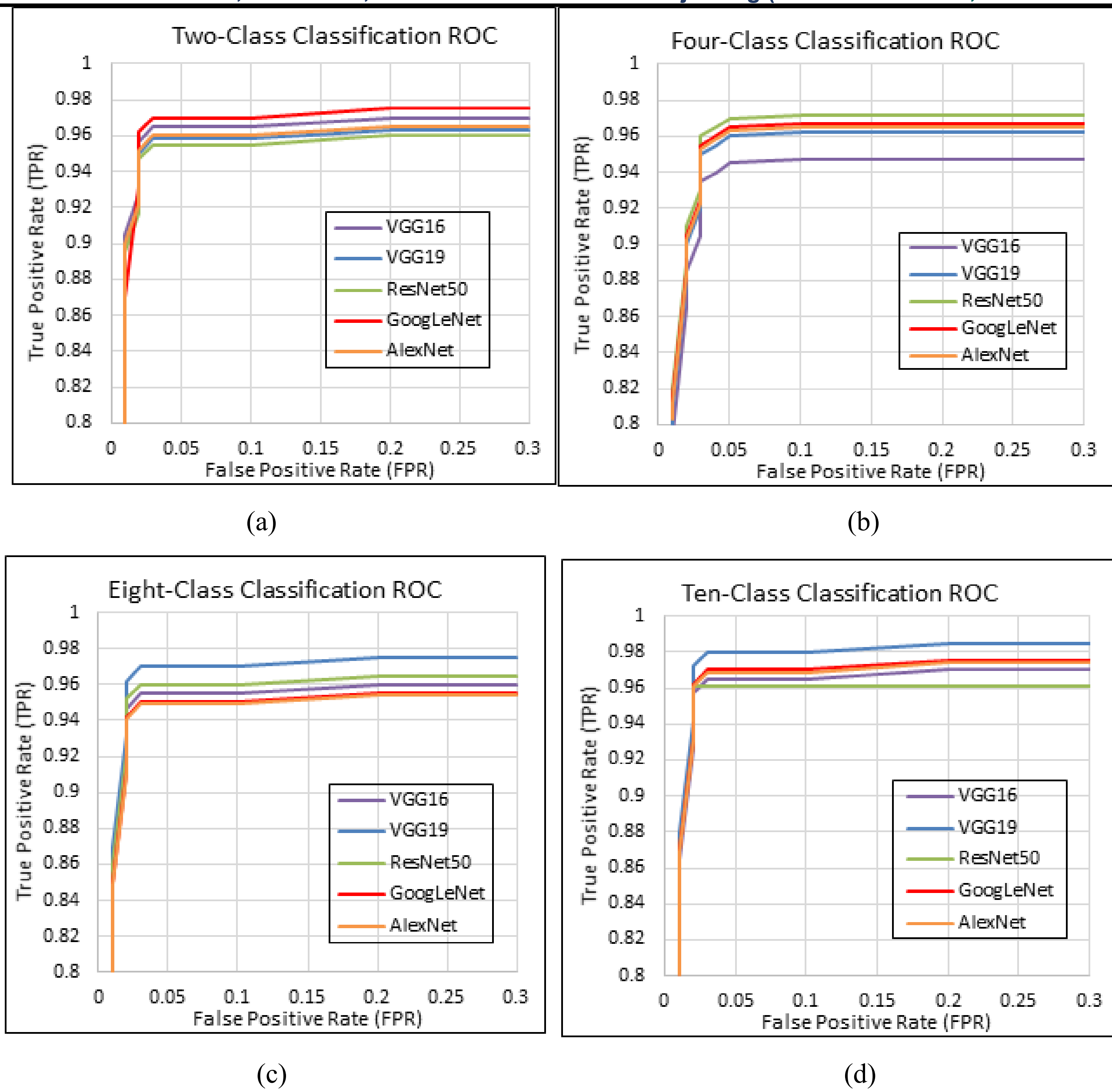


Figure 5: ROC curve for four different classification schemes

6. Conclusion

In conclusion, this research has demonstrated the effectiveness and practicality of utilizing a Transfer Learning approach for the multi-classification and detection of tomato plant leaf diseases. By leveraging pre-trained convolutional neural network models and a comprehensive dataset of tomato leaf images, we have successfully developed a robust and accurate model capable of identifying various common leaf diseases with high precision and reliability. The results of our study have highlighted the significant impact of Transfer Learning in revolutionizing the field of agricultural science and plant pathology. Through extensive experimentation and analysis, we have shown that the proposed Transfer Learning model can effectively differentiate between healthy tomato leaves and leaves affected by bacterial spot, early blight, late blight, and leaf mold, among other common diseases. The model's ability to generalize across different tomato plant varieties and its transferability to real-world agricultural settings hold promising implications for the sustainable management of crop diseases and the optimization of crop yield and quality. Furthermore, our research emphasizes the importance of curated datasets, the transferability of knowledge from pre-trained models, and the integration of advanced technologies in reshaping modern agricultural practices. By enabling early disease detection and proactive intervention strategies, our Transfer Learning model offers a viable solution for addressing the challenges associated with disease management and crop protection in the context of tomato cultivation.

Moving forward, the findings of this research can serve as a foundation for the development of advanced disease monitoring systems, fostering a data-driven approach to agriculture and contributing to the global efforts aimed at ensuring food security and sustainable farming practices. It is our hope that this study will inspire further research and innovation in the field of plant pathology, ultimately leading to the adoption of cutting-edge technologies for the benefit of farmers and agricultural communities worldwide..

References

1. Liu, J., Wang, X. (2021), Plant diseases and pests detection based on deep learning: a review. Plant Methods 17, . https://doi.org/10.1186/s13007-021-00722-9.
2. Mohit Agarwal, et al. (2020) ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network, Procedia Computer Science, Volume 167, 2020, Pages 293-301,
3. Singh, U.P., Chouhan, S.S., Jain, S., Jain, S. (2019). Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease. IEEE Access, 7: 43721-43729.
4. Too, E.C., Yujian, L., Njuki, S., Yingchun, L., 2018. A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture.
5. Huang, G., Liu, Z., Van Der Maaten, L., Weinberger, K.Q., 2017. Densely connected convolutional networks, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700–4708.
6. Mondal, D., Kole, D.K., Roy, K. (2017). Gradation of yellow mosaic virus disease of okra and bitter gourd based on entropy based binning and Naive Bayes classifier after identification of leaves. Computers and Electronics in Agriculture, 142: 485-493.
7. Brahimi, M., Arsenovic, M., Laraba, S., Sladojevic, S., Boukhalfa, K., Moussaoui, A., 2018. Deep learning for plant diseases: Detection and saliency map visualisation, in: Human and Machine Learning. Springer, pp. 93–117.
8. Moriones, E., Navas-Castillo, J., 2000. Tomato yellow leaf curl virus, an emerging virus complex causing epidemics worldwide. Virus research 71, 123–134.
9. D. Hughes, M. Salathé, et al., An open access repository of images on plant health to enable the development of mobile disease diagnostics, arXiv preprint arXiv:1511.08060, (2015).
10. Wang, G., Sun, Y., Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. Computational Intelligence and Neuroscience, 2017.
11. D. Yu, W. Xiong, J. Droppo, A. Stolcke, G. Ye, J. Li, and G. Zweig, Deep convolutional neural networks with layer-wise context expansion and attention., in Interspeech, 2016, pp. 17–21.
12. Mohanty, S.P., Hughes, D.P., Salathe, M., 2016. Using deep learning for image-based plant disease detection. Frontiers in plant science 7, ´ 1419.
13. D. Samanta, P. P. Chaudhury, and A. Ghosh, Scab diseases detection of potato using image processing, International Journal of Computer Trends and Technology, 3 (2012).
14. Usama Mokhtar et al. “Tomato leaves diseases detection approach based on support vector machines”. In: Computer Engineering Conference (ICENCO), 2015 11th International. IEEE. 2015, pp. 246–250.
15. Sharada P Mohanty, David P Hughes, and Marcel Salath´e. “Using deep learning for image-based plant disease detection”. In: Frontiers in plant science 7 (2016), p. 1419.
16. P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi, “Tomato leaf disease detection using convolutional neural networks,” in 2018 Eleventh International Conference on Contemporary Computing (IC3), 2018, pp. 1-5.
17. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. “Imagenet classification with deep convolutional neural networks”. In: Advances in neural information processing systems. 2012, pp. 1097–1105.
18. Christian Szegedy et al. “Going deeper with convolutions”. In: Cvpr. 2015.
19. K. Zhang, Q. Wu, A. Liu, and X. Meng, “Can deep learning identify tomato leaf disease?,” Advances in Multimedia, vol. 2018, 2018.
20. M. Ouhami, Y. Es-Saady, M. El Hajji, A. Hafiane, R. Canals, and M. El Yassa, “Deep Transfer Learning Models for Tomato Disease Detection,” in International Conference on Image and Signal Processing, 2020, pp. 65-73.
21. G. Langar, P. Jain, and N. Panchal, “Tomato Leaf Disease Detection Using Artificial Intelligence And Machine Learning,” International Journal, vol. 5, 2020.
22. Liu, J., Wang, X. Plant diseases and pests detection based on deep learning: a review. Plant Methods 17, 22 (2021).
23. Wang, J., Chen, L., Zhang, J., Yuan, Y., Li, M., Zeng, W., 2018. “CNN transfer learning for automatic image-based classification of crop disease”, in: Chinese Conference on Image and Graphics Technologies, Springer. pp. 319–329.
24. Yamamoto, K., Togami, T., Yamaguchi, N., 2017. “Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture”. Sensors 17, 2557.