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Tomato Leaf Disease Detection Using Deep Learning Ensemble Approach

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Abstract— Tomato leaf disease is a natural phenomenon that is considered a major hindrance to qualityful and desirable tomato production. Early disease detection is challenging, but accurate diagnosis can significantly reduce economic losses. This work proposes an improved deep learning ensemble approach combining MobileNet and DenseNet models for tomato leaf disease diagnosis. Unlike the convolutional neural network (CNN) approach, the proposed ensemble approach improves accuracy and individual limitations of predictions. The model utilized the tomato leaf disease dataset available on Kaggle, and a total of 16,031 RGB images of tomato leaf disease for the experiment purposes. From the experimental work, it was found that the proposed method ensured the highest accuracy of 98.21% which is 2.37% higher than DenseNet and 0.62% higher than MobileNet. The Precision, recall, and F1-scores were 0.933, 0.875 and 0.906. The method proposed in this paper can be used to other plants, and hopefully, we will extend our experiments to find more improvements in prediction accuracy.

Index Terms— Image processing, Deep Learning, MobileNet, DenseNet, CNN, Tomato leaf disease, ensemble approach.

1 Introduction

TOMATOES is one of the most widely cultivated and consumed vegetables worldwide, playing a significant role in human nutrition [1]. Leaf diseases by various fungi, viruses, and bacteria degrade crop production enormously [2]. Moreover, the thriving tomato industry faces challenges due to various leaf diseases that significantly affect crop yield and quality. During the past twenty years, there have been significant improvements in agriculture, specifically in the field of precision agriculture that involves the use of technology in agriculture enormously.

Deep learning techniques have revolutionized many fields in recent years, including agriculture [3]. Early detection and diagnosis of plant diseases is one area where these technologies have shown tremendous potential. By extracting complex patterns and characteristics from sample photos, deep learning has proven a powerful tool for effectively identifying different types of tomato leaf disease. Despite the numerous works carried out on this subject, there is a little investigation done using the combination of DenseNet and Mobilenet method over the traditional CNN approach. We employed the ensemble technique to take the benefits of both architectures.

In this study, we used the largest collection of tomato leaf disease dataset from the Kaggle [4], labeled as To- mato_mosaic_virus, Target_Spot, Bacterial_spot, Tomato_Yellow_Leaf_Curl_Virus, Late_blight, Leaf_Mold, Early_blight, Spider_mites, Two-spotted_spider_mite, Tomato_healthy, and Sep- toria_leaf_spot. This research investigates the implementation details, experimental findings, and comparative analyses, as well as the efficacy of the suggested ensemble approach in testing tomato leaf disease.

The paper is structured as follows: Section 2 focuses on the available related works in this field thoroughly. In section 3, we discussed the dataset and our proposed meth- ontology. Statistical measurements, experimental data analysis, result findings and overall discussions are illustrated in section 4. In the end in section 5, we shorten our conclusions and future work.

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2 Related Works

Addressing tomato disease classification, James and Punitha [5] proposed an ensemble learning solution, utilizing AdaBoost, LogitBoost, and TotalBoost algorithms with an emphasis on early detection benefits. Limitations include a lack of specificity on challenges faced, no comparative performance data for LogitBoost and TotalBoost, and insufficient discussion on environmental factors' impact on disease classification accuracy.

The work by Kaur and Devendran [6] concentrates on the identification of plant leaf diseases using a combination of ensemble classification and hybrid feature extraction. The suggested methodology utilises image processing techniques on the PlantVillage dataset, incorporating GLCM, LBP, Gabor features, and SIFT. Nevertheless, the research lacks a comprehensive analysis of the constraints, computational complexity, and potential obstacles of the suggested approach, which restricts its capacity to assess actual application.

Using a variety of classifiers, including SVM, Multilayer Perceptron, Random Forest, and Soft Voting, Jeyalakshmi and Radha's paper [7] focuses on illness classification in tomato plants. The proposed technique entails employing ensemble learning with a soft voting classifier, extracting features from the Grey Level Co-occurrence Matrix (GLCM), and utilising a dataset from the Plant Village dataset for research purposes. Nevertheless, the limitations encompass the absence of discourse regarding the difficulties in implementing the system, a comprehensive evaluation of the classifier's effectiveness, and the incorporation of strategies for handling imbalanced datasets and optimising computational efficiency.

Vallabhajosyula et al. [8] propose a deep ensemble neural network that utilises transfer learning to improve the diagnosis of plant leaf diseases. The network incorporates pre-trained models such as ResNet 50 & 101, InceptionV3, DenseNet 121 & 201, MobileNetV3, and NasNet. The proposed method surpasses the most advanced models currently available, showcasing its superiority in detecting diseases in plant leaves. Nevertheless, the limits of the model are apparent due to the lack of explicit discourse regarding its constraints, possible difficulties, and applicability to datasets other than the plant village dataset.

Important for precision agriculture, the study by Kaur, Singh, Mishra, Shankar, Singh, Diwakar, and Nayak [9] deals with the automated detection of illnesses in tomato plants. The proposed method, the deep ensemble learning model (DELM), utilises transfer learning to merge VGG16, InceptionV3, AlexNet, and GoogleNet for enhanced disease categorization. Nevertheless, the research fails to provide a thorough analysis of the limits associated with the DELM model, impeding a comprehensive comprehension of the possible obstacles and restrictions.

A powerful deep learning method called ResNet-34-based Faster-RCNN is proposed by Nawaz et al. [10] to address the detection and classification of leaf diseases in tomato plants. This approach utilises the Convolutional Block Attention Module (CBAM) and attains exceptional accuracy and mean average precision (mAP) scores on the PlantVillage Kaggle dataset. The proposed approach seeks to substitute manual disease detection devices, providing a cost-efficient and automation-compatible solution. Nevertheless, there are some constraints to consider, such as the possibility of seeing distorted, hazy, or noisy photos, the computational complexity involved, the absence of information regarding the applicability of the model to real-world scenarios, the possible issue of accurately identifying the precise locations of diseases, and the requirement for a substantial amount of training data.

In order to improve disease detection efficiency, Uluta and Aslantaş [11] have proposed new ensemble CNN models to address the automatic diagnosis of tomato plant illnesses. The models get an exceptional accuracy of 99.60%, enhanced and optimised using hyperparameter optimisation techniques to provide efficient training and testing durations. The research addresses a gap in knowledge by offering a thorough elucidation of deep learning techniques and assesses the suggested systems using multiple criteria. Although the report does not explicitly state any limits, the omission of such information implies possible areas for enhancement and additional investigation in future research.

A CNN model that uses morphological characteristics, colour, and texture for precise detection and classification is proposed by Pushpa B. R. and Aiswarya V. V. [12] to address the early detection of tomato leaf diseases. The model demonstrates exceptional performance with a remarkable accuracy of 96%, surpassing existing categorization methods. The project primarily examines diseases caused by antibiotics, with the possibility of extending its scope to include diseases caused by non-living factors. The significance of this work lies in the application of advanced techniques such as deep learning and computer vision to enhance food security and agriculture. This is achieved by leveraging a dataset of 14,531 photos sourced from Kaggle. Nevertheless, the research fails to address important aspects such as the difficulties encountered during implementation, the applicability of the findings to different plants, potential biases in the dataset, the computational resources required, and the capacity to scale the proposed approach for real-world use.

Mohit Agarwal et al. [13] present an article that introduces a new method for accurately detecting and classifying tomato leaf diseases using a Convolution Neural Network (CNN). The strategy includes 3 layers of convolution with max pooling. The suggested model effectively tackles the crucial issue of disease identification in tomato crops, surpassing pre-trained models such as VGG16, InceptionV3, and MobileNet with an average accuracy of 91.2%. Nevertheless, the publication fails to provide comprehensive information regarding the size and representativeness of the dataset, computational resources utilised, specific disorders encompassed, generalizability of the findings, and the obstacles associated with implementing the proposed approach in real-world scenarios.

Using K-nearest neighbor and support vector machine classifiers, Omneya Attallah [14] presents a framework that uses lightweight CNNs and transfer learning to achieve an astounding accuracy of 99.92% and 99.90%, respectively. Nevertheless, the shortcomings encompass a narrow scope that solely addresses ten specific tomato leaf diseases, limited suitability for laboratory settings, failure to consider disease severity, and a neglect of modern deep learning segmentation methods.

The method proposed by Emre Özbilge et al. [15] presents a deep CNN architecture that is computationally economical and designed for devices with limited memory or processing capacity. The network surpasses pre-trained models by achieving an impressive accuracy of 99.70%, F1 score of 98.49%, Matthews correlation coefficient of 98.31%, true positive rate of 99.81%, and true negative rate of 99.81%. However, the research does not explicitly acknowledge its limits, provide insights into scalability, discuss computational needs, or analyses the robustness of the results under different settings.

Chen et al. [16] offer a significant study demonstrating an Android-based application for accurate diagnosis of tomato diseases. By utilizing a modified version of AlexNet convolutional neural network (CNN) on a dataset consisting of 18,345 training images, the model attains a remarkable average accuracy of 98%. The work introduces innovative mobile-based CNN applications in agriculture, specifically focusing on automated disease diagnosis. However, it does not extensively address the constraints of implementing these applications, limitations of the dataset used, and the need to examine the applicability of the findings to different types of tomato plants and environmental conditions.

A convolutional neural network (CNN) is used in a deep learning-based method by Gnanavel Sakkarvarthi et al. [17] to detect and categorise tomato crop illnesses. The suggested model surpasses pre-trained models such as InceptionV3, ResNet 152, and VGG19 with exceptional accuracy in both training (98%) and testing (88.17%). This contribution expedites the identification of diseases at an early stage, hence improving the quality and quantity of food crops. It also reduces the need for crop specialists to diagnose diseases. Nevertheless, the paper is limited by its failure to describe the specific diseases encompassed in the dataset and its lack of information regarding the model's performance for each unique condition. Furthermore, the lack of discussion regarding the model's applicability to various geographical regions or tomato crop varieties is evident. The study's application and practical implementation in real-world scenarios are further limited by the lack of information regarding dataset size and diversity, processing needs, and potential biases in training data.

By combining CNN algorithms with image processing, Ashok et al. [18] present a novel method for the early diagnosis of diseases affecting the leaves of tomato plants. The proposed system, which attains a 98% accuracy rate, provides a viable answer for farmers. However, the absence of a thorough examination of its limitations necessitates additional investigation into its practicality and the obstacles it may face in real-world scenarios.

Kibriya et al. [19] present a strong method for promptly identifying tomato leaf illnesses. They utilise GoogLeNet and VGG16 CNN models, achieving remarkable accuracies of 99.23% and 98% respectively. Nevertheless, the research fails to address the issues of implementing the proposed method, its applicability to different datasets, computing efficiency, performance comparison, and potential biases in the dataset. This creates an opportunity for more investigation and verification in real-world situations.

Parvez et al. [20] present a deep learning methodology to identify tomato leaf diseases at an early stage. By utilising Convolutional Neural Networks (CNNs), notably GoogLeNet and VGG16, the model attains an impressive test accuracy of 98.39% on a dataset including 6,926 photos of tomato plants. The study seeks to boost agricultural output and profitability by equipping farmers with an efficient tool for autonomous disease identification and early prevention.

In order to automate the diagnosis of tomato leaf diseases, Nagamani H. S. et al. [21] propose a study that makes use of the fuzzy support vector machine (fuzzy-SVM), convolution neural networks (CNN), and region-based convolution neural networks (R-CNN). The R-CNN-based Classifier achieves a remarkable accuracy of 96.735% in early disease diagnosis by employing advanced approaches such as picture scaling, color thresholding, and gradient local ternary pattern. The research enhances the field of agriculture by presenting a streamlined and automated method for detecting diseases, highlighting the benefits of deep learning in enhancing agricultural yield. Nevertheless, the limitations encompass the absence of comprehensive dataset information, talks regarding computational resources, and insights regarding the applicability to other plant species.

3 Methodology

3.1 Dataset

We selected the dataset of "Tomato Leaf Disease Detection" from Kaggle, which consists of data related to different types of diseases of tomato leaves, such as tomato mosaic virus, target spot, bacterial spot, Tomato Yellow Leaf Curl Virus, Late blight, Leaf Mold, Early blight, Spider mites Two-spotted spider mite, Tomato healthy, and Septoria leaf spot.

We examined 16,031 RGB images, each size 224×224 pixels, representing various types of tomato leaf diseases. We divided 60% of the data for training, 20% for validation, and the remaining 20% for testing purposes. Table 1 presents the training, validation, and testing datasets. To mitigate overfitting, validation data are employed to determine the optimal hyperparameters. The training and validation datasets are visually depicted in Figures 1 and 2, respectively.

TABLE 1
Training, Validation and Testing Dataset

Class	Training Images	Validation Images	Testing Images
Tomato Target Spot	898	225	281
Tomato mosaic virus	238	60	75
Tomato Yellow Leaf Curl Virus	2054	514	614
Tomato Bacterial spot	1361	340	425
Tomato Early blight	640	160	200
Tomato healthy	1018	255	318
Tomato Late blight	1222	305	382
Tomato Leaf Mold	610	152	190
Tomato Septoria leaf spot	1134	283	354
Tomato Spider mites & two spotted spider mite	1073	268	335
Total	10,287	2,552	3,192

Fig. 1. Sample images of training data

Fig. 2. Sample images of validation data

3.1 Proposed Method

In this study, we proposed an ensemble technique to categorize tomato leaf disease, as shown graphically in Figure 3.

In our research, we implemented ensemble learning to improve the efficacy of our models for detecting tomato leaf diseases. Ensemble learning is a technique that enhances accuracy and addresses the limits of individual models by aggregating their predictions. For this study, we have used MobileNet and DenseNet as the base models. On the selection of base learners, we proceed to independently train our base model on the dataset. After the models have been trained, they are tested with a validation dataset to see how accurate they are. The trained models are now employed to expand or approximate the input data. The outcome of both models is obtained by employing the 'softmax' function. The probability vectors C_k are represented by the model's output for all input data T_i. The value of 'k' is selected from the set 1...nc, with 'nc' representing all the classes. We have multiplied the model's output by the proper multiplication factor, j. The ensemble method for the class is formed by adding up the computed probability for each class. The process for the weighted ensemble framework is shown in Algorithm 1, which makes it easy to understand and use.

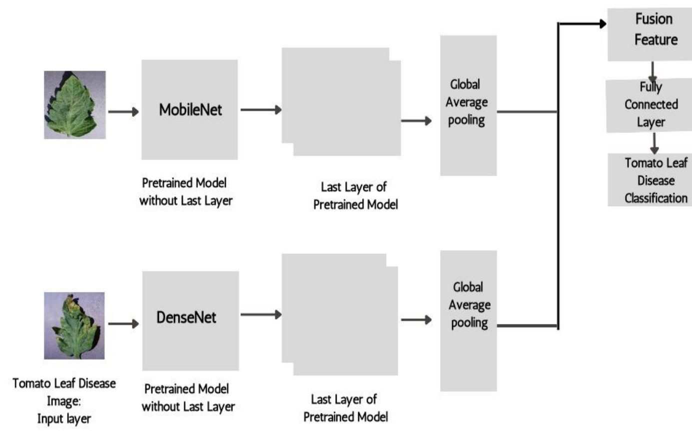

Fig. 3. Ensemble deep learning approach for tomato leaf disease classification

Algorithm 1: Ensemble Model for Tomato Leaf Disease

Input — *Tomato Leaf Disease Datasets S.*

Output — *Ensemble model M.*

Process
1. *for do j=1 to m*
   a) *Train model MobileNet and DenseNet using dataset S.*
   b) *Calculate the class probability for p_j using the trained model of MobileNet and DenseNet.*
   c) *Calculate output class of MobileNet and DenseNet*
   d) *Calculate accuracy of model M*
2. *for do j=1 to m*
   a) *Calculate weight of model M*
3. *Compute the output of the proposed model.*
4. *Calculate the accuracy of the proposed ensemble method.*

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4 Result and discussion

In this section, we represented the experiments conducted and the corresponding findings of our proposed model.

4.1 System Configuration

We used a GPU with tensor-flow capabilities for this experiment. As the experiment involves extensive matrix multiplication operations, a powerful GPU is crucial for effective training of deep learning models. The proposed architecture has been designed for training on the Google Colab cloud server because of the limitations imposed by the processing capabilities of a CPU. The Google Colab utilizes both the GPU and the Jupyter platform and is specifically designed to help overcome the computational challenges encountered in machine learning. We employed Google Colab to train and assess the presented deep learning methodology.

4.2 Hyper-parameters of the Proposed Model

To train the proposed model, we employed categorical cross entropy as the loss function. As there are no noticeable changes or improvements in the training and validation accuracies, we trained our proposed model for 50 epochs. The loss function is optimized using Adam's optimizer. Table 2 represents the hyper-parameters of the model we built that have been finely adjusted for optimal performance. In our research, we designated the number of epochs as 50 and the batch size as 32.

TABLE 2
Hper-parameters Settings

Hyper-parameters	Value
Loss Function	Categorical Cross-entropy
Batch Size	32
Epochs	50
Learning rate	0.001
Optimizer	Adam

4.2 Performance Metrics

We offered multiple performance criteria for the usual assessment of our approach. The classification accuracy measurement is commonly employed as the primary performance indicator. Classification accuracy is evaluated by calculating the proportion of correctly classified data out of the total amount of data. It is crucial to take into account precision, recall (or sensitivity), and specificity as fundamental measurements. The F-1 score, a significant statistical metric for categorization, is computed by obtaining the harmonic mean of precision and recall. The training, validation, and testing accuracy and loss of our proposed model are represented in Table 3. The table indicates that the training accuracy and loss are 99.58%, and 0.065% respectively. The accuracy for validation and testing is 98.13% and 97.19%, respectively. The loss for validation and testing is 0.113 and 0.286, respectively.

TABLE 3
Accuracy and Loss

Model Part	Accuracy	Loss
Training	99.58%	0.065
Validation	99.69%	0.113
Testing	98.12%	0.286

Classification accuracy is a valuable metric for evaluating performance, particularly when the test dataset has a balanced distribution of samples across all classes. The dataset used for the classification, however, has an imbalance. This requires a more comprehensive evaluation of the proposed system using additional performance metrics.

The Precision, Recall, and F1-score of our proposed ensemble approach are presented in Table 4. We also evaluate our method in comparison to other techniques, such as DenseNet and MobileNet. The technique we propose demonstrates a precision of 0.933, a recall of 0.875, and an F1-score of 0.906. The table demonstrates that our model overcomes the performance of the other two pre-trained models.

TABLE 4
Performance Comparison of Our Model

Model	Accuracy	Precision	Recall	F1-score
Ensemble Model (Dense-Net+MobileNet)	98.12%	0.933	0.875	0.906
Desnenet	95.75%	0.961	0.781	0.890
MobileNet	97.50%	0.946	0.807	0.878

The proposed ensemble learning model is trained using a considerable number of epochs (up to 50) with the default configurations. The ideal epoch for our model is 50, as there have been no modifications in training and validation accuracy levels. The figures illustrating the proposed model's accuracy and loss are labelled as Figure 4 and 5, respectively. Figure 5 shows that the training and validation losses are 0.927 and 0.625, respectively, after the first epoch. In Figure 4, the initial epoch shows a training accuracy of 0.94 and a validation accuracy of 0.96. By increasing the number of epochs, the accuracy of the model improves while the loss reduces. Figure 6 and 7 shows the training and validation accuracy and losses of Densenet, respectively. Figure 8 and 9 shows the training and validation accuracy and losses of Mobilenet, respectively.

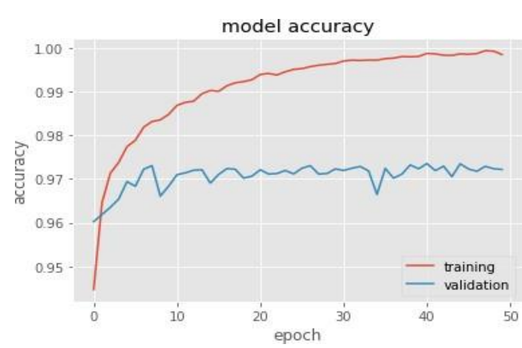

Fig. 4. Training and Validation Accuracy of our Proposed Framework

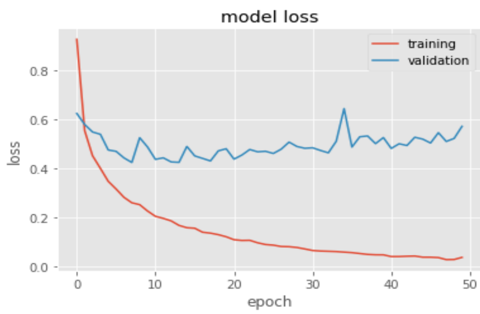

Fig. 5. Training and Validation Loss of our Proposed Framework

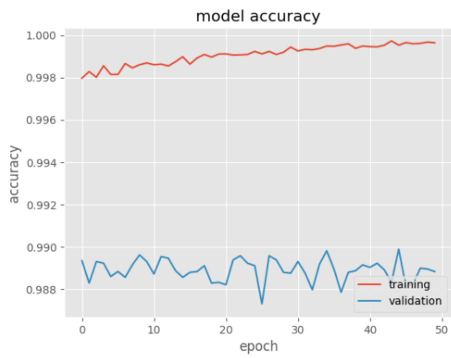

Fig. 6. Training and Validation Accuracry of Densenet

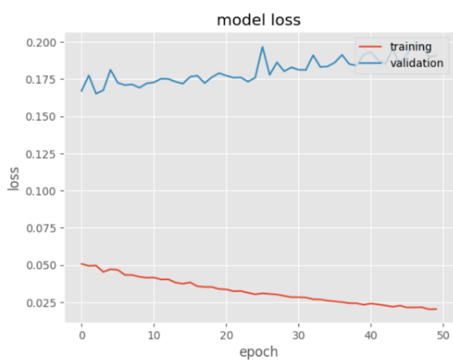

Fig. 7. Training and Validation Loss of Densenet

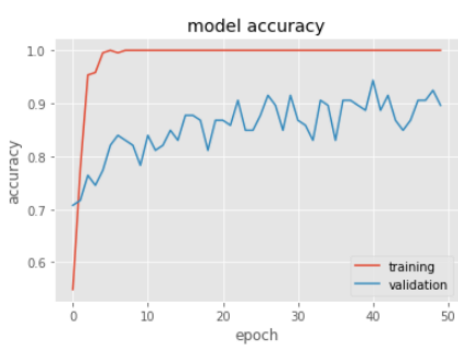

Fig. 8. Training and Validation Accuracy of Mobilenet

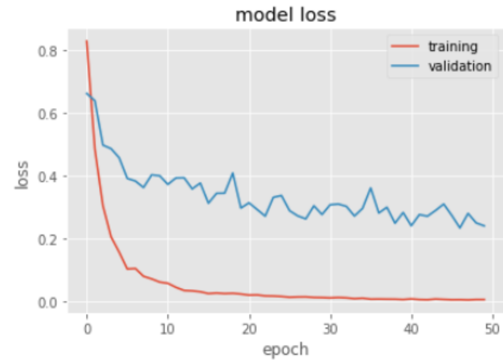

Fig. 9. Training and Validation Loss of Mobilenet

5 Conclusion

The objective of our present study was to design an ensemble (combination of Mobilenet and DenseNet model) deep learning approach for tomato leaf disease classification. The investigation has revealed that our proposed model ensures more accuracy than the conventional CNN model. The main findings can be summarized as follows: (1) our proposed ensemble model provides the highest accuracy of 98.12% while DenseNet provides 95.75% and MobileNet provides 97.50% accuracy. The Precision values of our proposed model are 0.933, the DenseNet model is 0.961 and the MobileNet model is 97.50%. This study has opened up several questions that need further investigation. Further research might explore our proposed model for other plants too.

References

[1] Riley, M. B., Williamson, M. R., & Maloy, O. (2002). Plant disease diagnosis. *The plant health instructor*, *10*.

[2] Mishra RK, Jaiswal RK, Kumar D, Saabale PR, Singh A (2014) Management of major diseases and insect pests of onion and garlic: A comprehensive review. J Plant Breed Crop Sci 6(11):160–170

[3] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, *147*, 70-90.

[4] Tomato leaf disease detection. Available in: https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf Accessed on: August 22, 2023.

[5] James, G. M., & Punitha, S. C. (2016). "Tomato Disease Classification Using Ensemble Learning Approach." *International Journal of Research in Engineering and Technology, 05*(10), 104. Available at http://ijret.esatjournals.org

[6] Kaur, N., & Devendran, V. (2021). "Plant leaf disease detection using ensemble classification and feature extraction." *Turkish Journal of Computer and Mathematics Education, 12*(11), 2339-2352.

[7] Jeyalakshmi, S., & Radha, R. (2021). "Classification of Tomato Diseases Using Ensemble Learning." *International Journal of Computer Science and Mobile Computing, 10*(8), 2408. DOI: 10.21917/ijsc.2021.0343

[8] Vallabhajosyula, S., Sistla, V., & Kolli, V. K. K. (2021). "Transfer learning-based deep ensemble neural network for plant leaf disease detection." *Journal of Plant Diseases and Protection*. DOI: https://doi.org/10.1007/s41348-021-00465-8

[9] Kaur, P., Singh, M. P., Mishra, A. M., Shankar, A., Singh, P., Diwakar, M., & Nayak, S. R. (2023). "DELM: deep ensemble learning model for multiclass classification of superresolution leaf disease images." *Turkish Journal of Agriculture and Forestry, 47*, 727-745. DOI: 10.55730/1300-011X.3123

[10] Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim, J., & Hussain, A. (2022). "A robust deep learning approach for tomato plant leaf disease localization and classification." *Scientific Reports, 12*, 18568. DOI: https://doi.org/10.1038/s41598-022-21498-5

[11] Ulutaş, H., & Aslantaş, V. (2023). "Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model." *Electronics, 12*, 827. DOI: https://doi.org/10.3390/electronics12040827

[12] Pushpa B R, Aiswarya V V. (2022). "Tomato Leaf Disease Detection and Classification Using CNN." *Mathematical Statistician and Engineering Applications, 71*(4), 2921-2930. ISSN: 2094-0343, 2326-9865.

[13] Mohit Agarwal et al. (2020). "ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network." *Procedia Computer Science, 167*, 293–301. DOI: 10.1016/j.procs.2020.03.225

[14] Attallah, O. (2023). "Tomato Leaf Disease Classification via Compact Convolutional Neural Networks with Transfer Learning and Feature Selection." *Horticulturae, 9*(2), 149. DOI: 10.3390/horticulturae9020149

[15] Özbilge, E., Ulukök, M. K., Toygar, Ö., & Özbilge, E. (2022). "Tomato Disease Recognition Using a Compact Convolutional Neural Network." *IEEE Access.* DOI: 10.1109/ACCESS.2022.3192428

[16] Chen, H.-C., Widodo, A.M., Wisnujati, A., Rahaman, M., Lin, J.C.-W., Chen, L., & Weng, C.-E. (2022). AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf. *Electronics, 11*(6), 951. [https://doi.org/10.3390/electronics11060951]

[17] Sakkarvarthi, G., Sathianesan, G.W., Murugan, V.S., Reddy, A.J., Jayagopal, P., & Elsisi, M. (2022). Detection and Classification of Tomato Crop Disease Using Convolutional Neural Network. Electronics, 11, 3618. https://doi.org/10.3390/electronics11213618

[18] Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G., & Pavithra, B. (2020). Tomato Leaf Disease Detection Using Deep Learning Techniques. In Proceedings of the Fifth International Conference on Communication and Electronics Systems (ICCES 2020). IEEE Xplore ISBN: 978-1-7281-5371-1, Conference Record # 48766.

[19] Kibriya, I., Rafique, R., Ahmad, W., & Adnan, S.M. (2021). Tomato Leaf Disease Detection Using Convolution Neural Network. Proceedings of 2021 18th International Bhurban Conference on Applied Sciences & Technology (IBCAST), IEEE Xplore ISBN: 978-1-6654-0516-4/21

[20] Parvez, S., Uddin, M.A., Islam, M.M., Bharman, P., & Talukder, M.A. (2023). "Tomato Leaf Disease Detection Using Convolutional Neural Network." In *Proceedings of the 2nd International Conference on Big Data, IoT, and Machine Learning (BIM 2023)* (pp. 1-10). Retrieved from https://doi.org/10.21203/rs.3.rs-3505828/v1

[21] Nagamani, H.S., Sarojadevi, H., et al. (2022). "Tomato Leaf Disease Detection using Deep Learning Techniques." *International Journal of Advanced Computer Science and Applications (IJACSA)*, 13(1).