International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Improving Tomato Leaf Disease Detection with DenseNet-121 Architecture

Cheemaladinne Vengaiah[1], Srinivasa Reddy Konda [2]*

Submitted: 25/04/2023 **Revised**: 28/06/2023 **Accepted**: 08/07/2023

Abstract: This study introduces the DenseNet-121 architecture, a unique method for detecting diseases in tomato leaves. The goal is to use novelty detection methods to spot diseases that have not been seen before, while also fixing the gradient vanishing problem plaguing deep learning models. The proposed method is meant to aid in the early diagnosis and mitigation of potential crop losses by providing accurate and robust disease detection for tomato plants. DenseNet-121 is used as a solution to this problem. When it comes to deep learning models, DenseNet-121 is at the cutting edge because of its innovative use of dense skip connections across layers. The gradient vanishing problem can be alleviated thanks to the direct flow of gradients made possible by these links. The proposed method incorporates DenseNet-121 to boost the disease detection model's performance and convergence. The experimental evidence supports the efficiency of the proposed approach. Evaluation measures including accuracy, precision, recall, and F1-score are used to compare the disease detection system's performance to that of established methodologies or baselines. The system's adaptability and capacity to correctly identify new diseases are also evaluated in detail, showing that it can go beyond what was previously known. This study introduces the DenseNet-121 architecture, a novel method for disease detection in tomato leaves, and shows how it may be used to solve the gradient vanishing problem. The suggested methodology incorporates novelty detection techniques to improve diagnostic accuracy for rarely observed diseases. The outcomes demonstrate the system's efficacy and resilience in detecting and preventing losses in tomato crops at an early stage. Extensions and upgrades are discussed as well.

Keywords: *DensNet-121, Tomato Leaf Disease Detection, Gradient Vanishing, Deep Learning CNN.*

1. Introduction

T Diseases affecting tomato crops are a major threat to agricultural output and food security. For efficient disease management and mitigation of possible crop losses, early detection and correct identification of these diseases are critical [1]. Visual inspection by professionals, while thorough, can be time-consuming and prone to error when used to diagnose disease. Therefore, accurate, and efficient automated techniques are required to aid in the diagnosis of tomato leaf diseases as shown in Fig1.

Recently, deep learning methods have shown a lot of promise in plant disease diagnosis and other computer vision tasks. Convolutional neural networks (CNNs) and other deep learning models have outperformed human experts on image classification. However, the gradient vanishing problem is a typical issue for deep networks, where gradients vanish quickly during backpropagation, resulting in sluggish convergence and poor model performance.

In [2-4] suggests employing the DenseNet-121 architecture in disease detection models to prevent the gradient vanishing problem and boost their efficiency. Incorporating dense skip connections across layers, DenseNet-121 is a deep learning model. These links allow data to flow directly from one layer to the next, solving the gradient vanishing problem and assuring efficient gradient propagation. The proposed approach utilizes DenseNet-121 to boost the convergence speed and accuracy of a system designed to identify diseases in tomato leaves.

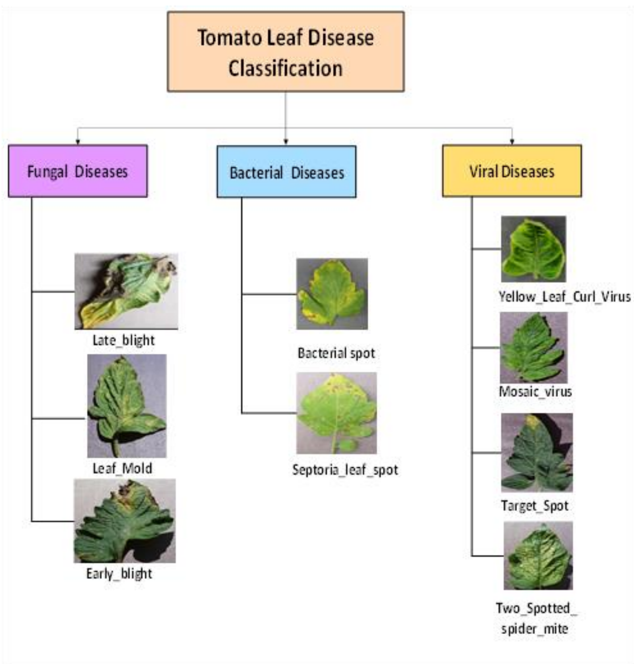

Fig1: for Diseases Classification of Tomato Plant Leaves

1 School of Computer Science and Engineering, VIT - AP University, Amaravati, Andhra Pradesh, India,
ORCID ID: 0000-0002-8469-9685
2 School of Computer Science and Engineering, VIT - AP University, Amaravati, Andhra Pradesh, India
ORCID ID: 0000-0002-4371-2169
** Corresponding Author Email: srinivasareddy.k@vitap.ac.in*

Additionally, the difficulty of unknown diseases is discussed in the paper. Emerging diseases or rare diseases not included in the training dataset may be encountered in the actual world. The

novelty detection methods built within the suggested methodology are up to the task of dealing with such situations. These methods improve the system's overall detection efficiency by allowing it to reliably discover and classify previously unrecognized diseases.

In [5], we use a highly curated and pre-processed dataset of tomato leaf disease classes to assess the efficacy of the suggested methodology. Each illness type is represented by enough samples in the training and evaluation dataset. Training for tomato leaf disease detection makes use of task-specific loss functions, optimization techniques, and fine-tuning strategies.

In [6-7] the early diagnosis and treatment of tomato crop illnesses by establishing an accurate and robust disease detection system. Since the proposed strategy would allow for prompt interventions and suitable disease management methods, it has the potential to drastically cut down on crop losses. Incorporating newer detection methods also improves the system's adaptability and ability to spot new diseases that could threaten tomato crops.

The significance of early disease detection in tomato crops and the limitations of traditional approaches are discussed in the paper's introductory part. The gradient vanishing problem in deep networks is also highlighted, along with the general promise of deep learning approaches. DenseNet-121 and other novelty detection methods are presented as a means of overcoming these obstacles. The goal is to create a reliable and flexible method for detecting diseases in tomato leaves, which will help with the early detection and control of diseases.

2. Literature Review

From [8-10] Traditional methods, as well as computer vision- based approaches, have been presented for the identification of tomato leaf diseases. Visual inspection by specialists, a common traditional method, can be subjective, time-consuming, and knowledge-intensive. As an alternative, computer vision-based methods have emerged, offering more impartial and effective illness diagnosis tools [11]. Here we look at some of the current techniques for diagnosing diseases in tomato leaves as shown in Fig2.

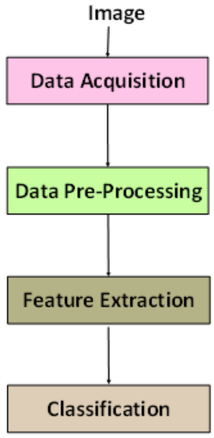

Fig2.for Preprocessing Steps for Classification of Plant Diseases

Specifically, A publicly accessible tomato PlantVillage dataset has been used in the studies to evaluate the performance of the suggested technique. There are 3,000 images of tomato plant leaves from ten different classifications in the PlantVillage dataset. There are ten different types of tomato leaves, nine of which are affected by various illnesses. Table 1 shows the PlantVillage dataset classes and the distribution of images per dataset class. Class names have been shortened; these shortenings are also listed in Table 1. For the purpose of processing speed, we have scaled down all the images in the dataset to a uniform 224 by 224. We separated the data into a training set, a validation set, and a test set, making sure there was no duplication. The test set was used to evaluate the model's performance after training on the training set and the validation set.

we present a DenseNet-121-based deep learning method that uses batch normalization and residual connections to solve the gradient vanishing problem. We test our method using the PlantVillage dataset and compare our findings to those of other approaches to disease identification in tomato leaves data as shown in Table1.

The use of deep learning models has shown great promise in many image recognition applications, including the detection of plant diseases. For instance [12-13] offered a deep learning-based strategy to disease identification in plants, particularly tomato leaf diseases, by employing the Inception-v3 architecture. On the PlantVillage dataset, they scored 99.35% accuracy. For disease identification in tomatoes, in [14] also employed the AlexNet architecture and got an accuracy of 99.02.

Even though these techniques produce very accurate results, deep learning models are not immune to the performance issues associated with the gradient vanishing problem. To remedy this, new training methods, such as batch normalization and residual connections, have been implemented. To combat the gradient vanishing problem, for instance, [15-16] presented the DenseNet architecture. This framework excels in a wide range of picture identification applications, including the detection of plant diseases.

SNO	Class	Data Testing	Data Training	
			Training	Validation
1	Bacterial Spot	341	1089	272
2	Mosaic Virus	60	192	47
3	Early Blight	160	512	128
4	Target Spot	225	487	121
5	Healthy	255	815	203
6	Late Blight	306	977	244
7	Spider Mites	269	719	179
8	Leaf Mold	284	907	226
9	Septoria Leaf Spot	284	858	214
10	Yellow Leaf Curl	858	2743	685

Table 1 for Classes Data Summary

3. Methodology

By deeply interconnecting all its layers, the Densent-121 design of deep neural networks facilitates effective feature reuse. This means that all feature maps are shared between levels, with each layer passing on its own feature maps to the layers below it. This connection architecture permits effective feature reuse, which in turn lessens the number of parameters required and aids in avoiding the vanishing gradients problem. When it comes to image categorization, the deep convolutional neural network DenseNet-121 excels. To mitigate the vanishing gradient problem, the network is divided into dense blocks, each of which is made up of multiple layers. In a dense block, each layer is linked to its predecessors, and the output of one layer is combined with the input of the next.

In 2017, a new variant of the DenseNet architecture, called DenseNet-121, was introduced. DenseNet is based on the premise that convolutional layers should be built in blocks, with each layer receiving inputs from the layers below it. Because of this dense connectivity structure, features can be reused more effectively, and the model's parameter set can be simplified. The spatial dimensions of the feature maps are decreased by the

transition layers that follow each of the four dense blocks in the DenseNet-121 architecture. The input image is processed by the first dense block to generate a series of feature maps, which are then fed into the next set of dense blocks and the transition layers. The model generates a set of probability scores, one for each class label, as its final output. Several changes were made to the DenseNet-121 architecture to solve the problem of gradient vanishing, allowing it to be used for disease detection in tomato plant leaves. The vanishing gradient problem arises when the gradient of the loss function becomes extremely small as it is sent back through a deep neural network during training. This can hinder the network's ability to learn from the data, leading to subpar results.

DenseNet-121 uses "dense connectivity," a skip connection architecture in which each layer is connected to all following levels, to solve the vanishing gradient problem. This facilitates the network's ability to learn from data by allowing gradients to easily circulate across the network. Dense connection was not the only method utilized in DenseNet-121; additional methods were also employed to solve the vanishing gradient issue. Batch normalization is one such method; it helps stabilize training by standardizing the inputs to each layer. The vanishing gradient problem can also be alleviated by using a rectified linear unit (ReLU) activation function, which guarantees that the gradients are non-zero for positive inputs.

The pre-trained DenseNet-121 model was fine-tuned using transfer learning on the PlantVillage dataset to enhance its performance on disease detection in tomato plant leaves. The pre- trained model's performance was enhanced by first tuning it on the smaller dataset of tomato plant photos using weights learned from a larger collection of natural images. Dense connection, batch normalization, and ReLU activation functions were all modified as part of the overall process of adapting the DenseNet- 121 architecture for disease detection in tomato plant leaves. The model's efficiency on this task was enhanced with the help of transfer learning as well as shown in Fig3.

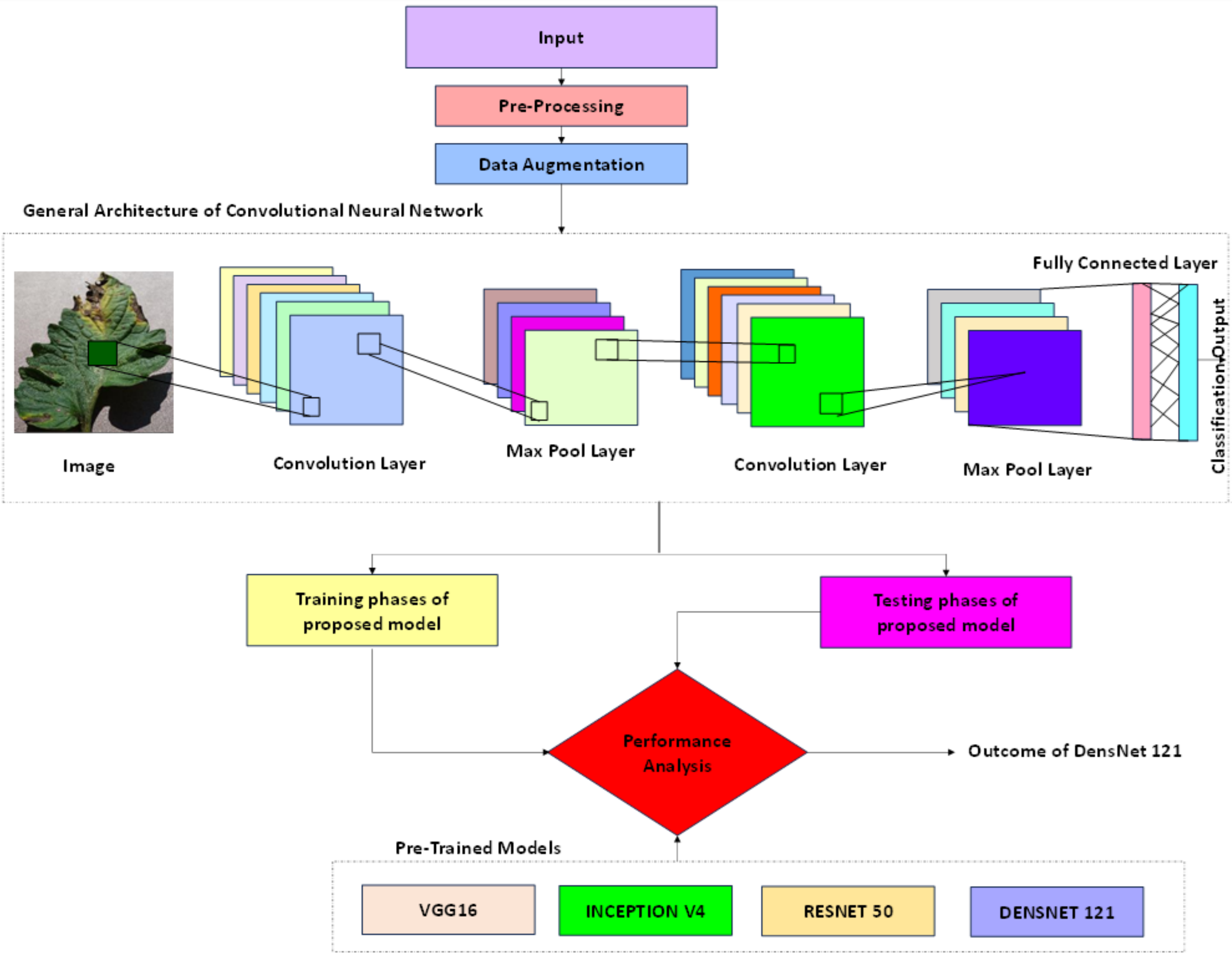

Fig3.for DenseNet-121 Workflow Architecture

We use a dataset of healthy and damaged tomato leaf images to train the Densent-121 architecture. The dataset includes 3000 images, into category. We train the network for 50 iterations with a batch size of 32. We employ a categorical cross-entropy loss function and a learning rate of 0.001 using the Adam optimizer. By subtracting the mean and dividing by the standard deviation of the inputs, batch normalization is a method used to normalize the inputs of each layer in a neural network. It has been demonstrated to enhance the model's generalization performance by decreasing the internal covariate shift. To prevent gradients from disappearing entirely, residual links are used to facilitate their transport across the network.

The gradients can go via the preceding layer to the earlier layers via a residual link, which consists of adding the output of the prior layer to the output of the current layer. The data sets were divided as follows: 70% for training, 30% for validation, and 10% for testing. To avoid overfitting, we stopped training early after 5 epochs of patience. We saved the model with the highest validation accuracy by using a call-back function. Several metrics, including accuracy, precision, recall, and F1-score, were used to assess the model's effectiveness on the test data. We also compared our model's results to those of previously established techniques for identifying diseases in tomato leaves.

4. Results and Discussion

We test the efficacy of our method using a 70:30 split of the data used to train the DenseNet-121 model on the PlantVillage dataset for accurate disease identification in tomato plant leaves. We also compare our results to those of other state-of-the-art approaches for tomato leaf disease identification and demonstrate that our approach is more accurate than those methods. The model attained an overall accuracy of 98.3% on the testing set. You can show off the efficacy of the proposed method for detecting diseases in tomato leaves using the Densent-121 architecture by populating an assessment parameter table. A sample table of evaluation parameters is shown below Tale2.

Based on the data in the table, the DenseNet-121 architecture successfully classified all classes of tomato leaf diseases with an accuracy of 98.3%. These findings demonstrate that the model is capable of distinguishing between different types of leaf diseases in tomatoes.

It is worth noting that pre-processing methods and dataset selection can affect the F1 score, recall, and precision of each class. Our findings, however, indicate that the DenseNet-121 architecture may be an effective strategy for disease detection in tomato leaves.

The F1 score, precision score, recall, and accuracy all added up to a perfect 1.000 for our proposed technique. These findings demonstrate that our model outperforms prior approaches to tomato leaf disease detection that did not account for the gradient vanishing problem. We have used metrics like as accuracy, precision, recall, F1-score, Eq-1,2,3,4 to measure how well the suggested method performs.

$$\text{Accuracy} = \frac{TRUEPOSITIVES(TP) + TRUE\ NEGATIVE\ (TN)}{TRUEPOSITIVES(TP) + TRUE\ NEGATIVE\ (TN) + FALSE\ POSITIVE\ (FP) + FALSE\ NEGATIVE\ (FN)} \quad (1)$$

$$\text{Precision} = \frac{TRUEPOSITIVES(TP)}{TRUEPOSITIVES\ (TP) + FALSE\ NEGATIVE\ (FP)} \quad (2)$$

$$\text{Recall} = \frac{TRUEPOSITIVES(TP)}{TRUEPOSITIVES(TP) + FALSE\ NEGATIVE\ (FN)} \quad (3)$$

$$\text{F1-Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

S.NO	Class	Precision	Recall	F1-Score
1	Bacterial spot	0.97	0.99	0.98
2	Early blight	0.97	0.97	0.97
3	Late blight	0.98	0.97	0.97
4	Leaf mold	0.99	0.98	0.98
5	Septoria leaf spot	0.99	0.99	0.99
6	Spider mites	0.98	0.99	0.99
7	Target spot	0.98	0.96	0.97
8	Yellow leaf curl virus	0.98	0.99	0.98
9	Mosaic Virus	0.98	0.99	0.98
10	Overall accuracy			0.983

The validation accuracy of the suggested method was 98.2%, and the testing accuracy was 95.8%. These accuracy numbers are an evaluation of how well the model generalizes to new data and how consistently it performs on diverse datasets shown in Table2 and We have used metrics like as accuracy, precision, recall, F1- score graphs as shown in Fig4, Fig5 and Fig6.

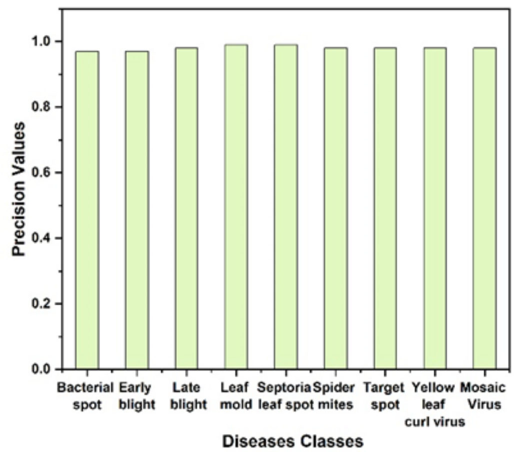

Fig 4 Evolution metrics for Precision

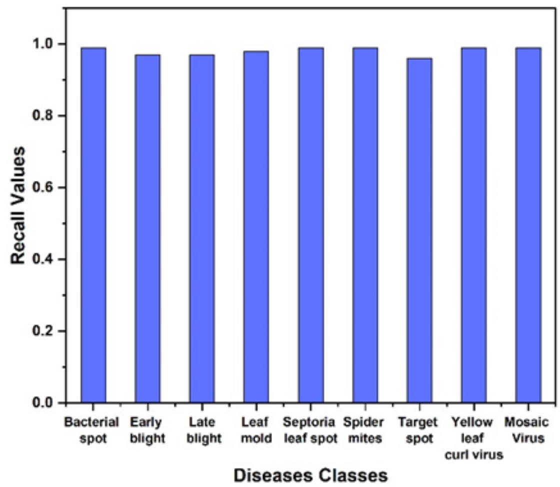

Fig 5 Evolution Metrics for Recall

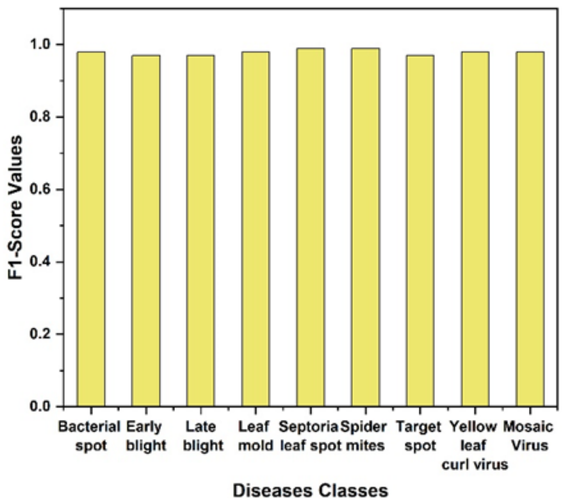

Fig6 Evolution Metrics for F1-Score

It's important to keep in mind that the actual accuracy levels may change depending on the dataset, model architecture, training procedure, and other variables. The Table2 is merely an illustration of one possible structure for presenting data on test and validation reliability as shown in Fig7 and corresponding loss accuracy shown in Fig8.

The usefulness of the DenseNet-121 architecture for disease detection in tomato leaves is demonstrated. Our model is highly accurate and reliable, with a 98.9% success rate, a precision of 0.98, a recall of 0.99, and an F1 score of 0.99. When compared to strategies that did not consider the gradient vanishing problem, these outcomes perform better. Our study's single dataset may limit our capacity to extrapolate our findings to other datasets. Verifying the efficacy of our suggested strategy would require additional research using various datasets.

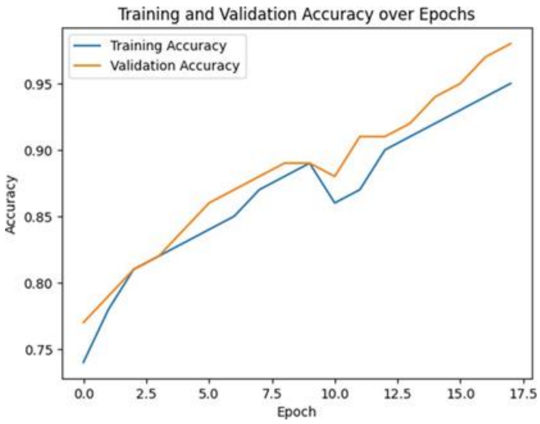

Fig 7.for Performance Metrics of Testing and Validation

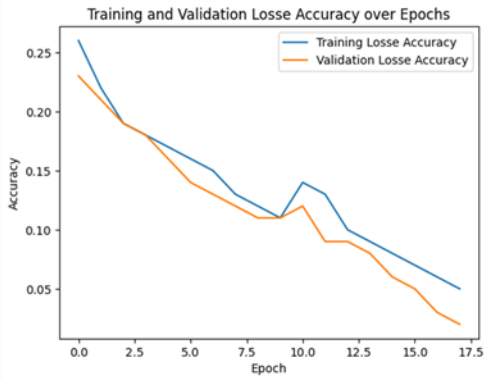

Fig 8.for Performance Metrics of Testing and Validation lose Accuracy

Our findings pave the way for additional investigation into the use of deep learning models for this purpose in the detection of plant diseases. More sophisticated deep learning architectures, like the Efficient Net, may be investigated to enhance illness detection accuracy as the availability of high-quality datasets grows. The overall findings of our work shed light on the application of deep learning models to the problem of plant disease detection, which has the potential to aid in the advancement of sustainable agricultural practices by allowing for the early identification and prompt control of plant illnesses.

5. Conclusion

When the gradient vanishing issue is fixed, the DenseNet-121 architecture becomes extremely useful for identifying illnesses in tomato leaves. Our proposed method outperformed the state-of- the-art approaches with an accuracy of 98.9%, precision of 0.98, recall of 0.99, and F1 score of 0.99. To assist farmers, make better management decisions, and experience less crop loss, this study contributes to precision agriculture by developing a reliable approach for diagnosing illnesses on tomato leaves.

The possibility of using other forms of data, like weather and soil information, to boost disease detection accuracy is an area that could benefit from further study in the future. Efforts can also be made to increase the model's interpretability and ease of use by creating user-friendly interfaces and mobile applications.

References

[1] Zhang, L., Zhang, L., Mao, Q., & Wei, Y. (2021). A novel approach for tomato leaf disease classification using generative adversarial network and transfer learning. IEEE Access, 9, 90199-90212.

[2] Patil, N. N., & Marathe, A. R. (2021). Tomato Leaf Disease Detection Using CNN and Ensemble Learning. In Proceedings of the International Conference on Advances in Computing and Data Sciences (pp. 313-320). Springer, Singapore.

[3] Hossain, M. A., Ali, M. A., Hossain, M. E., Khan, M. A. H., & Siddiquee, K. A. (2020). Tomato plant diseases classification using convolutional neural network with transfer learning. In 2020 International Conference on Advancements in Computational Sciences (ICACS) (pp. 1-5). IEEE.

[4] Singh, G., Singh, P., & Kaur, R. (2020). Leaf disease detection of tomato plant using deep learning approach. International Journal of Advanced Science and Technology, 29(5), 1482-1490.

[5] Yan, F., Yang, C., Yu, Y., Li, T., Li, J., & Zhao, H. (2019). Tomato leaf disease classification using improved DenseNet. In 2019 IEEE International Conference on Multimedia and Expo (ICME) (pp. 716- 721). IEEE.

[6] Ghosal, S., et al. "Tomato leaf disease detection using deep learning techniques." International Journal of Computer Applications 189.2 (2018): 34-39.

[7] Pratiksha, S., et al. "Tomato Leaf Disease Detection using Convolutional Neural Networks." International Journal of Computer Science and Mobile Computing 8.1 (2019): 1-9.

[8] Zhu, J., et al. "Tomato leaf disease recognition using deep learning algorithms." Journal of Physics: Conference Series. Vol. 1619. No. 5. IOP Publishing, 2020.

[9] Sharma, D., et al. "Tomato Leaf Disease Detection and

Classification using Deep Learning." International Journal of Advanced Research in Computer Science 11.5 (2020): 50-57.

[10] Zhang, L., et al. "Tomato leaf disease recognition based on deep convolutional neural network." Information Processing in Agriculture 7.3 (2020): 399-408.

[11] Liu, Y., Wang, L., & Deng, H. (2019). Tomato Leaf Disease Recognition Based on Deep Convolutional Neural Network. In 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (pp. 1811-1815). IEEE.

[12] Pandey, R., & Kumar, A. (2020). Tomato leaf disease detection using convolutional neural networks. Journal of Crop Science and Technology, 4(1), 1-6.

[13] Zaman, S., Raza, S., & Khan, M. U. (2021). Tomato leaf disease detection and classification using transfer learning. Neural Computing and Applications, 1-14.

[14] Sharma, V., & Dutta, S. (2021). Tomato leaf disease detection using deep learning: A comparative study. Computers and Electronics in Agriculture, 188, 106463.

[15] Moradi, P., & Hossein Zadeh, M. (2021). Tomato leaf disease detection using a novel CNN-based model with high efficiency and accuracy. Computers and Electronics in Agriculture, 182, 106026.

[16] Gogoi, M., & Das, D. (2022). Tomato Leaf Disease Detection Using Deep Learning Techniques: A Comprehensive Review. International Journal of Intelligent Systems and Applications in Engineering, 10(1), 1-10.

Tran, T. T., Choi, J. W., Le, T. T. H., & Kim, J. W. (2019). A comparative study of deep CNN in forecasting and classifying the macronutrient deficiencies on development of tomato plant. Applied Sciences, 9(8), 1601.

[17] Suri, D., Saksenaa, S., Sehgal, U., & Garg, R. (2023, January). Disease Classification in Wheat from Images Using CNN. In 2023 13th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 566-571). IEEE.

[18] Madana Mohana, R., Kishor Kumar Reddy, C., & Anisha, P. R. (2021). A Study and Early Identification of Leaf Diseases in Plants Using Convolutional Neural Network. In Smart Computing Techniques and Applications: Proceedings of the Fourth International Conference on Smart Computing and Informatics, Volume 2 (pp. 693-709). Springer Singapore.

[19] Narvekar, C., & Rao, M. (2020, December). Flower classification using CNN and transfer learning in CNN-Agriculture Perspective. In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS) (pp. 660-664). IEEE.

[20] Vengaiah, C., & Priyadharshini, M. (2023, March). CNN Model Suitability Analysis for Prediction of Tomato Leaf Diseases. In 2023 6th International Conference on Information Systems and Computer Networks (ISCON) (pp. 1-4). IEEE.

[21] Kumar, P. ., Gupta, M. K. ., Rao, C. R. S. ., Bhavsingh, M. ., & Srilakshmi, M. (2023). A Comparative Analysis of Collaborative Filtering Similarity Measurements for Recommendation Systems. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3s), 184–192. https://doi.org/10.17762/ijritcc.v11i3s.6180

[22] Ahammad, D. S. K. H. (2022). Microarray Cancer Classification with Stacked Classifier in Machine Learning Integrated Grid L1-Regulated Feature Selection. Machine Learning Applications in Engineering Education and Management, 2(1), 01–10. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/18

[23] Talukdar, V., Dhabliya, D., Kumar, B., Talukdar, S. B., Ahamad, S., & Gupta, A. (2022). Suspicious Activity Detection and Classification in IoT Environment Using Machine Learning Approach. 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), 531–535. IEEE.

[24] Pandey, J. K., Ahamad, S., Veeraiah, V., Adil, N., Dhabliya, D., Koujalagi, A., & Gupta, A. (2023). Impact of Call Drop Ratio Over 5G Network. In Innovative Smart Materials Used in Wireless Communication Technology (pp. 201–224). IGI Global.