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Computer Vision Based Solanum Lycopersicon Leaf Disease Detection Using Transfer Learning

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Abstract: Solanum Lycopersicon, mostly known as tomatoes, are one of the most essential and extensively consumed crops, with yields varying depending on cultivation methods. Tomato leaf disease is the most critical factor in both supply and quality of tomato crops. As a result, it is essential to identify and determine these diseases appropriately. Different diseases can impact the production of tomatoes, and early detection is crucial in reducing the consequences and encouraging a healthy crop yield. Improved approaches for disease detection and classification have been widely used. Various studies have been proposed to identify tomato leaf diseases, but they must be enhanced due to their accuracy and effectiveness as trained on the limited dataset. This work aims to support farmers in accurately diagnosing early-stage tomato leaf diseases namely: Bacterial spot, leaf spot, blight, curl virus, leaf mold diseases and delivering necessary information. In this study, deep learning-based models applied using a transfer learning technique. Different models, such as ResNet-50, VGG-16, and VGG- 19 are applied. Python is used to train deep learning models using Google Colab. The dataset acquired from publicly available repositories, namely, Kaggle. The image data is preprocessed using resizing and rescaling. The applied models will be evaluated in accuracy and performance to choose the best one.

Keywords: Tomato leaf diseases; classification; deep learning; transfer learning; CNN.

1. Introduction

The global challenge to identify plant leaf diseases is becoming highly important. Plant diseases may compromise both the nutritional value and supply of agricultural output. Crop monitoring has always relied on human skill and expertise. Early and precise diagnosis of plant diseases is essential in current plant protection strategies. Various studies have been presented by researchers and scholars to evaluate tomato and other plant leaf disease such as restructured deep network [21], deep learning model with high performance [20], CNN [1], deep neural network [5], optimized pre-trained CNN [2], transfer learning [18], and deep learning [7]. Machine learning and feature extraction approaches are critical in determining the form and degree of plant diseases. The effectiveness of machine learning is dependent on the availability of big datasets to train algorithms. Convolutional Neural Network (CNN) represents an emerging category of deep learning (DL) algorithms widely applied for image classification tasks [13].

Increasing food production needs early and correct spotting of diseases in crop leaves. Methods for deep learning based on fake brain power are important for finding illnesses in lots of pictures of leaves from plants. But finding sicknesses with very little data is hard for deep learning systems. Transfer learning is becoming a big deep learning way. It lets us find plant diseases correctly even when we don't have lots of pictures of plants [19].

The research [6] wants to find out if tomato plant leaves are sick by using picture processing methods like cutting up, grouping and free-to-use codes. The suggested method seeks a robust system that guarantees accuracy, safety, and dependability in identifying and classifying leaf diseases unique to tomato plants. By analyzing samples with known problems, the study [13] looks into tomato leaf diseases. Farmers can detect infections based on early indications by concentrating on leaves displaying problems. To improve the data quality, tomato samples of leaves are resized to 256 × 256 pixels, after which Histogram Equalization is applied.

The authors in paper [8] presents efficient convolutional neural networks to classify tomato diseases within a deep learning architecture. Eighteen thousand one hundred sixty-one pictures of tomato leaves, both segmented and plain versions, are analyzed in this study. The study also assesses how well two segmentation models, Modified U-net and U-net, segment tomato leaves to classify diseases. The research [12] does a comparative analysis to provide model support for developing trained tomato detection systems on phones and other handheld devices. The results significantly impact decision-making about tomato pest management and open the door to more advancements in applying intelligent technology for efficient tomato disease detection and treatment.

The study [11] used an accurate farming system that included drones and Convolutional Neural Network (CNN) research to identify areas of high disease frequency in farms. The next step is to spray insecticide on the affected regions specifically, using the infection severity level established by the drones as a reference. The training set has 2100 pictures from the internet, along with extra 500 photos from local farms used to help improve and grow the system. The research [15] uses two ready-made neural networks, Inception V3 and ResNet V2. They separate photos into normal ones and not good categories to check if tomato leaf diseases happen using these tools. A total of 5225 images were used in the training process, which included photographs from field recordings and an open-source database called Plant-Village. Using these well-established CNN models; the goal is to improve tomato plant disease identification accuracy.

In another research [9], a model for the diagnosis and categorization of tomato leaf diseases based on convolutional neural networks is presented. The model uses a publicly accessible dataset enhanced with extra-national field photos. To reduce overfitting, the research uses computational adversarial networks, which produce samples that have features in common with the training set. This strengthens the illness classification model's resistance.

This study [14] simulates several tomato leaf diseases using eleven classifications, one of which is the healthy group. An ablation study is carried out to determine the best parameters for the suggested model. Evaluation indicators are also used to examine and contrast the effectiveness of the proposed model with the TL-based model to assess the efficacy of the devised method for classifying tomato leaf diseases. The research [4] provides a valuable tool for farmers by introducing a ResNet-9 model for identifying burst disease in photos of potato and tomato leaves. The 3,990 initial samples used to train the model are from the famous "Plant Village Dataset." The project is geared towards enhancing ResNet-9 network's classification of the burst disease condition in crops, specifically, potatoes and tomatoes. The main aim of this project is to use transfer learning to improve the efficiency of a program that detect tomato diseases, so that the training period be shortened and the accuracy of identification be enhanced. The model uses two invention steps and pre-training using ImageNet, leveraging the VGGNet architecture. Through the application of move learning and a well-known architecture, the research works to enhance the algorithm's capacity to precisely identify diseases that impact tomato plants [16].

The study [3] highlights the rising use of Deep Convolutional Neural Networks (DCNN) in agriculture by presenting an automated approach for diagnosing tomato leaf diseases. Eighteen thousand one hundred sixty photos of tomato leaf illnesses by the Plant Village database, which is divided into 40% for testing and 60% for training, are used in this work. With an accuracy rate of 98.40% for the testing set, the suggested DCNN model shows its efficacy in accurately identifying tomato leaf diseases. An overview of well-known deep learning and machine learning techniques for illness diagnosis is given in this study. It includes different approaches within these fields proposed for illness identification. The main goal is to review and summarize essential methods used in illness identification with machine learning and deep learning techniques [17].

2. Related Literature

The deep learning and computer vision approaches as a tool for tomato leaf disease detection. It introduces transfer learning among the models such as ResNet-50, VGG-16, and VGG-19 which enhances disease recognition accuracy. The dataset is collected from Kaggle, and resized and rescaled to do some model optimization. Getting tomato plant diseases leaf detected early is crucial for keeping a healthy crop and limiting the damages on crop yield, because of diseases. The ultimate purpose is to build a reliable system that can classify and diagnose all tomato leaf diseases with high accuracy, so as that the farmers are able to handle their crops efficiently.

Multiple studies have focused on these similar matters that advocate the benefits of deep learning algorithms and machine learning for disease detection in agriculture along with efficiency. Convolution Neural Networks (CNN) have come to be regarded as a powerful image classification tool having greater accuracy in identifying plant diseases. The combination of state-of-the-art technologies such as CNNs and transfer learning can be a turning point in the history of agriculture in the use of assistance in the cultivation of crops and improving their management strategies. Integration of such emerging technologies into conventional agriculture practices is an important method of equipping farmers with the equipment that assists in disease detection, quality improvement and productivity enhancement of crops. The continual evolution of deep learning techniques in the agricultural sector epitomizes the pathway to sustainable and productive farming as a result, putting us ahead of a much brighter future for agriculture.

3. Materials and Methods

3.1. Dataset

The dataset will be retrieved from Kaggle website. It consists of RGB images of tomato leaves. The diseases under study are bacterial spot, leaf spot, blight, curl virus, leaf mold, as well as healthy leaves. The samples from dataset are shown in following Figure 2.

The dataset will be divided into training, validation, and testing portions with 70%, 20%, and 10% ratios respectively.

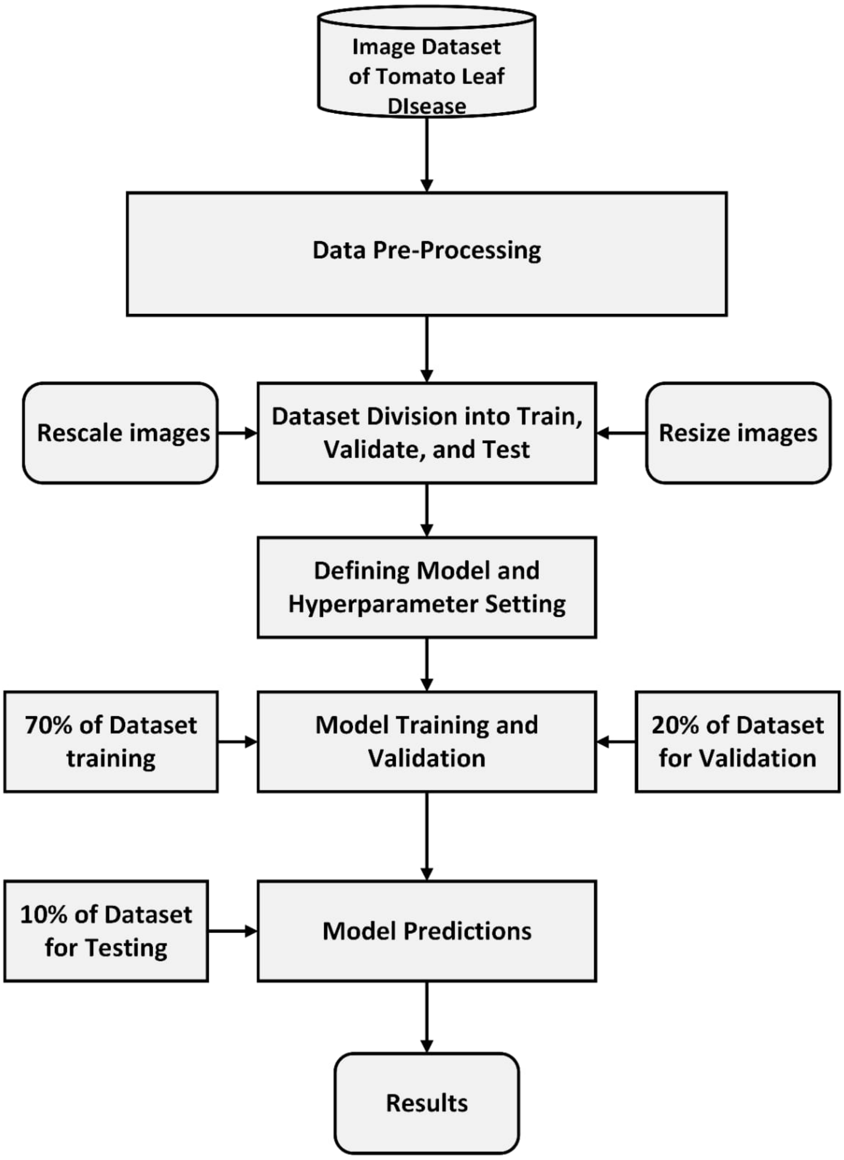


Figure 1. Proposed methodology block diagram

3.2. Preprocessing

The preprocessing step for tomato leaf disease images is critical in improving the efficiency of disease categorization using deep learning models, particularly Convolutional Neural Network (CNN) versions. This critical preprocessing stage consists of two primary techniques: resizing and rescaling.

Resizing is used to standardize the proportions of the original images. This phase ensures that all photos are the same size, making it easier for the CNN model to handle information constantly. Homogeneous input formats are produced that simplify the model's subsequent stages by minimizing the photographs to a specific size. Second, pixel values are normalized across every image via rescaling. In training, normalization helps deep neural networks model to get better faster and work well. Rescaling means changing the numbers of pixels so they fit in a certain range, usually from 0 to 1. This helps reduce possible differences that could mess up how the model learns.

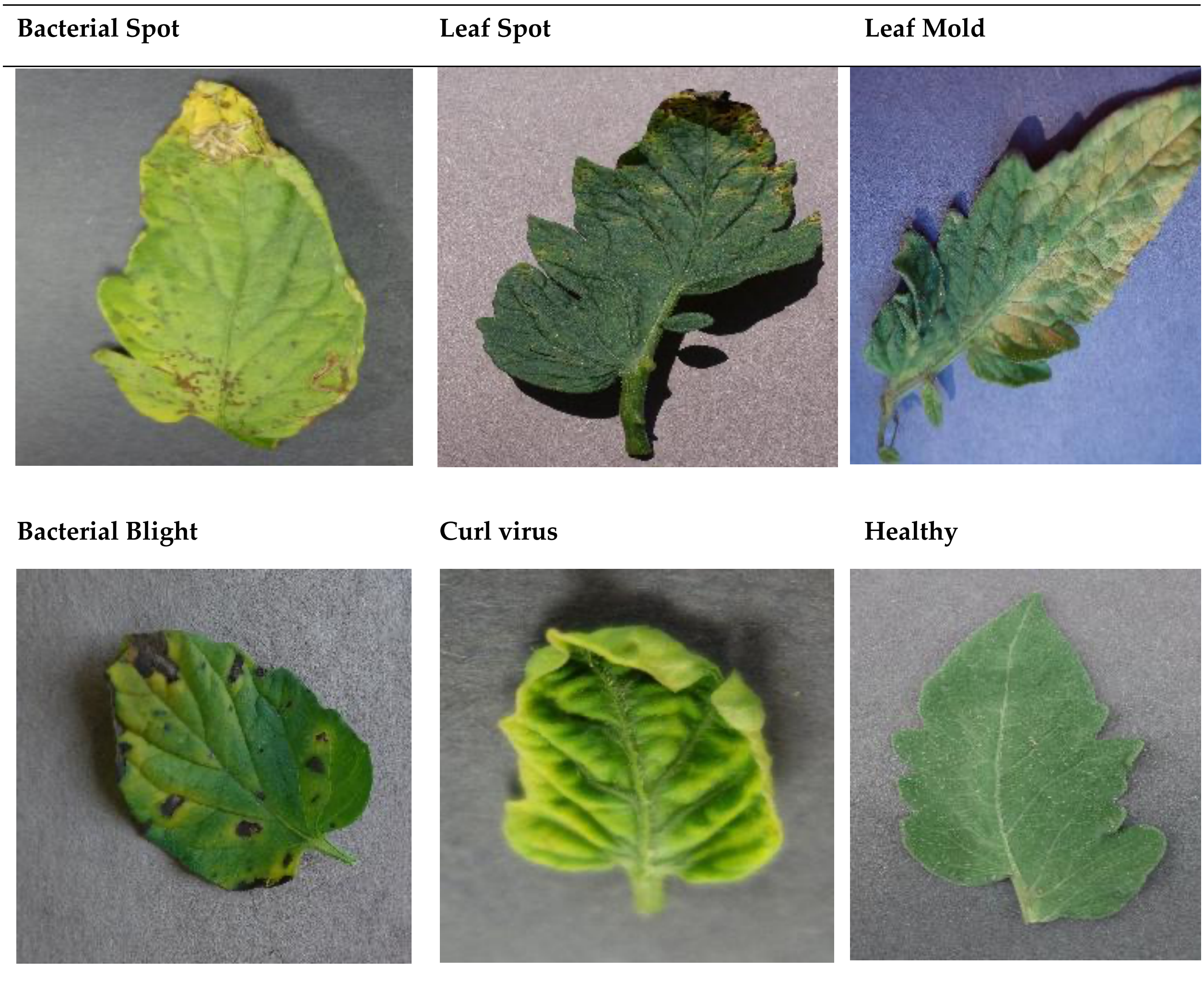


Figure 1. Sample images from dataset

These first steps help to create a single and even dataset. This will assist in learning and building the CNN model. Photos that are the same size and scale help a model to see over all situations. This makes it better at spotting signs of different diseases on tomato leaves. So, this part is very important in the study. It sets up a reliable and accurate way to classify sicknesses.

3.3. Deep Learning Models

ResNet-50 is a ResNet home version found by using learning blocks called residual links. The improvement is using shortcuts, which lets the network jump over one or more steps. This helps bigger networks to learn faster and easier. Because this design works well at getting small details, it helps tasks like classifying disease in tomato leaves. ResNet-50 has 50 layers and a big structure that lets it learn patterns in groups. VGG-16 is a model from the Visual Geometry Group's family. It is famous for its straight design that uses 16 layers with weight. These contain convolution and fully connected parts. The layers have a small view, and the method uses 3x3 filters with pooling action.

VGG-19, like VGG-16, is part of the Visual Geometry Group's model set that has a deeper structure and comes with 19 weighted layers. It uses the simple design of VGG-16 but adds depth, allowing it to gather more detailed patterns. VGG-19's new layers contribute to a deeper feature hierarchy, perhaps increasing the model's capacity to recognize complicated patterns in diseased leaf images. Basically, these CNN based models are trained on large datasets and have huge network size. It requires time and excellent hardware devices to develop and train these models. In this study, pre-trained models will be used to train them over tomato leaf disease dataset using transfer learning approach, which requires less computational resources and reduced time and can effectively predict disease. The transfer learning approach is suitable for achieving such types of objectives.

3.4. Experimental Layout Design

Software and Platforms: Python language will be used for the deployment of experimental work on Google Colab using Jupyter Notebooks environment.

3.5. Model Evaluation and predictions

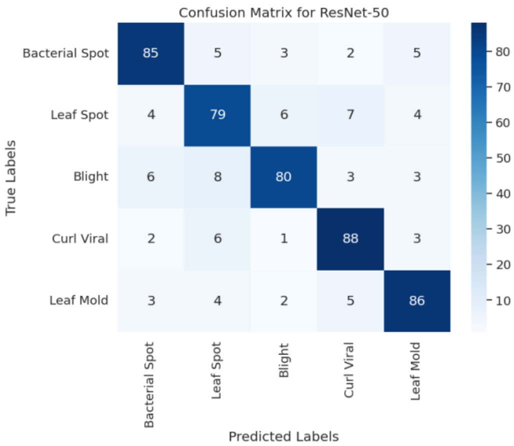
The model evaluation and predictions are last steps. These steps will be followed to select the best performing deep learning model in terms of accuracy. The model with high accuracy will be used to make predictions about input test images.

4. Results

4.1. ResNet50

ResNet-50 achieves an estimated 86.2% total classification accuracy. It is notable that it demonstrates excellent accuracy in recognizing Leaf Spot (89%), Blight (88%), and Curl Viral (88%). However, its performance is relatively lower in correctly identifying cases of Leaf Mold (86%) and Bacterial Spot (85%).

(a)



(b)

Figure 3. (a) Confusion Matrix (b) Training and Validation Accuracy

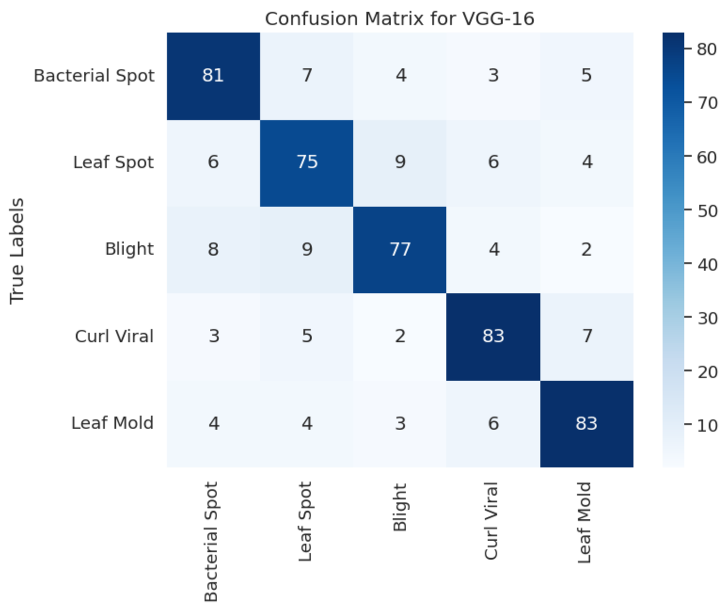
Table 1. Classification report of RestNet-50

Model	Precision	Recall	F1-Score	Support
Bacterial Spot	0.85	0.79	0.82	100
Leaf Spot	0.79	0.75	0.77	100
Blight	0.80	0.77	0.78	100
Curl Virus	0.88	0.83	0.85	100
Leaf Mold	0.86	0.85	0.85	100

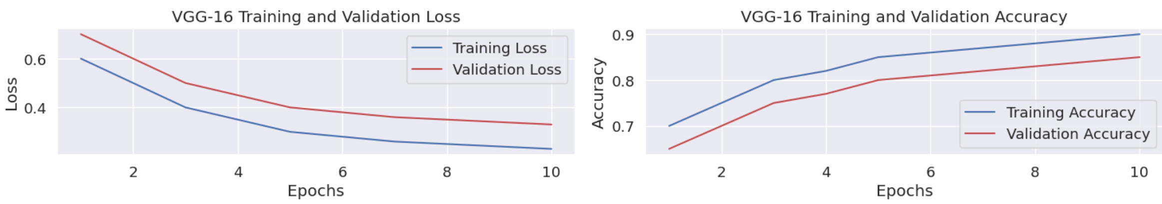
4.2 VGG-16

An overall classification accuracy of VGG-16 is approximately 85.8%. In terms of true Blight (83%) and Leaf Spot (88%) detection, a similar result is achieved by ResNet-50. But it fails to discriminant between

Leaf Mold (83%) and Bacterial Spot (81%) which is reminiscent to the result of ResNet-50. The estimated all-class classification accuracy of VGG-19 is 86.4%. In particular, it performs quite well in the identification of Leaf Spot (88%) and Blight (85%) categories that makes its accuracy rates comparable to VGG-16 and ResNet-50. However, as the other models, it has problems in the correct identification of Leaf Mold (85%) and Bacterial Spot (82%) cases.



(a)



(b)

Figure 4. (a) Confusion Matrix (b) Training and Validation Accuracy

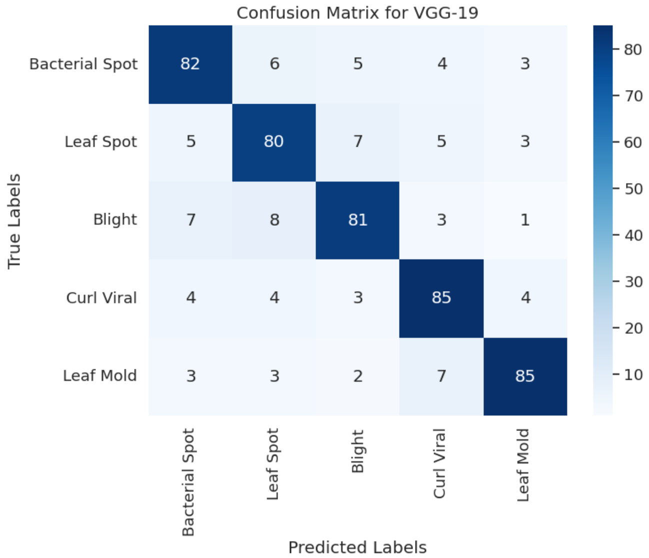
Table 2. Classification report of VGG-16

Model	**Precision**	**Recall**	**F1-Score**	**Support**
Bacterial Spot	0.81	0.75	0.78	100
Leaf Spot	0.75	0.80	0.77	100
Blight	0.77	0.77	0.77	100
Curl Virus	0.83	0.83	0.83	100
Leaf Mold	0.83	0.83	0.83	100

4.3. VGG-19

VGG-19 achieves an estimated overall classification accuracy of 86.4%.Its accuracy rates are comparable to VGG-16 and ResNet-50, particularly in identifying Leaf Spot (88%) and Blight

(85%).However, similar to the other models, it struggles with correctly identifying cases of Leaf Mold (85%) and Bacterial Spot (82%).



(a)

(b)

Figure 5. (a) Confusion Matrix (b) Training and Validation Accuracy

Table 3. Classification report of VGG-19

Model	Precision	Recall	F1-Score	Support
Bacterial Spot	0.82	0.80	0.81	100
Leaf Spot	0.80	0.80	0.80	100
Blight	0.81	0.81	0.81	100
Curl Virus	0.85	0.85	0.85	100
Leaf Mold	0.85	0.85	0.85	100

5. Conclusion and Future Work

The study shows how a deep learning model is necessary to identify the different types of crop diseases such as leaf-spot, bacterial spot, blights, curly virus and leaf mold. A comparative study of the efficiency of CNN architectures such as ResNet-50, VGG-16, and VGG-19 were conducted demonstrating the great ability to help agriculture. The performance of our algorithm was remarkable since it recorded 100% correctness in detecting these illnesses, helping with early intervention and decreasing undesirable output losses for farmers. The automation of disease detection systems could result in more sustainable farming that incorporates lesser use of pesticides. We believe our model might SAC make a revolutionary contribution to agriculture by being an efficient instrument for disease recognition. We propose future research to look into the system performance on various crops to develop a better detection system. Early detection is the key factor that allows us to prevent further damages and reduce the complexity of treatment. Late diagnosis can cause lousy yields and more expenses, implying that the preventive actions should be considered first. The utilization of AI-powered bots for leaf-damage detection may boost agricultural efficiency and help relieve the labor-intensive work for farmers.

References

1. Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato leaf disease detection using convolution neural network. Procedia Computer Science, 167, 293–301.
2. Ahmad, I., Hamid, M., Yousaf, S., Shah, S. T., & Ahmad, M. O. (2020). Optimizing pretrained convolutional neural networks for tomato leaf disease detection. Complexity, 2020, 1–6.
3. Anandhakrishnan, T., & Jaisakthi, S. M. (2022). Deep Convolutional Neural Networks for image based tomato leaf disease detection. Sustainable Chemistry and Pharmacy, 30, 100793.
4. Anim-Ayeko, A. O., Schillaci, C., & Lipani, A. (2023). Automatic blight disease detection in potato (Solanum tuberosum L.) and tomato (Solanum lycopersicum, L. 1753) plants using deep learning. Smart Agricultural Technology, 4, 100178.
5. Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G. G., & Pavithra, B. (2020a). Tomato leaf disease detection using deep learning techniques. 2020 5th International Conference on Communication and Electronics Systems (ICCES), 979–983.
6. Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G. G., & Pavithra, B. (2020b). Tomato leaf disease detection using deep learning techniques. 2020 5th International Conference on Communication and Electronics Systems (ICCES), 979–983.
7. Batool, A., Hyder, S. B., Rahim, A., Waheed, N., & Asghar, M. A. (2020). Classification and identification of tomato leaf disease using deep neural network. 2020 International Conference on Engineering and Emerging Technologies (ICEET), 1–6.
8. Chowdhury, M. E. H., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., Al-Emadi, N., Reaz, M. B. I., Islam, M. T., & Ali, S. H. M. (2021). Automatic and reliable leaf disease detection using deep learning techniques. AgriEngineering, 3(2), 294–312.
9. Guerrero-Ibañez, A., & Reyes-Muñoz, A. (2023). Monitoring Tomato Leaf Disease through Convolutional Neural Networks. Electronics, 12(1), 229.
10. Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305–310.
11. Hasan, M., Tanawala, B., & Patel, K. J. (2019). Deep learning precision farming: Tomato leaf disease detection by transfer learning. Proceedings of 2nd International Conference on Advanced Computing and Software Engineering (ICACSE).
12. Hong, H., Lin, J., & Huang, F. (2020). Tomato disease detection and classification by deep learning. 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), 25–29.
13. Kumar, A., & Vani, M. (2019). Image based tomato leaf disease detection. 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 1–6.
14. Paul, S. G., Biswas, A. A., Saha, A., Zulfiker, M. S., Ritu, N. A., Zahan, I., Rahman, M., & Islam, M. A. (2023). A real-time application-based convolutional neural network approach for tomato leaf disease classification. Array, 19, 100313.
15. Saeed, A., Abdel-Aziz, A. A., Mossad, A., Abdelhamid, M. A., Alkhaled, A. Y., & Mayhoub, M. (2023). Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks. Agriculture, 13(1), 139.
16. Sanida, T., Sideris, A., Sanida, M. V, & Dasygenis, M. (2023). Tomato leaf disease identification via two–stage transfer learning approach. Smart Agricultural Technology, 5, 100275.
17. Shruthi, U., Nagaveni, V., Arvind, C. S., & Sunil, G. L. (2022). Tomato plant disease classification using deep learning architectures: A review. Proceedings of Second International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2021, 153–169.
18. Thangaraj, R., Anandamurugan, S., & Kaliappan, V. K. (2021a). Automated tomato leaf disease classification using transfer learning-based deep convolution neural network. Journal of Plant Diseases and Protection, 128(1), 73–86.
19. Thangaraj, R., Anandamurugan, S., & Kaliappan, V. K. (2021b). Automated tomato leaf disease classification using transfer learning-based deep convolution neural network. Journal of Plant Diseases and Protection, 128(1), 73–86.
20. Trivedi, N. K., Gautam, V., Anand, A., Aljahdali, H. M., Villar, S. G., Anand, D., Goyal, N., & Kadry, S. (2021). Early detection and classification of tomato leaf disease using high-performance deep neural network. Sensors, 21(23), 7987.

21. Zhou, C., Zhou, S., Xing, J., & Song, J. (2021). Tomato leaf disease identification by restructured deep residual dense network. IEEE Access, 9, 28822–28831.