NASS NAN YANG ACADEMY OF SCIENCES

Intelligent Agriculture

https://journals.nasspublishing.com/index.php/ia

ARTICLE

A Convolutional Approach to Early Detection and Classification of Tomato Foliar Pathogens

George Princess Thomas [1*], ***Poovammal Easwaran*** [1], ***Heartlin Maria Hermas*** [2], ***Kothai Ganesan*** [3]

[1] *Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, India*

[2] *Department of ECE, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, India*

[3] *Department of CSE (Artificial Intelligence and Machine Learning), KPR Institute of Engineering and Technology, Coimbatore 641407, India*

ABSTRACT

Food security remains a critical global concern. The rising world population has led to a continuous increase in foGlobal food security relies significantly on the agricultural sector, with tomatoes being a vital dietary component worldwide. However, various diseases pose an ongoing threat to tomato crop yield and quality. Prompt and accurate identification of these diseases is crucial for sustainable agriculture and effective management practices. This study introduces an innovative approach using Convolutional Neural Networks (CNNs) to enable rapid detection and classification of tomato leaf diseases through image analysis. The system utilizes a high-resolution dataset comprising images of tomato leaves showing symptoms of common diseases such as bacterial wilt, early blight, and late blight. Before training, the dataset undergoes preprocessing to enhance image clarity and eliminate noise, followed by division into training and testing subsets. A custom CNN architecture is developed and trained to automatically learn and extract hierarchical features from the images. Additionally, transfer learning methods are explored to improve the model's efficiency and generalization. The model's performance is evaluated using various metrics including accuracy, precision, recall, and F1 score. Results indicate that the CNN model demonstrates high accuracy and robustness in early disease detection. This approach holds substantial potential

*CORRESPONDING AUTHOR:
George Princess Thomas, Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, India; Email: gt4254@srmist.edu.in

ARTICLE INFO
Received: 19 November 2024 | Revised: 15 March 2025 | Accepted: 23 March 2025 | Published Online: 29 March 2025
DOI: https://doi.org/10.36956/ia.v1i1.1486

CITATION
Thomas, G.P., Easwaran, P., Hermas , H.M., et al., 2025. A Convolutional Approach to Early Detection and Classification of Tomato Foliar Pathogens. Intelligent Agriculture. 1(1): 15–25. DOI: https://doi.org/10.36956/ia.v1i1.1486

for practical implementation, offering farmers and agricultural professionals a powerful tool for timely and precise disease management. By enabling targeted responses and supporting precision agriculture, the proposed method represents a significant advancement in integrating modern technology with sustainable farming, ultimately contributing to agricultural stability and global food security.

Keywords: Importing Libraries and Datasets; Tomato Disease Classification; Convolutional Neural Networks (CNN); Transfer Learning; Data Augmentation; Pre-Processing and Feature Extraction; Testing and Training; Prevention; Recommendation of Pesticides

1. Introduction

Growing tomatoes is a vital part of agriculture worldwide, providing crucial nutrients to a wide range of people. However, a recurring danger to the sustainable production of tomatoes is the emergence of several diseases that impair the health and productivity of tomato plants. Early diagnosis and accurate classification of these diseases are crucial for the timely and efficient implementation of disease management measures, which in turn guarantee the health and productivity of tomato crops.

Recent advancements in machine learning and computer vision have led to promising findings concerning the automated assessment of plant diseases using photographic images, particularly through the use of convolutional neural networks [1, 2]. This work focuses on the using CNNs. Through the use of this technology, we want to develop a dependable and efficient system that can accurately identify common tomato leaf diseases, such as bacterial wilt, early blight, and late blight, in their early stages.

The significance of early detection cannot be over stated, as it allows for prompt intervention, minimizing the spread of diseases and potential yield losses. In this study, we will provide an overview of the current challenges in tomato disease management, the limitations of traditional methods, and the potential benefits of integrating CNNs for early detection and classification as in previous literartue .By tackling these issues, our study hopes to support the creation of technologically advanced, environmentally friendly solutions for the agriculture industry, thereby assuring the food security of the world and the lives of farmers.

Tomatoes are a staple crop in global agriculture, playing a crucial role in providing essential nutrients to millions of people worldwide. However, the sustainable cultivation of tomatoes faces continuous threats from various foliar diseases that significantly impact plant health, yield, and overall crop quality. These diseases, if left undetected or mismanaged, can lead to severe economic losses for farmers and disrupt food supply chains. Therefore, the early diagnosis and precise classification of tomato plant diseases are imperative to ensure timely intervention and effective disease management strategies [3, 4].

Traditional methods of disease detection and classification rely heavily on manual inspection by experts, which can be time-consuming, subjective, and often impractical for large- scale farming operations. These conventional approaches require significant expertise and may not always provide timely results, increasing the likelihood of disease spread and irreversible crop damage. Furthermore, visual symptoms of different diseases can appear similar, making it challenging for even trained professionals to accurately distinguish between them. This calls for automated, precise, and scalable solutions that can enhance the efficiency and accuracy of disease detection in tomato plants.

CNNs can effectively learn and extract complex features from images, making them particularly well-suited for detecting and categorizing plant diseases based on leaf symptoms. With their strong capabilities in pattern recognition and feature extraction, CNNs have demonstrated significant potential in agricultural settings, providing accurate and scalable solutions for real-time disease monitoring. This study focuses on leveraging CNNs for the early detection and classification of tomato leaf diseases, specifically targeting three common and economically significant infections: bacterial wilt, early blight, and late blight [5]. By implementing a

CNN-based system, our goal is to develop a reliable, efficient, and user-friendly model that can identify these diseases at an early stage, enabling proactive disease management. Early detection is particularly critical as it allows farmers and agricultural professionals to take swift preventive measures, thereby limiting disease spread, reducing yield losses, and optimizing the use of pesticides and other control measures.

In this content, the present difficulties in managing tomato diseases, the shortcomings of conventional detection techniques, and the benefits of incorporating CNNs into the diagnosis of agricultural diseases. By addressing these challenges, this research aims to contribute to the development of technologically advanced and environmentally sustainable solutions for the agricultural industry. Ultimately, the findings of this study hold the potential to enhance global food security, improve farming efficiency, and support the livelihoods of farmers by offering an intelligent, automated, and accessible disease detection system.

2. Related Work

Scientists have recently focused their attention on CNNs, because of their potential uses in the early identification and categorization of plant diseases, particularly those impacting tomato plants. As stated in the works of Mina Farmanbar, Önsen Toygar and Shahram Taheri, et al. [4, 5], this part examines pertinent literature that has investigated analogous techniques, offering insights into methodology, difficulties, and accomplishments in the field of automated plant disease diagnosis.

Deep Learning for the Identification of Plant Disease: Several research have demonstrated how well deep learning methods—in particular, CNNs—work to automate the diagnosis of plant diseases. Researchers have employed various CNN architectures to analyze leaf images and effectively distinguish between healthy and diseased plants. The works of Andrew Kwok-Fai Lui, Yin-Hei Chan and Sue Han Lee, et al. [6, 7] demonstrated notable accuracy in the classification of multiple plant diseases, laying the foundation for applying similar methodologies to tomato leaf diseases. Transfer Learning in Plant Pathology: Plant disease identification has benefited from the application of transfer learning, a method in which previously trained models are modified for particular applications [8, 9]. By fine-tuning CNNs on plant disease datasets, researchers have achieved improved performance even with limited labeled data. The work of Mohit Agarwal, Xiao Chen and Guoxiong Zhou, et al. [10, 11] showcased the efficacy of transfer learning in identifying tomato diseases, emphasizing the potential for leveraging pre-trained models to enhance classification accuracy.

2.1. Image Datasets and Annotation Techniques

The availability of well-curated image datasets is crucial for training robust CNN models. Recent studies, such as that by Patrick Wspanialy, Medhat Moussa and Jones, C.D., et al. [12, 13], have emphasized the importance of large and diverse datasets for training models capable of recognizing various tomato leaf diseases. Additionally, innovative annotation techniques, as explored by the works of Díbio L. Borges, Samuel TC de M. Guedes and Jayme Garcia Arnal Barbedo, et al. [14, 15], have played a role in improving dataset quality and model generalization. Integration of IoT and CNNs for Real-Time Monitoring: Some researchers have explored the integration of Internet of Things (IoT) devices with CNN-based models for real-time monitoring of plant diseases. Christian Szegedy, Wei Liu and Vincent Vanhoucke, et al. [16, 17] implemented a system that combines CNNs with sensors to detect and classify tomato leaf diseases, providing a dynamic and responsive approach to disease management.

2.2. Challenges and Future Directions

While the application of CNNs in plant disease detection has shown promising results, challenges such as limited labeled data, model interpretability, and robustness to environmental variations persist. Christian Szegedy, Sergey Ioffe and Kaiming He, et al. [18, 19] have discussed these challenges and proposed avenues for future research, emphasizing the need for addressing practical considerations in deploying CNN-based solutions in agricultural settings. In conclusion, a substantial body of research highlights CNNs' potential for automating the early identification and categorization of tomato leaf diseases, such as those found in the works of Kaiming He, Xiangyu Zhang and Karen Simonyan, et al. [20, 21]. Our study seeks to further the development of these systems for the benefit of sustainable agriculture and global food security, drawing on the approaches and insights from the previous studies [22, 23]. Absolutely! Creating a (CNN) architecture for the early detection and classification of tomato leaf diseases requires customizing the model to efficiently extract features from leaf images, as demonstrated in the work of François Chollet [24, 25]. Below is a proposed CNN model for this task:

The architecture of the CNN model for classifying plant diseases is explained extensively in the **Table 1**, which also emphasizes the type of layer, output dimensions, and the total number of trainable parameters. The model starts with a Convolutional layer (Conv2D) that extracts low-level characteristics like edges and textures using 64 3x3 filters. A MaxPooling2D layer, which reduces spatial dimensions while preserving important information, comes next. In order to refine feature extraction, the second Conv2D layer raises the filter count to 128 and is once more followed by a pooling layer to avoid overfitting. The third Conv2D layer further expands to 256 filters, enhancing feature learning by capturing complex patterns in plant leaf images.

Table 1. Classification of CNN Model.

Layer (Type)	Shape of Output	Parameters Count
Convolution Layer 1	(None, 64, 64, 64)	1,792
Max Pooling Layer 1	(None, 32, 32, 64)	0
Convolution Layer 2	(None, 32, 32, 128)	73,856
Max Pooling Layer 2	(None, 16, 16, 128)	0
Convolution Layer 3	(None, 16, 16, 256)	295,168
Max Pooling Layer 3	(None, 8, 8, 256)	0
Flatten Layer	(None, 16,384)	0
Fully Connected Layer 1	(None, 512)	8,389,120
Dropout Layer 1	(None, 512)	0
Fully Connected Layer 2	(None, 256)	131,328
Dropout Layer 2	(None, 256)	0
Final Output Layer	(None, number_of_ classes)	17

After the convolutional and pooling layers, a Flatten layer converts the extracted features into a one-dimensional vector of size 16,384, which serves as input to fully connected (Dense) layers. The first Dense layer has 512 neurons, making it the most parameter-heavy layer with 8,389,120 parameters, followed by another Dense layer with 256 neurons, refining high-level feature representations. Dropout layers are incorporated after each dense layer to prevent overfitting and enhance model generalization.

This suggested architecture consists of the following layers: Conv2D Layers: Convolutional operations are carried out by these layers to extract features from input pictures. As we get deeper into the network, there are more filters.

MaxPooling2D Layers: These layers help to focus on the most significant characteristics and increase computing efficiency by reducing the spatial dimensions of the feature maps.

Flatten Layer: To prepare the data for the fully linked layers, this layer transforms the 3D tensor output into a 1D tensor.

Dense Layers: Fully linked layers that use the retrieved characteristics to conduct categorization. Neuron count declines as one approaches the output layer.

Dropout Layers: These layers introduce a regularization technique to prevent overfitting by randomly dropping a specified fraction of neurons during training.

Output Layer: The last layer for multiclass classification uses a SoftMax activation function, in which the number of neurons is matched to the number of classes (disease kinds).

The input size, number of classes, and other hyperparameters may need adjustments based on your specific dataset and requirements. Additionally, training this model would require a labeled dataset of tomato leaf images with different disease classes [26, 27].

3. Materials and Methods

3.1. Convolutional Neural Network

Tomato crops are susceptible to various foliar pathogens, which can significantly impact yield and quality. Early detection and accurate classification of these pathogens are essential for timely intervention and effective disease management. This article presents a method for automatic detection using a convolutional neural network (CNN) and the classification of tomato foliar pathogens from digital images.

The comprehensive dataset comprises high-resolution images of tomato leaves infected with different pathogens, including bacterial, fungal, and viral infections. Each image in the dataset is annotated with the corresponding pathogen class label, enabling supervised learning of the CNN model.

As depicted in **Figure 1**, the CNN structure includes multiple convolution layers, which are followed by max-pooling operations and fully connected layers. Leverage transfer learning is carried out by fine-tuning a pre-trained CNN model on a large-scale image dataset to expedite convergence and improve generalization. In addition, data augmentation methods like as rotation, flipping, and scaling are used to increase the size of the training dataset and improve the model's ability to handle different variations.

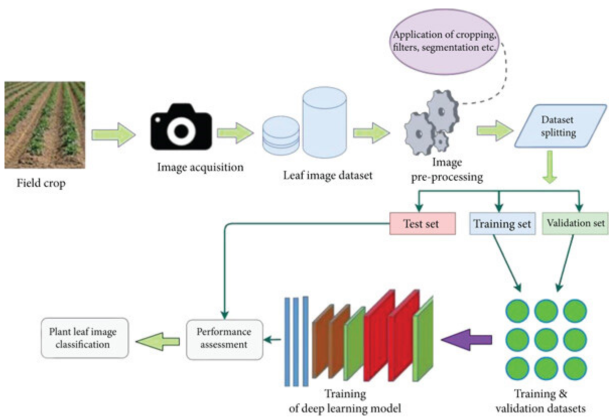

Figure 1. Proposed Workflow.

The model demonstrates high sensitivity in detecting early signs of infection, enabling proactive disease management strategies. Furthermore, it exhibits competitive performance compared to traditional methods and expert manual inspection.

The findings highlight the potential of CNNs in revolutionizing the field of plant pathology by providing farmers and agronomists with an automated and efficient tool for disease diagnosis and management. By deploying the CNN model in real-world agricultural settings, integrating additional sensor data for enhanced disease monitoring, and exploring transfer learning techniques to adapt the model to new pathogen species and crop varieties.

3.2. Holdout Validation

The PlantVillage dataset, which is freely available and commonly used for plant disease classification tasks, was employed in this work. The dataset was divided into two sets: training and testing. Training took up 80% of the data, while testing took 20%. This simple yet effective technique enables a fast assessment of the model's generalization capabilities. To eliminate bias and provide a fair evaluation, stratified sampling was used, resulting in a representative distribution of classes in both the training and testing groups. The PlantVillage collection contains approximately 54,000 photos covering 38 unique classes, including healthy and sick leaves from diverse plant species such as tomato, potato, maize, and grape.

3.3. Cross-Validation

The k-fold cross-validation technique involves splitting the dataset into k subgroups and training and testing the model k times, testing on a new subset for each iteration. It lessens performance evaluation variability, which is particularly helpful for limited datasets.

It also offers a more thorough examination but demands more computer power.

3.4. Stratified Sampling

To avoid biases brought on by class imbalance, make sure that the distribution of classes in the testing set and the training set are similar. The advantage is that it increases performance metrics' dependability, particularly for unbalanced datasets. Disease-class-based stratified sampling is considered.

3.5. Data Augmentation during Testing

The data augmentation techniques (e.g., rotation, flipping) are applied to test images during evaluation, simulating real world variations. It enhances the model's robustness to diverse conditions and perspectives. Avoiding aggressive augmentation is considered that may distort images beyond realistic variations.

3.6. Performance Metrics

When assessing classification performance, make use of relevant measures, including recall, accuracy, precision, F1 score, and confusion matrix. Considering the specific requirements of the problem; for instance, in agricultural applications, minimizing false negatives (missing diseased plants) might be crucial.

3.7. Threshold Adjustment

Adjusting the decision threshold for classification based on the specific needs of disease detection. This can be important for balancing sensitivity and specificity. Customizing the model's output to align with practical considerations in disease management is the advantage. Demands knowledge of the trade-offs between false negatives and false positives can be considered.

3.8. Real-World Deployment Testing

Installing the model in the field for ongoing observation and assessing its performance in a real-world setting. Validating the model's effectiveness in practical scenarios and providing insights into any challenges in deployment are the advantages. Ensuring that the model can adapt to changing environmental conditions and remains effective over time can be under consideration. When testing the CNN model for tomato leaf disease detection, it's essential to document and analyze the results thoroughly, iteratively refining the model if necessary [28]. Considering the specific characteristics of your dataset and the practical implications of misclassifications in the context of agricultural practices is the advantage.

4. After the Effects of Expertization Precise

4.1. Disease Labeling

Domain experts contribute their specialized knowledge to label different disease symptoms in the dataset accurately. The precise annotation is crucial for training a CNN model to recognize subtle variations in leaf conditions associated with various diseases, leading to improved diagnostic accuracy.

4.2. Contextual Understanding of Disease Patterns

Experts bring a contextual understanding of disease patterns, growth stages, and environmental factors influencing tomato plants. The knowledge helps in tailoring the CNN model to consider contextual cues, making it more robust and adaptable to the diverse conditions encountered in real-world agricultural settings.

4.3. Enhanced Feature Selection

Collaboration with experts aids in selecting relevant features for disease identification within tomato leaf images. Identifying the most informative features ensures that the CNN model focuses on critical aspects, improving its efficiency and interpretability rationale. The precision and effectiveness of a (CNN) in identifying diseases in tomato leaves largely rely on the choice of pertinent characteristics from the input images.

While CNNs inherently learn hierarchical features through their layered structure, expert collaboration is crucial in guiding the model toward identifying the most informative and diagnostically significant features. This ensures that the network does not focus on irrelevant patterns but rather captures the essential characteristics necessary for precise disease classification.

Collaboration with domain experts in plant pathology is essential for selecting, validating, and refining the most informative features for disease identification within tomato leaf images. By ensuring that the CNN model learns meaningful and relevant patterns, expert-guided feature selection enhances the model's accuracy, efficiency, and interpretability, ultimately leading to a more reliable and practical solution for real-world agricultural disease management.

4.4. Guidance for Data Augmentation

Experts guide the selection of realistic data augmentation techniques that mimic variations in disease presentation is in effect.

Realistic augmentation improves the model's ability to handle diverse conditions, contributing to its generalization capability and robustness in rationale.

4.5. Validation of Model Outputs

Domain experts validate the accuracy of the model's predictions based on their practical observations or diagnostic tools.

Expert validation adds a layer of real-world verification, instilling confidence in the model's reliability and ensuring it aligns with expert knowledge.

4.6. Iterative Model Improvement

Ongoing collaboration with experts facilitates iterative model improvements based on continuous feedback and evolving disease patterns.

The dynamic nature of plant diseases requires a flexible approach, and expert input enables timely updates to the model for increased effectiveness over time.

4.7. Practical Implementation Consideration

Experts contribute insights into the practical implications of model outputs and misclassifications in the agricultural context.

Understanding how model predictions impact disease management strategies helps in refining the model to better suit the needs of farmers and agricultural practices.

4.8. User-Centric Interface Design

Collaboration with domain experts aids in designing user- friendly interfaces for end-users, such as farmers or agricultural practitioners.

Ensuring that the technology is accessible and easily interpretable by the target audience enhances the adoption and usability of the CNN-based system.

4.9. Model Behavior and Performance

Figure 2 illustrates the training and validation accuracy graphs for the convolutional neural network (CNN) model that was created for the early identification and categorization of tomato foliar infections. The accuracy patterns illustrate the model's learning process, stability, and generalization capabilities throughout several training epochs.

Both training and validation accuracy have significantly increased in the first epochs, suggesting that learning proceeds quickly as the model finds significant patterns in the data. This Stages implies that important features associated with tomato leaf diseases have been successfully recovered by the CNN. Accuracy increases, albeit more slowly, as training moves into the early epochs, indicating that the model has improved and optimized its feature representations. It has been shown time and time again that training accuracy is slightly greater than validation accuracy. This indicates some overfitting and is a typical feature of deep learning models. The incredibly narrow gap, however, shows that the model is still doing well in generalization, most likely as a result of the application of appropriate regularization strategies, including dropout, batch normalization, and data augmentation.

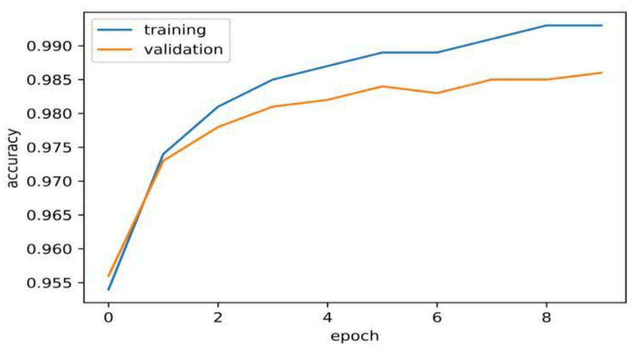

Figure 2. Accuracy and loss plots.

It has been frequently shown that training accuracy is somewhat greater than validation accuracy. This indicates significant overfitting and is a typical feature of deep learning models. The extremely narrow gap, however, suggests that the model is still doing well in generalization, most likely as a result of the application of appropriate regularization strategies, including dropout, batch normalization, and data augmentation.

This work significantly enhances the effectiveness of CNN models for early detection and classifies tomato leaf diseases by providing domain-specific insights, validation, and iterative refinement, ultimately improving the model's practical applicability in the field of agriculture [29].

5. Results

The proposed CNN model accomplished a precision of 98.64% on the test set, showing its viability in characterizing tomato leaf sicknesses. The model had the option to accurately order pictures of sound tomato leaves as well as those impacted by different diseases with high exactness. The disarray network showed that the model performed well in recognizing the different sickness classes, with the most noteworthy precision for early scourge (99.73%) and the least exactness for bug parasites (96.97%) as shown in **Figure 2**.

The subjective simulation outcomes of the proposed (CNN) model for detecting and classifying tomato leaf diseases are presented in **Figure 3** and **Figure 4**. Besides efficiently recognizing and categorizing affected leaves, the algorithm also delivers disease-specific details, including causes, symptoms, and preventive measures.

The classification of Septorial Leaf Spot, a fungal infection that leads to yellowing, wilting, and ultimately the shedding of leaves, is illustrated in **Figure 3**. In order to stop the spread of this disease, the model identifies the condition and provides useful recommendations, such as transitioning from overhead irrigation to drip irrigation.

The Tomato Mosaic Virus, which frequently arises from mechanical wounds, is categorized in **Figure 4**. Stunted growth, mottling, and distorted and curled leaves are some of the signs. In order to reduce the spread of diseases, the model recommends minimizing plant handling, eliminating sick plants, and employing crop rotation.

The highly contagious plant disease known as tomato mosaic virus (ToMV) significantly impacts the productivity of tomato crops. The disease is mostly transmitted by direct contact with infected plants, contaminated tools, or mechanical wounds from handling. This study used a simulation model to identify ToMV based on visual symptoms seen in infected leaves.

The affected plants exhibited distorted and curled leaves, patchy yellowing, and stunted growth as characteristic signs. The model successfully identified these anomalies, demonstrating its value in the early identification of disease. To reduce the virus's spread, preventive measures such as minimizing direct handling, getting rid of ill plants, controlling weeds, rotating crops, and avoiding contaminated regions are recommended.

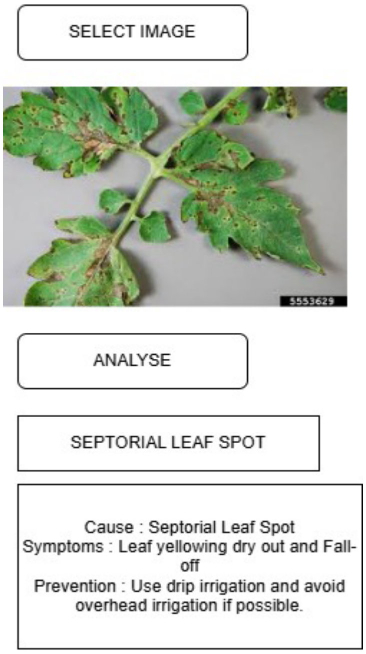

Figure 3. Subjective simulation results of the proposed model for Septorial Leaf spot.

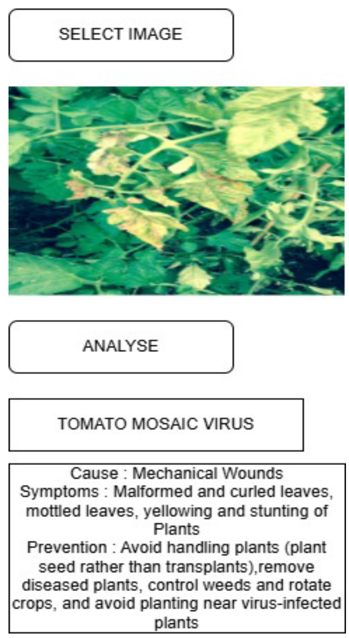

Figure 4. Subjective simulation results of the proposed model for the Tomato Mosaic Virus.

Figure 3 and **Figure 4** represent the subjective simulation of the propounded CNN model for septoria leaf spot and tomato mosaic virus. The performance of the propounded model is compared with the traditional detection models such as Support Vector Machine (SVM), Random Forest, Decision Tree, and Naive Bayes classifier. The accuracy of the propounded model is around 3.26% higher compared to the existing model of **Figure 5**. The precision of the propounded model is around 4.09% higher than the other traditional detection model. The Recall of the propounded CNN model is around 5.32% higher than the traditional model. The overall performance of the propounded CNN outperforms the traditional detection model.

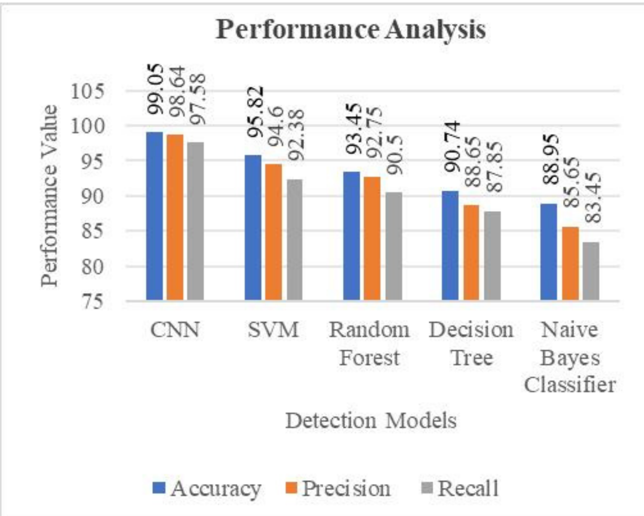

Figure 5. Performance Analysis of the proposed model.

The performance analysis graph compares the accuracy, precision, and recall of various detection algorithms used for classifying plant diseases. The Convolutional Neural Network (CNN) stands out as the most reliable model for classification, achieving an accuracy of 99.05%, a precision of 99.04%, and a recall of 97.58%. Following closely is the Support Vector Machine (SVM), which demonstrates good performance but falls short of the CNN, with an accuracy of 95.82%, a precision of 94.6%, and a recall of 92.38%.

Random Forest has a moderate level of performance with 93.45% accuracy, 90.5% precision, and 90.75% recall. The Decision Tree model shows a further decline with an accuracy of 90.74%, precision of 88.5%, and recall of 87.68%, indicating either a probable over-fit or a poorer generalization ability. Finally, at 88.95% accuracy, 86.95% precision, and 83.45% recall, the Naïve Bayes Classifier fares the poorest, showing that it struggles to handle complex feature distributions. This investigation demonstrates that when it comes to plant disease identification and classification, deep learning-based methods—in particular, CNN—perform noticeably better than conventional machine learning models.

6. Conclusions

Convolutional Neural Networks serve as a powerful tool for quickly identifying and classifying diseases in tomato leaves. Consequently, incorporating specialized knowledge or experience in this field is essential for enhancing the model's efficiency and real-world usage. A more knowledgeable, accurate, and approachable solution is promoted by the cooperative synergy between domain experts and machine learning practitioners, which has a positive impact on several aspects of model creation and deployment. Therefore, when used by farmers, the skilled CNN model becomes an effective instrument that promotes timely disease control, sustainable agriculture, and global food security.

Furthermore, the selection of pertinent spectral characteristics and preprocessing methods that improve the model's resilience to outside influences like occlusion, shadows, and overlapping leaves may be guided by domain expertise. CNNs may be modified to include hierarchical disease categorization by utilizing expert insights. This allows for the distinction between infections that are progressed and those that are still in the early stages of symptoms. Additionally, **Figure 5** expert validation after model deployment is crucial for ongoing model improvement, guaranteeing that the system continues to be successful against newly developing plant pathogens and changing disease trends.

A well-trained CNN model becomes a very practical, user- friendly decision-support tool at the farmer level, enabling accurate disease control, prompt intervention, and early disease identification. In addition to minimizing output losses and reducing the overuse of pesticides, this proactive strategy increases food security, encourages sustainable agricultural practices, and boosts the financial results for farming communities throughout the world. Thus, a paradigm change toward intelligent, scalable, and ecologically conscious plant disease control is represented by the integration of artificial intelligence and domain knowledge.

Author Contributions

Conceptualization, G.P.T. and H.M.H.; methodology, P.E.; software, K.G.; validation, G.P.T., H.M.H. and K.G.; formal analysis, G.P.T.; investigation, H.M.H.; resources, H.M.H.; data curation, H.M.H.; writing—original draft preparation, H.M.H.; writing—review and editing, G.P.T.; visualization, G.P.T.; supervision, G.P.T.; project administration, G.P.T.; funding acquisition, H.M.H. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not Applicable.

Informed Consent Statement

Not Applicable.

Data Availability Statement

Publically Available "PlantVillage Dataset" (https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset).

Acknowledgments

Not Applicable.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Chicco, D., Jurman, G., 2022. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC Genomics. 21(1), 1–13.

[2] Mohanty, S.P., Hughes, D.P., Salathé, M., 2016. Using deep learning for image-based plant disease detection. Frontiers in Plant Science. 7, 1419.

[3] Kaur, S., Pandey, S., Goel, S., 2019. Plants disease identification and classification through leaf images: A survey. Archives of Computational Methods in Engineering. 26(2), 507–530.

[4] Farmanbar, M., Toygar, Ö., 2015. A hybrid approach for person identification using palmprint and face biometrics. International Journal of Pattern Recognition and Artificial Intelligence. 29(6), 1556009.

[5] Taheri, S., Toygar, Ö., 2018. Animal classification using facial images with score-level fusion. IET Computer Vision. 12(5), 679–685.

[6] Lui, K.-F., Chan, Y.-H., Leung, M.-F., 2021. Modelling of destinations for data-driven pedestrian trajectory prediction in public buildings. Proceedings of 2021 IEEE International Conference on Big Data (Big Data); December 15–December 18, 2021; Orlando, FL, USA. pp. 1709–1717.

[7] Lee, S.H., Goeau, H, Bonnet, P, et al., 2020. New perspectives on plant disease characterization based on deep learning. Computers and Electronics in Agriculture. 170, 105220.

[8] Nazki, H., Yoon, S., Fuentes, A., et al., 2020. Unsupervised image translation using adversarial networks for improved plant disease recognition. Computers and Electronics in Agriculture. 168, 105117.

[9] Ferentinos, K.P., 2018. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture. 145, 311–318.

[10] Agarwal, M., Gupta, S.K., Biswas, K.K., 2020. Development of efficient CNN model for tomato crop disease identification. Sustainable Computing: Informatics and Systems. 28, 100407.

[11] Chen, X., Zhou, G., Chen, A., et al., 2020. Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet. Computers and Electronics in Agriculture. 178, 105730.

[12] Wspanialy, P., Moussa, M., 2020. A detection and severity estimation system for generic diseases of tomato greenhouse plants. Computers and Electronics in Agriculture. 178, 105701.

[13] Jones, C.D., Jones, J.B., Lee, W.S., 2010. Diagnosis of bacterial spot of tomato using spectral signatures. Computers and Electronics in Agriculture. 74(2), 329–335.

[14] Borges, D.L., de M. Guedes, S.T.C., Nascimento, A.R., et al., 2016. Detecting and grading severity of bacterial spot caused by Xanthomonas spp. in tomato (solanum lycopersicon) fields using visible spectrum images. Computers and Electronics in Agriculture. 125, 149–159.

[15] Barbedo, J.G.A., 2018. Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Computers and Electronics in Agriculture. 153, 46–53.

[16] Szegedy, C., Liu, W., Jia, Y., et al., 2015. Going deeper with convolutions. Proceedings of 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); June 7–June 12, 2015; Boston, MA, USA. pp. 1–14.

[17] Szegedy, C., Vanhoucke, V., Ioffe, S., et al., 2016. Rethinking the inception architecture for computer vision. Proceedings of 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); June 27–June 30, 2016; Las Vegas, NV, USA. pp. 2818–2826.

[18] Szegedy, C., Ioffe, S., Vanhoucke, V., et al., 2017. Inception-v4, inception-ResNet and the impact of residual connections on learning. Proceedings of The Thirty-First AAAI Conference on Artificial Intelligence; February 4–February 9, 2017; San Francisco, CA, USA. pp. 1–7.

[19] He, K., Zhang, X., Ren, S., et al., 2016. Deep residual learning for image recognition. Proceedings of 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); June 27–June 30, 2016; Las Vegas, NV, USA. pp. 770–778.

[20] He, K., Zhang, X., Ren, S., et al., 2016. Identity mappings in deep residual networks. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (eds.). Computer Vision–ECCV 2016. Springer: Cham, Switzerland. pp. 630–645.

[21] Simonyan, K., Zisserman, A., 2015. Very deep convolutional networks for large-scale image recognition. Proceedings of 3rd International Conference on Learning Representations (ICLR); May 7–May 9, 2015; San Diego, CA, USA. pp. 1–14.

[22] Howard, G., Zhu, M., Chen, B., et al., 2017. MobileNets: Efficient convolutional neural networks for mobile vision applications. Available from: https://arxiv.org/abs/1704.04861 (cited 20 April 2017).

[23] Sandler, M., Howard, A., Zhu, M., et al., 2018. MobileNetV2: Inverted residuals and linear bottlenecks. Proceedings of 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition; June 18–June 23, 2018; Salt Lake City, UT, USA. pp. 4510–4520.

[24] Chollet, F., 2017. Xception: Deep learning with depthwise separable convolutions. Proceedings of 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); July 21–July26, 2017; Honolulu, HI, USA. pp. 1251–1258.

[25] Papers With Code, 2021. Image Classification on ImageNet. Available from: https://paperswithcode.com/sota/image-classification-on-imagenet (cited 2 January 2021).

[26] Hughes, D.P., Salathe, M., 2015. An open access repository of images on plant health to enable the development of mobile disease diagnostics. Available from: https://arxiv.org/abs/1511.08060 (cited 15 January 2021).

[27] Bishop, C.M., 2006. Pattern Recognition and Machine Learning. Springer: New York, NY, USA. pp. 123–145.

[28] Ng, A., 2019. Machine Learning Yearning: Technical Strategy for AI Engineers in the Era of Deep Learning. Available from: https://nessie.ilab.sztaki.hu/~kornai/2020/AdvancedMachineLearning/Ng_MachineLearningYearning.pdf (cited 10 January 2018).

[29] Billings, S., Wei, H.-L., 2019. NARMAX model as a sparse, interpretable and transparent machine learning approach for big medical and healthcare data analysis. Proceedings of 2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS); August 10–August 12, 2019; Zhangjiajie, China. pp. 2743–2750.