Harnessing Transdisciplinary Knowledge: Integrated Deep Learning Techniques for Accurate Tomato Leaf Disease Classification

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Abstract:The study proposes a transdisciplinary approach integrating knowledge from fields such as computer science, botany, and data science to classify leaf diseases. We integrated two deep-learning models that combine the strengths of the Inception network and the ResNet architecture to address the challenge of accurately classifying tomato leaf diseases. The Inception network's ability to quickly pick up visual features on multiple scales is used to pull out fine-grained details that are needed to tell the difference between small changes in the shape of tomato leaves and disease symptoms. The ResNet architecture is good at learning deep representations and getting around the vanishing gradient problem. This lets the model learn the high-level concepts and complicated connections between different tomato leaf disease patterns. The integration of these two powerful deep-learning techniques results in a robust and highly performant tomato leaf classification model. Extensive tests on a 10-class dataset of tomato leaves, with 9 disease categories and 1 healthy class, show that the proposed model works better than others, with a test set accuracy of 98.07%. The findings of this research contribute to the advancement of automated and efficient tomato leaf disease detection systems, which can aid in the early identification and management of tomato diseases, leading to improved crop yields and quality.

Keywords:Agriculture, Leaf Disease, Sustainability, Artificial Intelligence, Deep Learning

1 Introduction

Disease classification varies significantly across humans, animals, and plants due to differences in biology, ecology, and the pathogens involved. In humans, diseases are often categorized based on their causes—such as infectious, genetic, or environmental factors [1, 2]—while in animals, classifications may consider the type of host, the mode of transmission, and the impact on populations. Fungi, bacteria, viruses, and nematodes are just a few examples of the causal agents that cause diseases in plants, along with the symptoms they cause. These variations highlight the complexity of disease dynamics in different kingdoms of life, necessitating tailored approaches for diagnosis, treatment, and management.

The tomato, scientifically known as Solanum lycopersicum, is a highly-grown and economically significant vegetable crop on a global scale. However, tomato plants are susceptible to a variety of bacterial, fungal, and viral diseases that can have a substantial effect on the productivity and excellence of crops. Prompt and precise detection of tomato leaf diseases is essential for implementing suitable disease management measures and avoiding crop losses.

Conventional techniques for diagnosing tomato leaf diseases typically depend on visual examination by specialists, a process that can be time-consuming, subjective, and require substantial expertise. The development of automated and efficient leaf disease finding and its classification systems using advanced machine-learning techniques has become an active area of research in recent years. An effective method involves utilizing convolutional neural networks (CNNs) to classify tomato leaf diseases based on images. CNNs have exhibited exceptional efficacy in diverse image recognition assignments, encompassing the identification of plant diseases. Transfer learning, a method that takes what a CNN has learned from being trained on a large, general dataset and tweaks it for a specific task, has shown a lot of promise in making tomato leaf disease classification models more accurate and useful.

Saeed et al [3] compared the Inception ResNet V2 and Inception V3 networks to classify whether tomato leaf is healthy. They investigated the model at various dropout layers and achieved 99.22% two-class classification accuracy with 15% dropout. A multiclass categorization of leaf disease plays a crucial role compared to binary classes. Reference [4] combined the datasets of leaves for fourteen species. Later, a comparison of Inception-v3, Inception-ResNet-v2, and ResNet34 networks was presented with the highest accuracy of 97.03% using ResNet35. The Plant Village dataset was used by the authors [5]. They proposed using the inception v3 network to classify these images into four categories, including healthy tomato leaves. In terms of performance, Inception-v3 outperforms ResNet-50 with a validation accuracy of 98.3%. A lightweight CNN network was presented by Li Sun et al. [6] using SqueezeNet and SENet and the model succeeded with 98.39% in detecting diseases and pests. A Generative Adversarial Network was used for image augmentation and augmented images were classified using the Inception V3 network. The author was able to achieve 88.6% accuracy [7]. A lightweight CNN network was presented in [8] for grid stability analysis and presented an interdisciplinary approach to the CNN network.

Leaf segmentation from plant image is a big challenge before classifying its diseases. Mewada and Patoliya presented a real-time leaf image acquisition process and later SVM was used to classify its disease [9]. Seven diseases were accounted for [10] and improved YOLOv7 was used to locate and classify leaves of tomatoes in the field. The images were segmented using the Scale-Invariant Feature Transform (SIFT), and feature values were retrieved from the important regions. Subsequently, these features were transmitted to a CNN for recognition, boasting an impressive accuracy rate of 98.8%. Pravin and Deepa [18] used a deep CNN network for feature extraction and later machine learning models were used to classify pepper plants into fifteen categories from the leaf images. The integration of deep network with Random Forest classifier performed best among all with an 88% classification rate. Bharali et al. [17] employed image augmentation techniques to enhance the dataset size essential for deep learning training. With a total of 152,850 trainable parameters, their Improved CNN achieved an impressive training accuracy of 99.68% and a validation accuracy of 89%. However, the significant deviation between the training and validation accuracies suggests that their model may be overfitting.

In this article, we explore a transdisciplinary approach to classifying leaf diseases of tomato plants from images using Convolutional Neural Networks (CNNs). By integrating knowledge from fields such as computer science, botany, and data science, we harness advanced machine-learning techniques to analyze and interpret complex biological data. This collaborative framework not only enhances the accuracy of disease identification but also bridges the gap between technology and agriculture, fostering innovative solutions that can significantly impact crop health management and food security. Through this interdisciplinary lens, we aim to contribute to a more sustainable agricultural future.

The primary contribution of this work is the development of a robust and accurate tomato leaf classification model combining the features of the Inception network and ResNet architectures. Previous approaches have typically utilized a single DL model for this task, but we hypothesized that integrating multiple network types could enhance the overall classification performance. By adopting the Inception network to capture fine-grained visual features and the ResNet architecture to model higher-level abstractions, our hybrid model was able to achieve cutting-edge classification accuracy across 10 distinct tomato leaf classes. This is a significant advancement over existing methods, which have struggled to reliably distinguish between the subtle visual differences in tomato leaf morphology and disease symptoms. The ability to automatically and precisely classify tomato leaf types has important implications for precision agriculture, enabling farmers to quickly identify and respond to emerging plant health issues. The promising results of this work demonstrate the value of strategically combining complementary deep learning techniques to handle complex visual classification issues in the agricultural domain. Overall, the paper structure is as follows: Section 2 presents the proposed model. The subsequent findings and their analysis were presented in Section 3, followed by a conclusion and future work in Section 4.

2 Proposed Model

To address the challenge of accurately classifying tomato leaf diseases, our proposal entails an integrated DL network that amalgamates the distinguishing characteristics of the Inception network and the ResNet architecture. The residual features provide low-level details [11] which are necessary to differentiate the leaf spots. The rationale behind this hybrid approach is to leverage the complementary capabilities of these two well-established neural network models.

The Inception network is known for its ability to efficiently capture multi-scale visual features by employing parallel convolutional filters of varying sizes. This allows the model to extract fine-grained details that are crucial for distinguishing between the subtle differences in tomato leaf morphology and disease symptoms. The network's depth and the use of inception modules enable it to learn complex visual representations that are well-suited for the 10-class tomato leaf classification task, which includes 9 disease categories and 1 healthy class. On the other hand, the ResNet architecture is renowned for its effectiveness in learning deep representations and overcoming the vanishing gradient problem, which is a prevalent obstacle in training very DL networks. The residual connections in ResNet allow the model to maintain a stable flow of gradients during backpropagation, enabling the training of an exceptionally deep network with 824 layers. This depth is necessary to effectively model the high-level abstractions and complex relationships between the various tomato leaf disease patterns. By integrating the Inception network and the ResNet architecture, our proposed model can leverage the best of both worlds. The Inception modules capture the fine-grained visual features, while the deep ResNet structure learns the higher-level representations necessary for accurate disease classification.

2.1 Architecture overview of Inception-ResNet

Inception-ResNet v2 consists of several blocks that alternate between Inception modules and residual connections. The architecture typically starts with a stem that processes the input image, followed by a series of Inception-ResNet blocks. These blocks can be categorized into two types:

- Inception-ResNet-A: These blocks feature a combination of 1x1, 3x3, and 5x5 convolutions, with residual connections that add the input to the output of the block.

- Inception-ResNet-B and C: These are variations that adjust the configuration of the convolutions to optimize performance for different tasks.

The final layers of the network include global average pooling followed by a fully connected layer, producing the output probabilities for classification tasks.

As suggested by [12], every Inception block is followed by a filter-expansion layer consisting of a 1 × 1 convolution without activation. The purpose of this layer is to augment the dimensionality of the filter bank to align it with the dimension of the input. In addition, the inception-Resnet uses a batch normalization layer compared to the Inception network without a residual layer. Figure 1 shows a schematic opted from [12] for the Inception-Resnet-V2 network's component. Combining these powerful deep-learning techniques results in a robust and highly performing tomato leaf classification model

The overall flowchart of the proposed integrated Inception-ResNet network is depicted in Figure 2. Dividing a dataset into training, testing, and validation sets is a fundamental practice in machine learning and helps ensure the robustness and reliability of a model. The training set is used to train the model. It contains the input data along with the corresponding labels. The model learns the patterns and relationships in the data from this set. A well-sized training set enables the model to capture the underlying trends effectively. The validation set is used to fine-tune the model's hyperparameters and evaluate its performance during training. It provides a way to monitor the model's ability to generalize to unseen data. By using this set, you can assess how changes in hyperparameters (like learning rate or architecture) affect performance without touching the test set. The test set is used only after the model has been trained and validated. It serves as a final evaluation of the model's performance. By testing the model on this independent set, we can gauge its performance on new, unseen data in real-world scenarios.

3 Results and Discussion

3.1 Dataset

The original dataset contains images of leaf diseases from 38 species [13]. A total of 10 classes of tomato leaves were extracted from this dataset and used to validate the performance of the used network. This dataset has images of nine diseases, including Yellow-leaf mold, leaf curl virus, light blight, Mosaic virus, early blight, Septoria leaf spot, target spot, bacterial spot, Spider mites Two-spotted spider mite. One class of healthy images is also provided separately. The breakdown of the number of images in each category is listed in Table 1.

Table 1: *Leaf disease types and set of images from the dataset*

Leaf disease type	Number of Images
Bacterial_spot	1702
Early_blight	1920
Late_blight	1851
Leaf_Mold	1882
mosaic_virus	1790
Septoria_leaf_spot	1745
Spider_mites Two-spotted_spider_mite	1741
Target_Spot	1827
Yellow_Leaf_Curl_Virus	1961
Healthy	1926

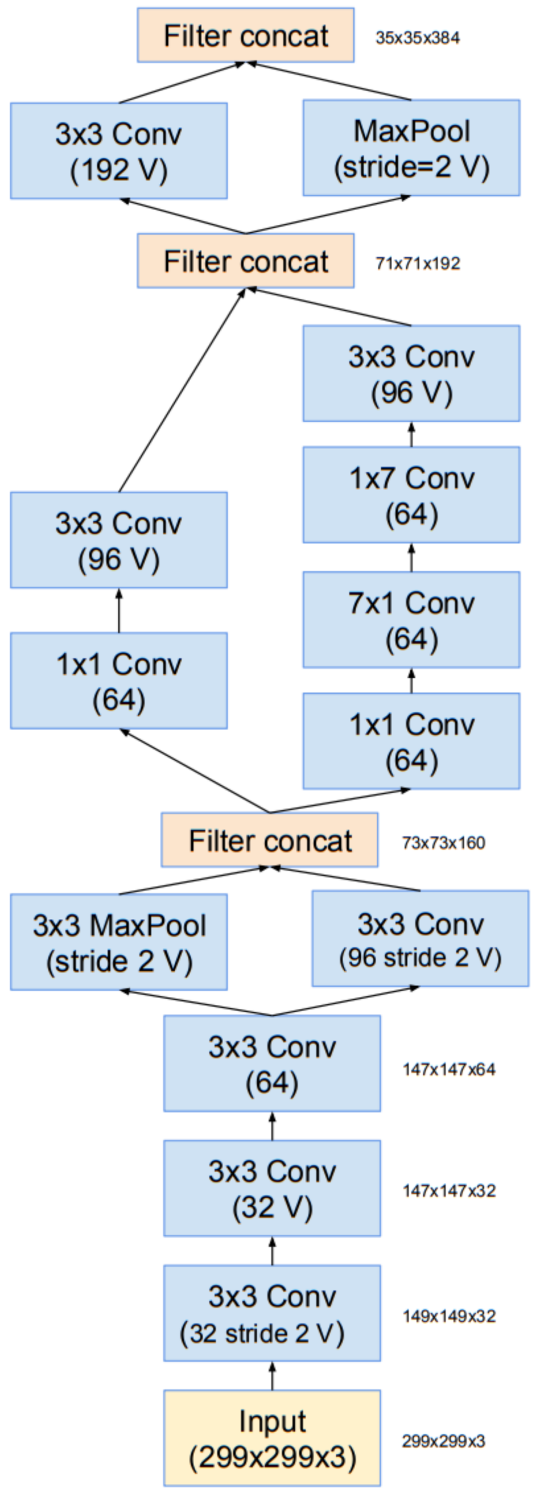

Figure 1: *A component of Inception-ResNet-V2 Schematic [12]*

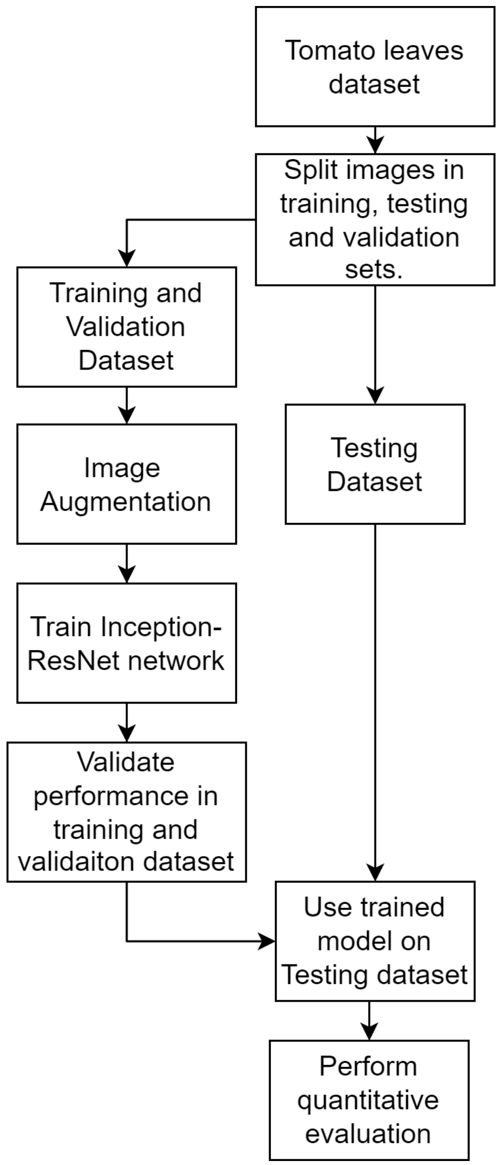

Figure 2: *Flow chart for the Inception-Resnet network-based classification*

3.2 Experiment Results and analysis

The collection of images is partitioned into training, validation, and testing sets in a ratio of 70:15:15.. The proposed model was trained for 10 epochs with 200 iterations per epoch. Figure 3 shows the accuracy and loss over the epoch during the training process. The model succeeded with 96.87% accuracy on the validation images and the model achieved 99% accuracy on the training image set.

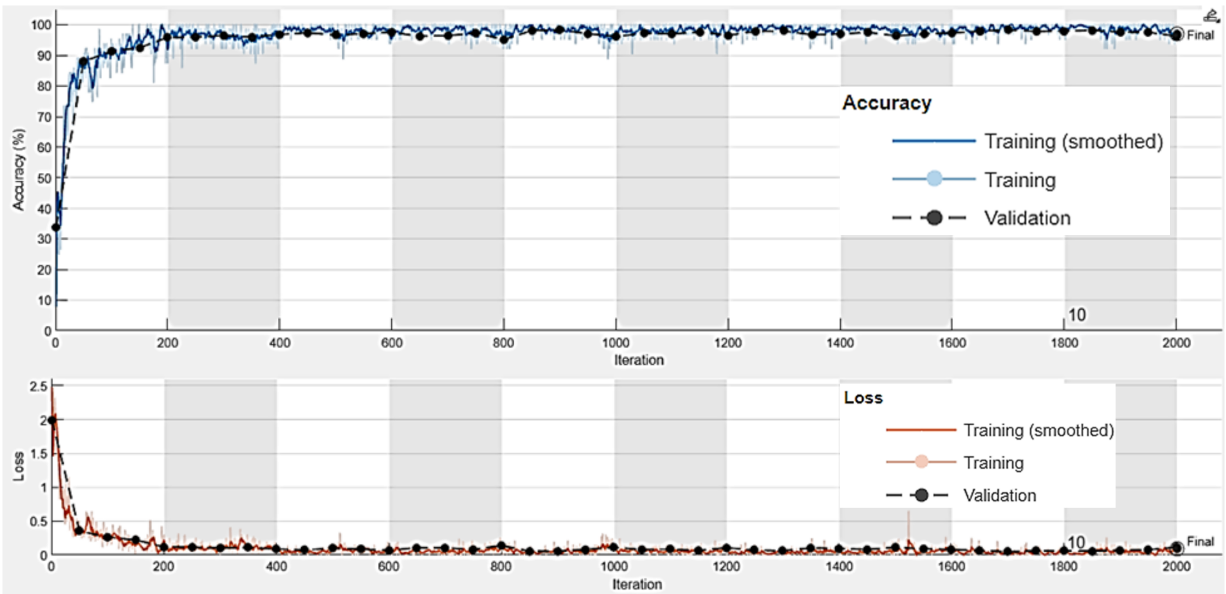

Figure 3: *Accuracy and Loss variation over epochs during network training*

A confusion matrix summarizes the performance of a classification model by displaying the number of correct and incorrect predictions made for each class. Figures4 and 5 show the confusion matrix obtained on the validation and test dataset. On the validation dataset, 13 images out of 143 images of the early bright disease were misclassified as septoria leaf spots. The large numbers in the diagonal and the least numbers in other cells show that the model is able to differentiate all 10 classes well. The accuracy, precision, recall, and F1-score for the test dataset are listed in Table 2.

Table 2: *Quantitative evaluation of the network on the test dataset*

Parameter	Score
Precision	0.9806
Recall	0.9810
Specificity	0.9979
Accuracy	0.9807
F1-Score	0.9804

Further assessment of the model is performed by comparing its accuracy with recent literature. Arnes et al [14] presented a deep CNN network with 43.652 million parameters to classify tomato leaves into ten classes, including the healthy class. They compared the VGG Net, ShuffleNet, and SqueezeNet and their presented network and achieved a comparable accuracy of 97.15%. A deep CNN network was developed to classify leaves into 10 classes. The author validated the model for various epoch numbers and they observed that their model obtained maximum accuracy, i.e., 98.4% by training the model with 5000 epochs [15]. Their model observed a large training time and it needed a large number of epochs. A deep CNN for mobile application was built to detect 10 most diseases [16]. However, their model obtained 88.4%

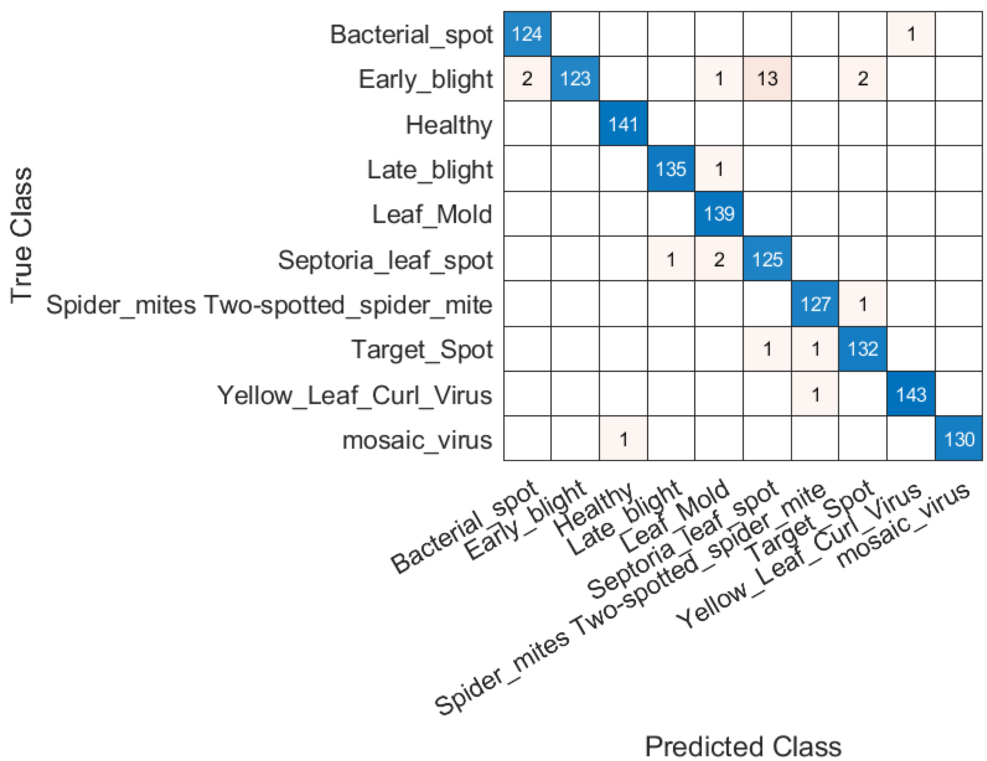

Figure 4: *Confusion matrix for validation datasets*

accuracy only. Debabrat Bharali [17] enhanced the CNN model using image augmentation and tomato leaves were categorized into several diseases with 89% accuracy on the test dataset [17]. Thus, the training time required for the proposed model is much less. Table 3 compares the results of the proposed model with recent literature. It shows that the proposed Inception-ResNet v2 model succeeded in achieving the same accuracy level within 5 epochs only. In [18], authors extracted CNN features and these features were used for the classification. Various machine learning models, including Naive Bayes, support vector machine, logistic regression model, and random forest were compared. In their experiment, the authors used only 132 images of tomato leaves. Their random forest model performed best among all with 96% precision 94% recall and 92% F1-Score for tomato leaves and received 88% accuracy overall for 12 leave plants.

Overall, the comparison highlights that the Proposed Network is a strong candidate, achieving a high classification accuracy of 98.07% on the 10-class tomato leaf disease dataset, making it a competitive and potentially superior solution compared to the other models presented. The findings of this research will

Table 3: *Accuracy comparison with literature on tomato leaf dataset*

Algorithm	Number of Classes	Accuracy (in%)
Deep CNN Network [14]	10	97.15
CNN network [15]	10	98.4
Hu-moments+HSV features + ANN [15]	10	92.9
MobileNet [16]	10	88.4
Enhanced CNN [17]	7	89
Deep CNN Features + Random Forest [18]	2	94
Proposed Network	10	98.07

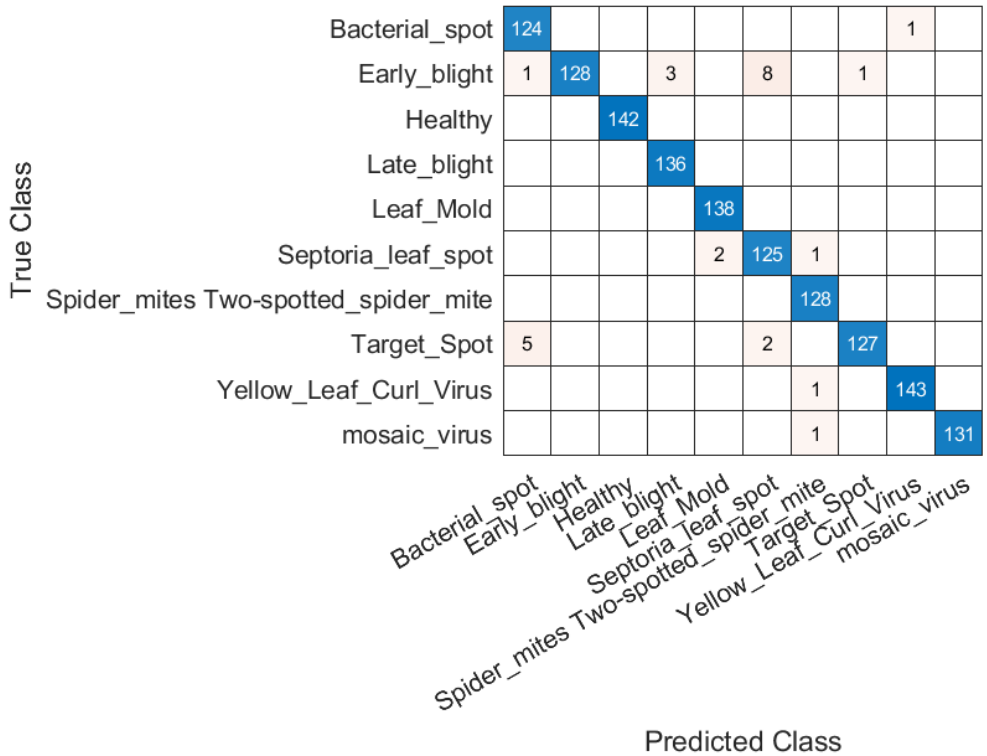

Figure 5: *Confusion matrix for test datasets*

contribute to the advancement of automated and efficient tomato leaf disease detection systems, which can aid farmers, extension workers, and researchers in the early identification and management of tomato diseases, leading to improved crop yields and quality.

4 Conclusion

The proposed integrated Inception-ResNet model has proven to be highly effective in accurately categorizing tomato leaf diseases, achieving a high classification accuracy of 98.07% on a 10-class dataset. By leveraging the complementary strengths of the Inception network and the ResNet architecture, the model is able to capture fine-grained visual features as well as learn the complex representations necessary for distinguishing between the various tomato leaf disease patterns. The performance of the integrated network outperforms recent cutting-edge DL models in identifying leaf disease types, highlighting its potential as a competitive and superior solution. The findings of this study contribute to the advancement of automated and efficient tomato leaf disease detection systems, which can aid farmers, extension workers, and researchers in the early identification and management of tomato diseases, ultimately enhancing the quality and productivity of tomatoes.

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