Journal of Advances in Plant Biology

Comparative Study of Deep Learning Techniques for Detecting Corn Plant Leaf Diseases Using Transfer Learning

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Review Article
Open Access &
Peer-Reviewed Article
DOI: 10.14302/issn.2638-4469.japb-25-5395

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Keywords:
Plant Leaf Disease, Deep Learning, Neural Networks, VGG16, InceptionResNetV2, Corn

Received: January 15, 2025

Accepted: March 11, 2025

Published: March 20, 2025

Academic Editor:
Laura Scrano, University of Basilicata, Potenza, Italy

Citation:
Chennamsetti Divakar (2025) Comparative Study of Deep Learning Techniques for Detecting Corn Plant Leaf Diseases Using Transfer Learning. Journal of Advances in Plant Biology - 1(4):7-19. https://doi.org/10.14302/issn.2638-4469.japb-25-5395

Abstract

Plant leaf diseases pose significant threats to crop yield and agricultural sustainability, making early and accurate detection crucial for effective disease management. In current years, deep neural network (DNN) techniques have shown remarkable potential in the field of image classification, including plant disease detection. The study aims to investigate the performance of two popular deep learning architectures, namely, VGG16 and InceptionResNetV2, for the detection of tomato plant leaf disease. The proposed methodology involves acquiring a diverse dataset comprising high-resolution images of healthy and diseased leaves from the target crops. Preprocessing techniques such as image augmentation and normalization are applied to enhance the generalization ability of the models and mitigate overfitting. Transfer learning is employed to initialize the deep learning architectures with weights pre-trained on large-scale image datasets to accelerate convergence and improve the models' performance in limited data scenarios. To evaluate performance of proposed networks various metrics such as validation and test accuracies, precision and recall, F1 score, and the area under the curve (AUC) are considered. From the investigations, the classification accuracy of the finest architectures is as follows: 99.8 percent for VGG16 and 99.4 percent for InceptionResNetV2 on Corn Leaves. The results suggest that the models developed during the investigation phase to identify the leaf disease were superior to any existing Deep Neural Networks (DNNs).

Introduction

The agricultural industry has been facing a significant challenge in accurately and efficiently identifying plant diseases, which can have a devastating impact on crop yields and quality. Among the various crops, corn is a crucial staple food source that is susceptible to a range of leaf diseases, which can lead to substantial yield losses if not addressed promptly. [1] [2] [3] The traditional method of manual inspection and diagnosis of corn leaf diseases by experts is time-consuming, labor-intensive, and often requires extensive knowledge of plant pathology. [3]

Advancements in deep learning, a subset of machine learning, have revolutionized the field of plant disease detection and classification. Deep learning algorithms, particularly convolutional neural networks, have demonstrated remarkable performance in accurately identifying various plant diseases, including those affecting corn leaves. [4][5]

The development of robust and efficient deep learning models for the detection of corn leaf diseases is essential to support farmers and agricultural professionals in making timely and informed decisions to mitigate the impact of these diseases.

One of the key challenges in developing effective deep learning models for corn leaf disease detection is the availability of high-quality and diverse datasets. Researchers have been working on creating and curating comprehensive datasets of corn leaf images, capturing a wide range of disease symptoms, environmental conditions, and image resolutions.

Another important aspect in the development of deep learning models for corn leaf disease detection is the choice of appropriate neural network architectures. Architectures such as VGG16 and InceptionResNetV2 have shown promising results in the detection and classification of various plant diseases, including those affecting corn leaves.

Recent studies have demonstrated the capabilities of deep learning models in accurately identifying multiple types of corn leaf diseases, including common rust, gray leaf spot, and northern corn leaf blight, among others.

The development of user-friendly and accessible tools for farmers and agricultural professionals, enabling them to quickly and accurately identify and address corn leaf diseases, ultimately leading to improved crop yields and economic benefits.

The subsequent portions of this paper are organized as follows: Section II offers a summary of pertinent research in plant disease detection and highlights the contributions of Deep Learning Neural Networks (DLNNs). Section III provides a comprehensive discussion of the approach, encompassing dataset specifics, experimental configuration, and architectural specifications of VGG16 and Inception-ResNetV2. Section IV presents the experimental results and performance assessments of each DNN architecture for disease detection in tomatoes. Section V examines the findings, compares the architectures, and evaluates the generalizability of the results across different crops. Section VI closes the work by summarizing the principal insights and potential avenues for future research. This comparative study aims to enhance the understanding of DNN-based plant leaf disease detection and to aid in the creation of reliable and precise systems that promote sustainable agricultural practices and food production.

Literature Review

The objective of this section is to offer a thorough comprehension of the current corpus of research in the field of plant disease detection based on deep learning. Numerous studies have emphasized the effectiveness of deep learning in the automated identification of plant diseases. Convolutional neural networks (CNNs) have been extensively utilized in this context due to their ability to learn intricate patterns from raw image data. Nevertheless, the decision to choose an appropriate deep learning architecture is still a critical one, as the accuracy, computational cost, and complexity of different models can vary. Our objective is to comprehend the current state-of-the-art in deep learning-based plant disease detection, identify voids in the existing research, and establish a solid foundation for our comparative study of four distinct deep learning architectures by conducting a thorough review of the existing literature.

Padilla, D. A.[6] et al.With a detection accuracy of 93%, the CNN using OpenMP was able to identify the corn leaf diseases as leaf blight, rust, and spot. Using a Deep Learning VGG – 16 network.

Malusi Sibiya [7] et al. got an overall testing accuracy of 89% by pre-training a model for the early detection, middle stage, later stage, andhealthy stage of the common rust illness. This model was able to detect the disease at all stages: early, middle, and later.

Climate changes and abiotic stresses significantly impact crop production. Early disease detection in corn crops is essential for timely intervention. Using the PlantVillage dataset, this study presents a machine learning-based model achieving 94% accuracy, outperforming traditional methods across metrics like precision, recall, and AUC-RoC, enabling effective early-stage disease diagnosis by M. Agarwal et.al [8]

A Bhatia et al. [9] employed an imbalanced dataset comprising plant images classified as either diseased or healthy. A machine learning algorithm known as ELM was utilized to develop a model for disease prediction, resulting in an accuracy of 89.19%.

A Bhatia et al. [10] introduce a hybrid classifier that integrates Support Vector Machines (SVM) with Logistic Regression (LR). The proposed hybrid classifier utilizes the advantages of both SVM and LR algorithms for tomato leaf disease, resulting in an accuracy of 92.73%.% and 90.43%.

Brahimi, Boukhalfa, and Moussaoui [11] employed a CNN-based model using 14,828 tomato leaf images, achieving 99.18% accuracy, significantly outperforming shallow models for effective disease detection.

Chen et al. [12] utilized deep transfer learning with pre-trained VGGNet and Inception models for plant disease identification, achieving 92% accuracy on rice plant images, surpassing state-of-the-art methods.

Bachhal et al. [13] proposed the PRF-SVM model, integrating PSPNet, ResNet50, and Fuzzy SVM, achieving 96.67% accuracy and 0.81 mAP on the Plant Village dataset for maize disease detection.

Biradar et al. proposed a customized deep learning model, PaddyLeaf15 CNN, using transfer learning for rice leaf disease prediction. Evaluated on Kaggle's benchmark dataset, it achieved 95% accuracy, outperforming VGG-16 and Inception V3 models. [14]

S.Verma et. al.[15] proposed a Capsule network a novel type of neural networks that aim to overcome the limitations of traditional CNNs in capturing complex spatial relationships between image features. The authors explore the potential of capsule networks in the context of plant disease classification, which is an important task for monitoring and managing crop health and achieved an overall efficiency of 91.83%.

Ahmad et al. [16] evaluated tomato leaf disease classification using CNN architectures—VGG-16, VGG-19, ResNet, and Inception V3. Tested on laboratory and field datasets, Inception V3 performed best, with a 10%–15% variance between datasets.

To conclude the literature survey, it is evident that deep learning-based models for plant leaf disease detection have seen extensive exploration. Various models have been designed, trained, and tested, with each research contributing its own unique insights [17-18].

Materials & Methodology

Corn, a staple food crop, is susceptible to various leaf diseases that can have a significant impact on its yield and quality. These diseases are often caused by fungal, bacterial, or viral pathogens, and can manifest through a range of symptoms, such as discoloration, lesions, and necrosis.

Some of the common corn leaf diseases include:

Common Rust: Caused by the fungus Puccinia sorghi, this disease is characterized by the appearance of reddish-brown powdery pustules on the leaves, which can lead to reduced photosynthesis and stunted plant growth [2].

Leaf Spot: Caused by the fungus Cercosporazeae-maydis, this disease is marked by the presence of rectangular, gray-colored lesions on the leaves, which can lead to premature leaf senescence and yield loss.

Corn Leaf Blight: Caused by the fungus Exserohilumturcicum, this disease manifests as long, elliptical, grayish-green lesions on the leaves, which can significantly impact the plant's photosynthetic capacity and overall productivity.

Accurate and timely identification of these corn leaf diseases is crucial for farmers and agricultural professionals to implement appropriate management strategies, such as the application of fungicides, cultural practices, and the selection of resistant cultivars.

This advances by comparing two state-of-the-art designs rather than evaluating a single model, emphasizing essential crops such as maize. By contrasting VGG16 and InceptionResNetV2, one can gain a comprehensive grasp of their respective advantages and disadvantages in the realm of plant leaf disease identifying purposes. Figure 1 illustrates the framework of the suggested leaf disease detection methodology.

For analysis there are 10 different types of tomato leaf diseases are considered. The entire dataset is devided into training, validation and testing datasets. Fig. 2 depicts plant disease of corn leaves and their distributions.

The resolution of the image in the dataset is exactly 256 by 256 pixels and is encoded in RGB. This is apparent in every image. Fig.3 depicts a sample of images for each leaf.

Utilizing DNNs is crucial for accurately classifying large and complex datasets. Such networks are known to enhance success rates significantly by uncovering intricate, hidden features within the data. This enhanced detection capability stems from the multiple hidden layers and neurons in DNNs, which enable rapid assimilationof new information. However, the complexity of these networks also arises

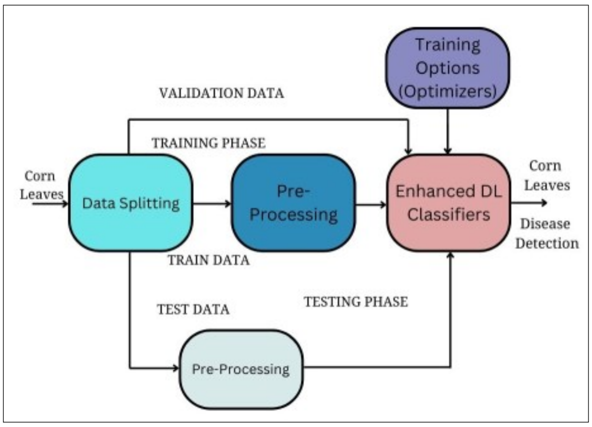

Figure 1. Proposed Framework

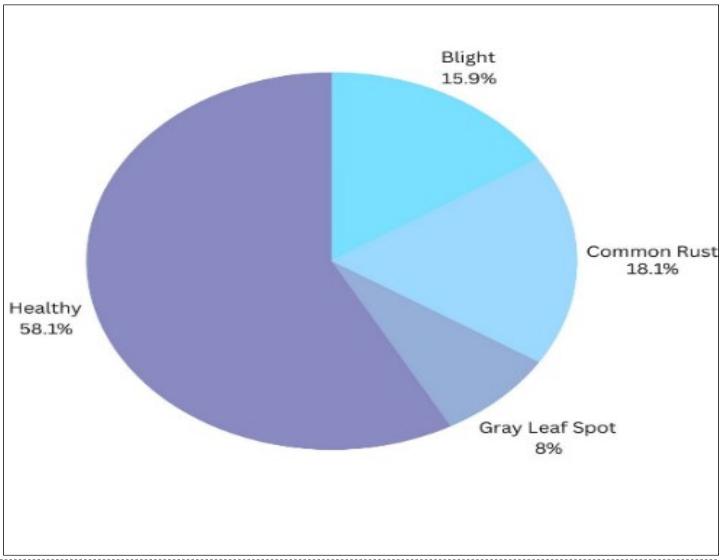

Figure 2. Corn Leaf Disease varieties and their Distribution

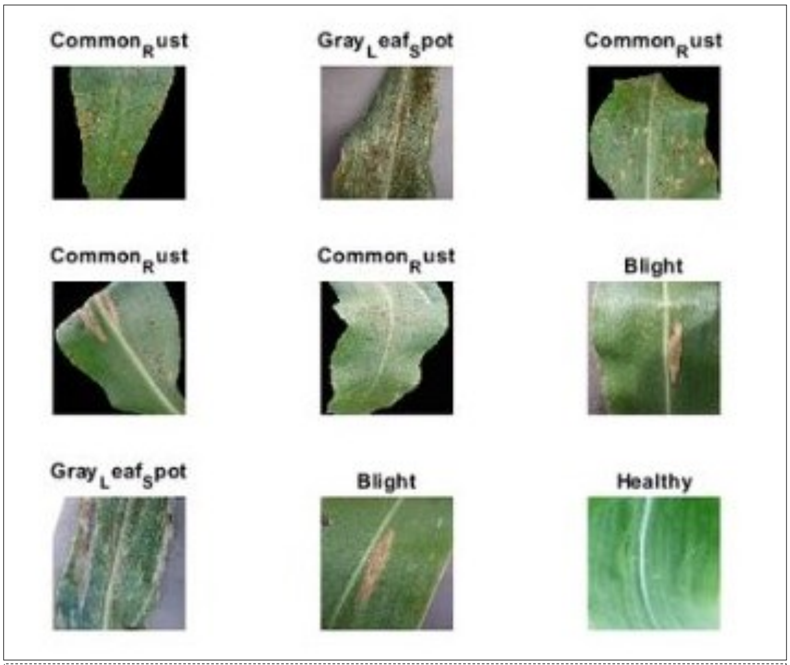

Figure 3. Disease Leaves of Corn

from their extensive layering.

Furthermore, deep neural networks can be effectively trained using various optimizers like SGDM (stochastic gradient descent with momentum), ADAM (adaptivemoment estimation), and RMSprop (root mean squarepropagation). These optimizers play a key role in preventing overfitting during the training process.

The dataset is evaluated for three different training rates 70%, 80% and 90%.

ENHANCED DNN ARCHITECTURES

VGG16

Figure 4. Architecture of Xception

VGG-16 is a prominent deep neural network designed for tasks like image classification and feature extraction. It features 16 trainable layers, comprising 13 convolutional layers and 3 fully connected layers. The architecture utilizes 3×3 convolutional filters arranged in sequence to identify detailed spatial patterns and incorporates max-pooling layers to reduce dimensionality. Its consistent structure offers a balance between simplicity and computational efficiency. Renowned for its strong generalization capabilities across diverse computer vision problems, VGG-16 continues to serve as a reference model. Although it demands more computational resources than newer architectures, it is valued for its reliability and robust performance.

INCEPTIONRESNETV2

The Inception-ResNet-v2 is a convolutional neural network architecture that integrates principles from both Inception and Residual Network (ResNet) frameworks. The aim of Inception-ResNet-v2 is to improve the efficiency and processing speed of deep learning networks. The proposed architectural design efficiently integrates the Inception architecture, recognized for its network-in-network feature learning approach, with the ResNet architecture, celebrated for its use of shortcut or residual connections to mitigate training difficulties in deep networks. The Inception-ResNet-v2 design is distinguished by its considerable depth, comprising 164 layers. Furthermore, it utilizes expansive architectures through parallel concatenations, commonly known as "towers," in accordance with the Inception paradigm.

The architectural design in Fig. 5 adeptly identifies intricate patterns inside datasets using numerous repetitions of Inception blocks (Inception-A, Inception-B, Inception-C), focused on achieving network homogeneity and enhancing factorization. Residual connections in this architecture establish shortcuts, enhancing gradient transmission and mitigating the vanishing gradient issue in deep networks. A scaling factor of 0.1 for residual branches prior to summing with preceding layer outputs guarantees network stability. This model exhibits great accuracy in large-scale picture recognition tasks while

Figure 5. Architecture of InceptionResNetV2 [16]

maintaining a lower parameter count and computational complexity compared to models such as VGG, yet it delivers higher performance. Utilized in diverse fields necessitating precise image classification, including medical imaging and autonomous driving, it implements a comprehensive data augmentation strategy during training to reduce the risk of overfitting.

Optimization tasks focus on finding the best inputs for a specific goal to either boost or diminish performance. This process, from the onset of deploying models to the advanced training of neural networks on the ground, presents a significant challenge across different DNN methods. The model is evaluated for three different optimizers named ADAM, SGDM and RMSProp.

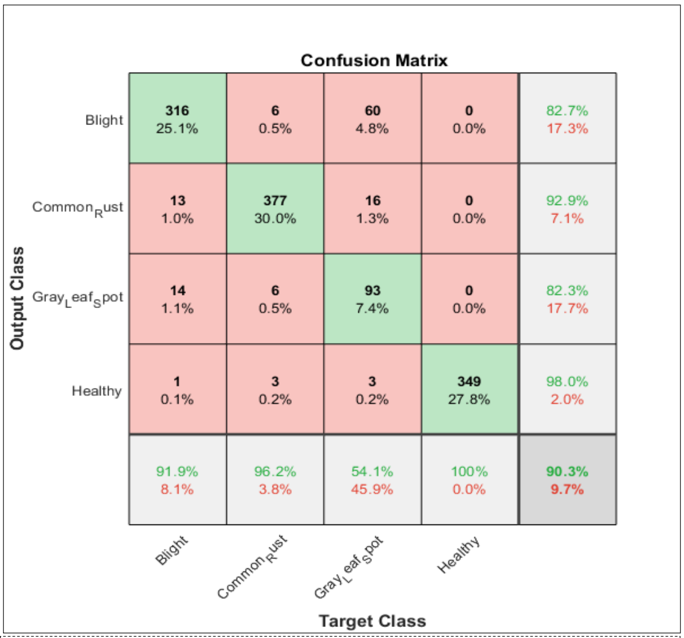

Figure 6. Confusion Matrix for VGG16 at 70% training rate

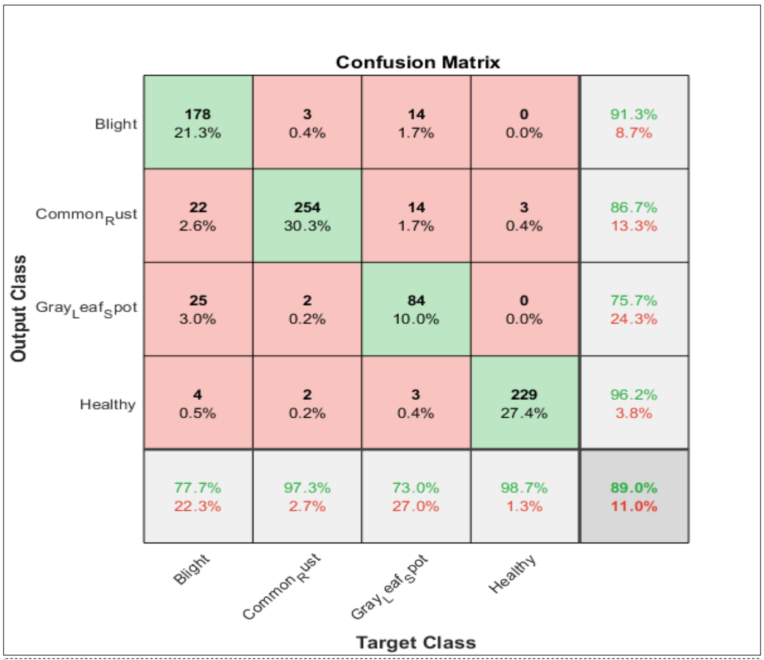

Figure 7. Confusion Matrix for VGG16 at 80% training rate

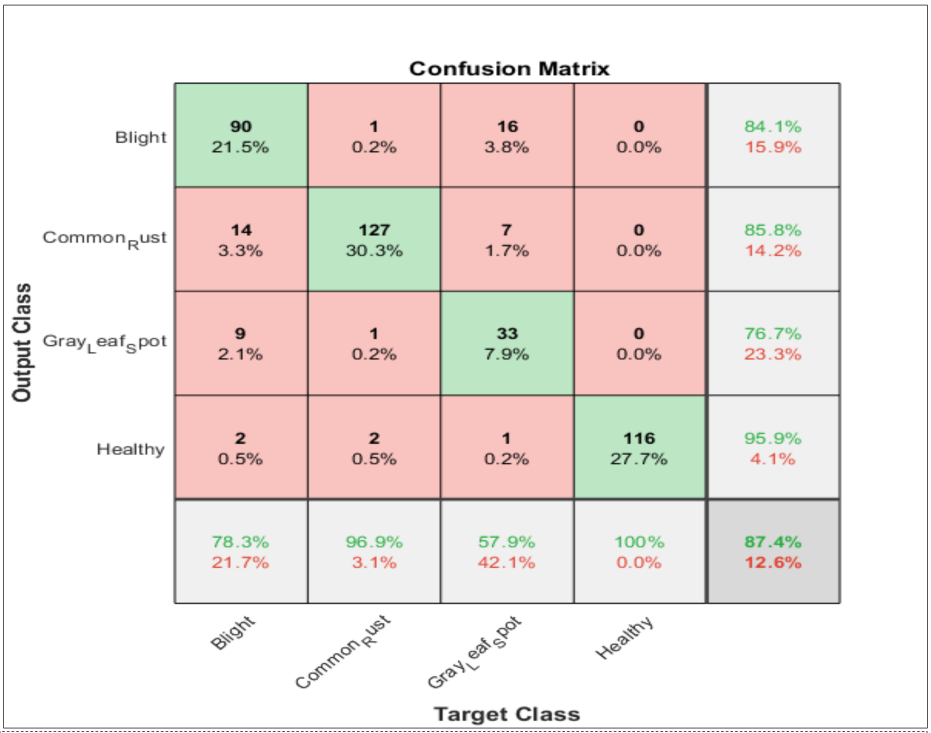

Figure 8. Confusion Matrix for VGG16 at 90% training rate

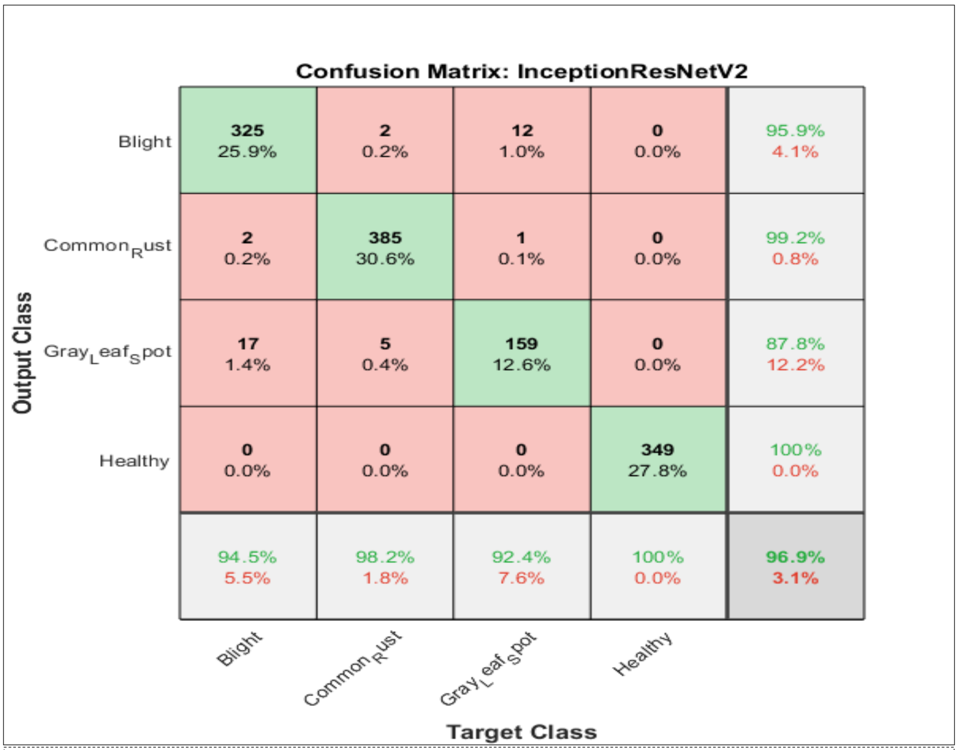

Figure 9. Confusion Matrix for InceptionResNetV2 at 70% training rate

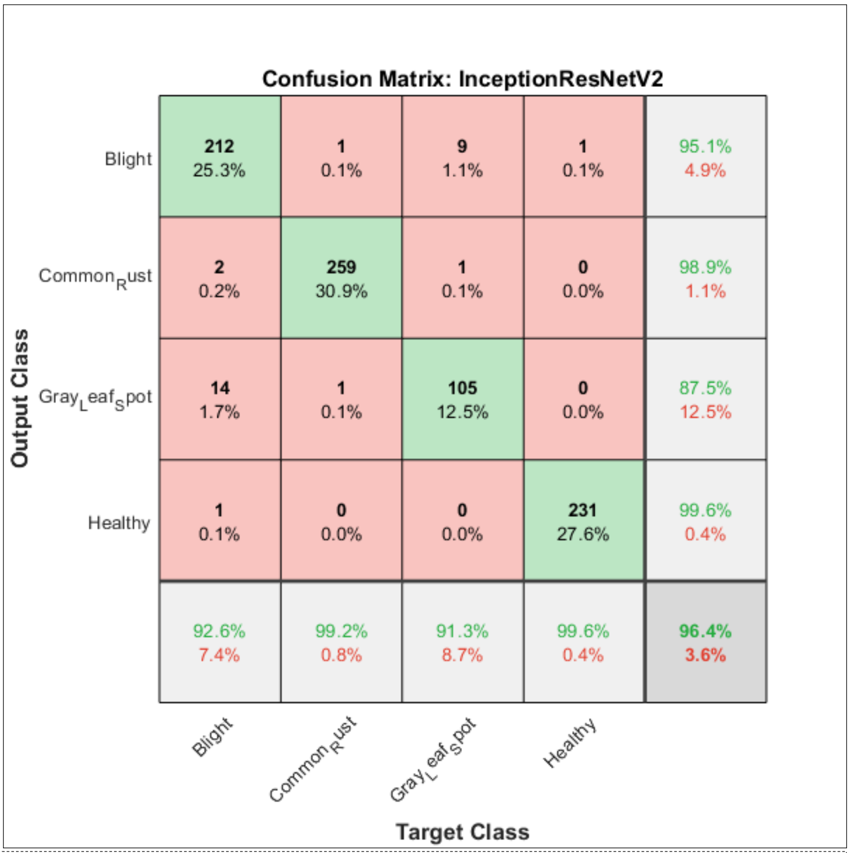

Figure 10. Confusion Matrix for InceptionResNetV2 at 80% training rate

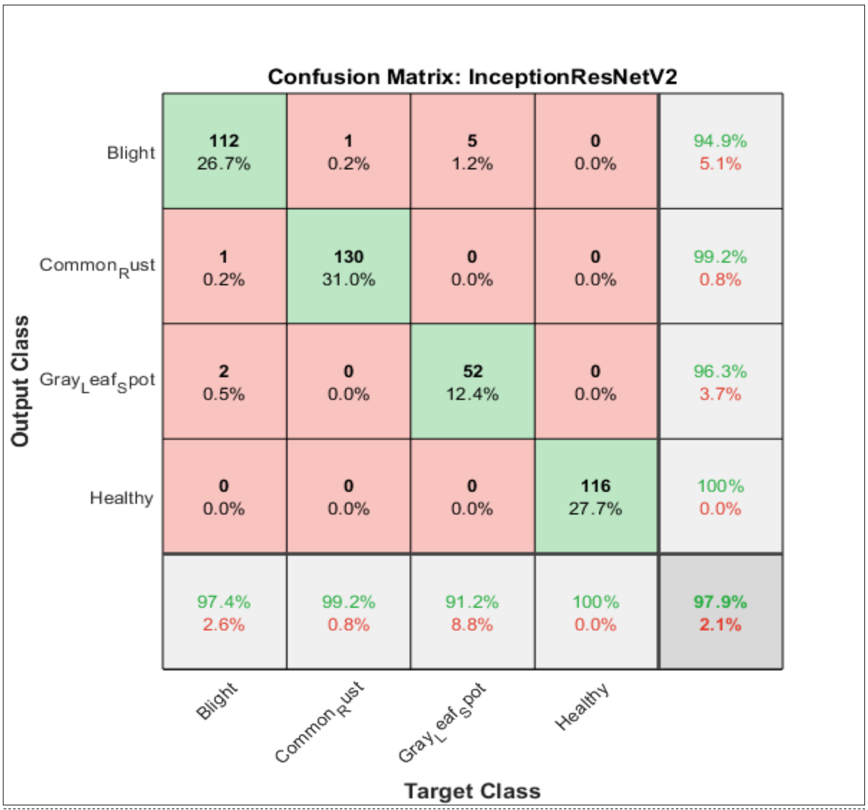

Figure 11. Confusion Matrix for InceptionResNetV2 at 90% training rate

Results and discussions

Using a dataset of 7214 images of corn leaves, various DNNs' classification performance was assessed. Each solitary leaf in the RGB photos in this collection represents a picture that is precisely 250 pixels by 250 pixels in size. Every image contains this size. The suggested classifiers' performance is assessed at 70%, 80% and 90% training rate. Table I displays a chart listing the diseases and their corresponding class number.

The Confusion matrices from an Xception& InceptionResNetV2 classifier for tomato leaves, trained with three independent optimizer at an 80% rate, are shown in Table II and Table III. When using the RMSProp optimizer, the InceptionResNetV2 classifier achieved a validation accuracy of 99.5% (Fig. 6), but the Xception classifier achieved testing accuracy of 99.8% (Fig. 7). Fig 7 demonstrates that when compared to other classiferes for tomato leaves, Xception DNN.

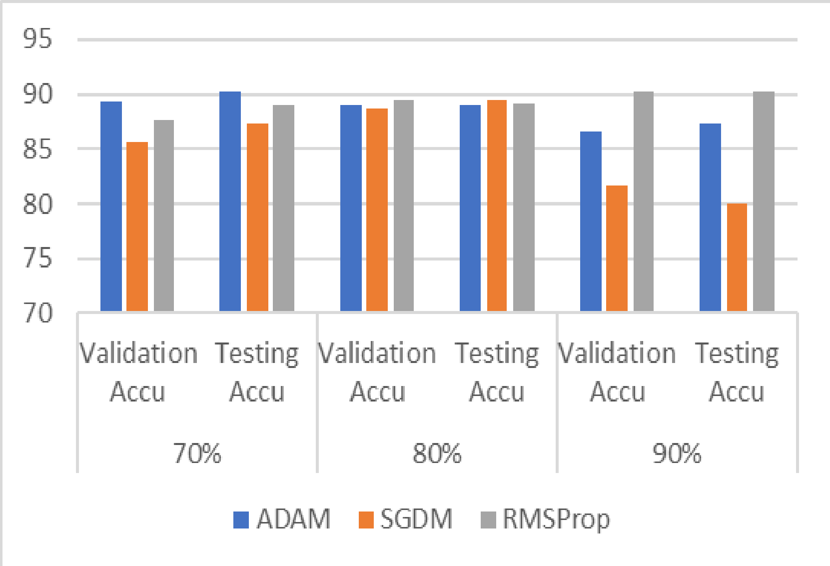

Figure 12. Performance metrics of VGG16

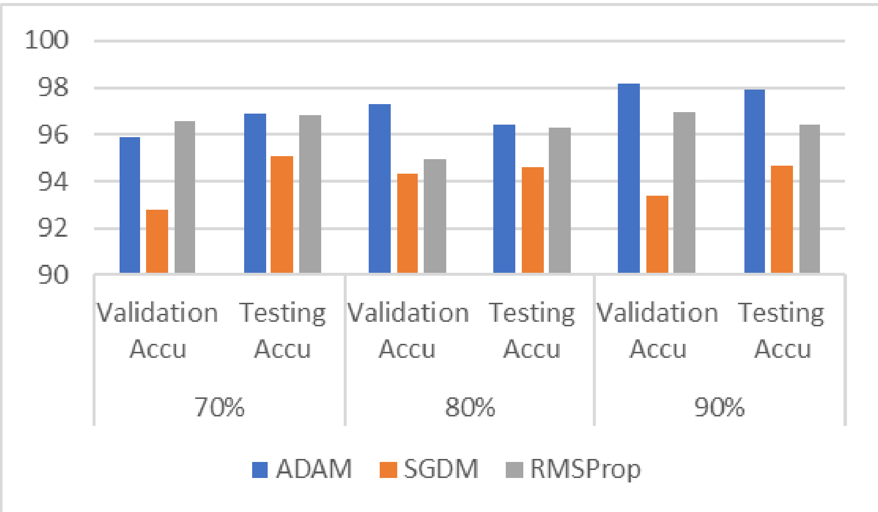

Figure 13. Performance Metrics of InceptionResNetV2

Table 1. Performance Comparison

RefNo	Method Used	No. of Classes	Size of the Data Set	Accuracy (%)
[13]	CNN	4	3000	94.49
[14]	CNN	4	4000	91.2
[15]	CNN	4	5000	95
	Inception ResNetV2	4	7214	97.9

Table 1 shows the results of the performance comparison, which shows that the suggested method obtained higher accuracy than the current ML and DL classifiers. From the analysis it is oobserved that two advanced deep learning models, VGG16 and InceptionResNetV2, are most suitable to the detection of diseases in corn plant leaves. It uniquely demonstrates the superior performance of the InceptionResNetV2 Network, especially when optimized with the RMSProp optimizer, at an 70% training rate. This specificity in application, combined with a detailed examination of the models' effectiveness in plant disease diagnosis, offers new insights into precision agriculture and highlights the practical implications of deep learning in enhancing crop health management strategies.

Conclusion

This current study compares the performance of VGG16 and InceptionResNetV2 deep learning models for detecting corn leaf diseases, highlighting their high accuracy. The analysis revealed that Xception, combined with the RMSProp optimizer, outperformed InceptionResNetV2 in diagnosing tomato leaf diseases, particularly at an 80% training rate. The findings emphasize the potential of deep learning in automating plant disease detection. Future research should focus on integrating advanced models with IoT for real-time monitoring systems, enabling early disease identification and providing actionable insights. Such systems could revolutionize precision agriculture by improving crop health management and promoting sustainable farming through timely and capable interventions.

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