INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 24-02-2024

Accepted: 01-04-2024

Published: 19-04-2024

Citation: Kaur K, Bansal K (2024) Enhancing Plant Disease Detection using Advanced Deep Learning Models. Indian Journal of Science and Technology 17(17): 1755-1766. https://doi.org/10.17485/IJST/v17i17.536

* **Corresponding author**.

kkamaldeep11@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Enhancing Plant Disease Detection using Advanced Deep Learning Models

Kamaldeep Kaur[1]*, Khusboo Bansal[2]

1 Research Scholar, Desh Bhagat University, Mandi Gobindgarh, Punjab, India
2 Associate Professor, Department of Engineering and Applied Science, Desh Bhagat University, Mandi Gobindgarh, Punjab, India

Abstract

Objective: The aim of this paper is to analyze the efficacy of employing multiple advanced convolutional neural networks (CNNs) for the purpose of enhancing the accuracy in detecting and classifying various plant diseases. **Methods:** The research involves the analysis of 7623 training images as well as 1906 validation images of different plant diseases and employed advanced deep learning models like DenseNet169, Xception, InceptionV3, MobileNetV2, and ResNet50V2 to classify them. At first the RGB images are converted to Grayscale and later to enhance their quality, few techniques have been used such as Otsu thresholding, noise removal, distance transform, and watershed techniques. Subsequently, contour features are extracted by calculating morphological values to obtain the necessary region that correspond to diseased areas in plant images. **Findings:** On evaluating the performance of the applied models on the basis of various metrics, MobileNetV2 and ResNetV2 achieved the highest validation accuracy scores of 99.42% each, with their respective loss values of 0.19 and 0.49. In terms of recall, precision, and F1 score, all models, except MobileNetV2 and InceptionV3, attained optimal scores of 0.99 each. **Novelty:** The novelty of this paper resides in the incorporation of multiple image segmentation techniques with fine tuning the parameters of advanced Convolutional Neural Network (CNN) models on the basis of various factors such as the number of images, size, channel, classes etc to generate the optimal results.

Keywords: Agriculture; Plant diseases; Artificial Intelligence; Advanced CNN models; Watershed Technique

1 Introduction

Plant diseases have always been a threat to the global food security despite having significant steps in the technology of agricultural sector. These diseases are responsible of disrupting supply chains, jeopardizing crop yields, as well as escalate the growth of malnutrition and hunger worldwide. There have been various traditional techniques to combat such diseases, but they rely on human inspection, call for excessive labor, and consume lot of time[1,2]. In addition to this, it is a known fact that agriculture systems have become complex at a large scale which requires the urgency towards the reliable as well as efficient detection method. Hence, in light of these pressing concerns, there is a critical need to harness emerging technologies and innovative approaches to bolster plant disease management efforts [3,4]. Among these, the application of AI based learning techniques holds promise for revolutionizing disease detection in agriculture. By automating the process of analyzing plant images and identifying disease symptoms, AI-based systems offer the potential to enhance diagnostic accuracy, streamline decision-making processes, and ultimately mitigate the socioeconomic impacts of plant diseases on a global scale [5,6].

From the past years, a number of research studies have put forth various machine learning and deep learning methodologies which aimed at the detection of various disease-based plants. Deep Learning models like MobileNet architectures and Convolutional Neural Networks were used to accurately and swiftly identify plant illnesses by Khalid and Karan (2024) [7]. They employed GradCAM and eXplainable Artificial Intelligence (XAI) to visualize plant disease signs. That clarified model decision-making. CNN model had 89% accuracy, 96% recall, F1 score, and precision. In contrast, MobileNet has 96% accuracy. Precision, recall, and F1-score were lower at 90%, 89%, and 89%, respectively. According to Nawaz et al. (2024) [8] proposed CoffeeNet as a new Deep Learning (DL) model. This methodology was created to address coffee plant leaf disorder identification issues. To investigate disease-related sample characteristics, they used an upgraded CenterNet technique with a ResNet-50 model and spatial-channel attention strategy. The study focused on the Arabica coffee leaf repository and its practical and complex environmental constraints. CoffeeNet produced excellent classification accuracy of 98.54% and 0.97 as mAP. Khanna et al. (2024) [9] employed Deep Convolutional Neural Network image analysis to identify and classify plant diseases in leaf photos at different resolutions. PlaNet was compared against 18 popular CNN models, including a top-5 ensemble model. PlaNet performed well throughout all testing experiments, with an average-wise accuracy of 97.95%, AUC of 0.9752, F1-score of 0.9686, sensitivity of 0.9707, precision of 0.9576, and specificity of 0.9456. Haridasan et al. (2023) [10] proposed a computer vision-based approach to reliably detect and classify rice plant illnesses. They used image processing and AI learning to combat fake smut, bacterial leaf blight, rice blast, brown leaf spot, and sheath rot in Indian rice fields. First, image pre-processing and segmentation identify the affected area, then convolutional neural networks and support vector machine classifiers classify diseases. Deep learning had 0.9145 validation accuracy. Javidan et al. (2023) [11] employed SVM to diagnose and classify grape leaf diseases as black rot, black measles, and leaf blight. K Means clustering technique is used to automatically separate illness symptoms from healthy leaf portions. HSV, l*a*b, and RGB color models extract features. Principal component analysis for dimension reduction gave SVM 98.97% accuracy. The suggested technique classifies grape leaf diseases more accurately and faster than CNN and GoogleNet. Guo et al. (2020) [12] proposed a deep learning-based mathematical model for plant disease diagnosis. The goal was to improve accuracy, variety, and training efficiency. This method utilizes the region proposal network (RPN) to locate leaves in complex situations. Using RPN results, the Chan-Vese (CV) algorithm segmented images and extracted symptom information. The model outperformed conventional methods in bacterial plaque, black rot, and rust disease evaluations with an accuracy rate of 83.57%. Chen et al. (2020) [13] investigated plant leaf disease identification using deep convolutional neural networks and transfer learning. Pre-trained models like VGGNet on ImageNet and Inception were used. Pre-trained ImageNet networks were used to initialize weights. Their method performed well and had an average accuracy of 92.00% for rice plant picture class prediction even in difficult backdrop settings. Chohan et al. (2020) [14] developed a deep learning-based "plant disease detector" to detect plant illnesses using leaf pictures. The method used the PlantVillage dataset for training, augmented the dataset to boost sample size, and used a CNN with several convolution and pooling layers. After training, the model was extensively evaluated and obtained 98.3% accuracy in studies utilizing 15% of the PlantVillage dataset, which contained healthy and diseased plant photos. Ahmed and Yadav (2023) [15] detected plant diseases using linear regression, random forest-nearest neighbors, neural networks, SVM, and Naive Bayes. The ensemble plant disease model outperformed other suggested and developed plant disease detection methods. Panigrahi et al. (2020) [16] examined maize plant disease detection using supervised machine learning. These categorization algorithms were compared to get the best disease prediction model. Other algorithms were less accurate than the Random Forest algorithm (79.23%). The models were trained to help farmers prevent new plant illnesses by detecting and classifying them early. In 2020, Jasim et al. [17] developed a deep learning strategy to detect plant leaf diseases using convolutional neural networks. The study examined tomatoes, peppers, and potatoes using Plant Village dataset photographs. The CNN classified 15 groups, including 12 disease classes (bacteria, fungi, etc.) and three healthy leaf classes. They found 98.29% training accuracy and 98.029% testing accuracy across the dataset with their proposed approach. Atila et al. (2021) [18] suggested classifying plant leaf disease with EfficientNet deep learning. The original and enhanced PlantVillage datasets containing 55,448 and 61,486 photos were utilized for training. Transfer learning made all layers trainable in the EfficientNet architecture and other models. EfficientNetB5 had 99.1% accuracy and 98.42% precision in the test dataset, while EfficientNetB4 had 99.39%.

Albeit, several research have studied the application of deep learning and machine learning approaches for plant disease detection and classification, but there is still room for improvement.

Inadequate Performance: Various learning models have been applied by the researchers, but they fail in achieving the satisfactory scores of accuracy. Despite considerable efforts, many studies have stated the suboptimal performance of their applied models which showed a significant gap in achieving reliable as well as robust classification outcomes.

Model Comparison and Benchmarking: In the realm of detecting diseases in plants, various models have been used by the researchers, but they neither measure the performance of the models for the different classes of the plant diseases nor with the existing techniques.

Limited Model Diversity: Researchers used limited models for the identification as well as classification of plant disease. They mostly focused on the small subset of the AI learning models and restricts in exploring the usage of more advanced models in order to generate to optimal results.

By focusing these gaps, this paper focuses on the development of an advanced deep learning model that uses various classifiers to generate the optimal results as well as enhance the accuracy of plant disease detection and classification. Apart from this, the paper also addresses the merits and limits of these technologies and their impact on the area of plant pathology.

1.1 Contribution of the work

The following are the contributions made in designing an AI-based system for identifying and classifying diseases in plants:

- This research focuses on using various machine learning and deep learning techniques to accurately detect and classify plant diseases.
- In order to improve the dataset's quality, several operations have been employed. These include converting the images to grayscale and applying Otsu thresholding, noise removal, distance transform, and watershed techniques.
- To classify diseases effectively, contour features have been computed using morphological values to identify significant characteristics. The purpose of this phase is to accurately define the specific areas in plant images that correspond to diseased regions.
- Within the domain of convolutional neural networks (CNNs), various advanced architectures have been used, such as DenseNet169, Xception, InceptionV3, MobileNetV2, and ResNet50V2. The assessment of these models is carried out using evaluative metrics such as precision, accuracy, recall, loss, as well as F1 score.

1.2 Structure of the manuscript

The manuscript is structured such that Section 1 acts as an Introduction which defines the role of traditional approaches and AI techniques in identifying plant diseases. Section 2 outlines the approach for constructing the deep learning system, which involves several phases. Section 3 then evaluates the system based on numerous metrics and in the end Section 4 provides a comprehensive summary of the entire work.

2 Methodology

The section includes the phases (Figure 1) that have been taken into account during the design of the deep learning model for identifying and classifying different plant diseases.

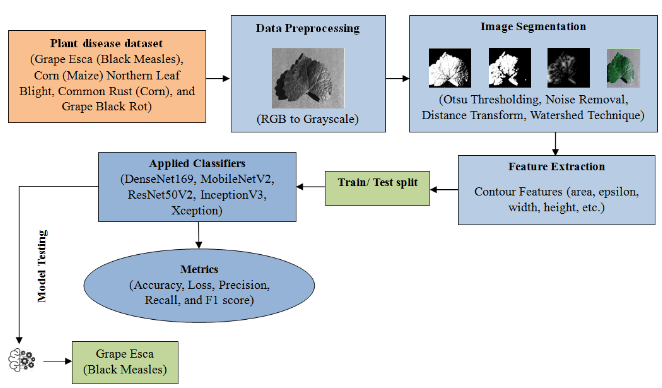

Fig 1. Proposed system to detect and classify plant diseases

2.1 Depiction of the dataset

The dataset included in the article was sourced from the New Plant Diseases dataset, which encompasses a collection of leaf images from 38 distinct plant categories. This study focuses on four categories of plant diseases (Figure 2): Corn (Maize) Northern Leaf Blight, Grape Esca (Black Measles), Common Rust (Corn), and Grape Black Rot. The diseases are represented as RGB photographs, with a total of 9529 images, each measuring 224x224 pixels[19].

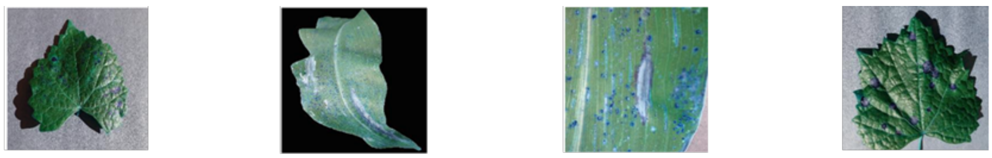

Fig 2. Original sample of plant diseases

2.2 Data Preprocessing

In this process, we convert a color image from the RGB color space to a grayscale image, as shown in Equation (i) (Figure 3). Each pixel in the grayscale image is given a luminance value that represents its perceived intensity[20].

$$Gray\ scale\ value = 0.299\ x\ Red + 0.587\ x\ \ Green + 0.114\ x\ \ Blue \tag{i}$$

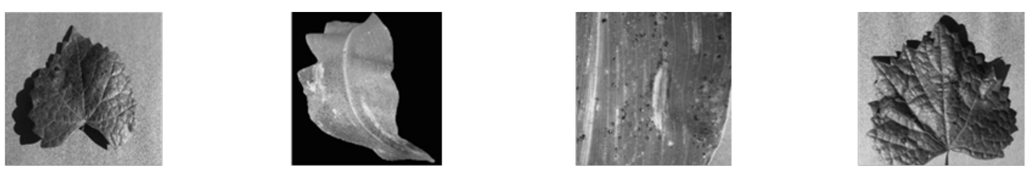

Fig 3. RGB to grayscale conversion of plant disease images

2.3 Segmentation

In this research work, we have used various techniques to enhance the quality of image such as Otsu thresholding, Noise removal, distance transformation, and watershed segmentation.

Otsu's thresholding is applied to convert the image into black and white format (binary) and to identify a threshold which splits the pixels into two classes i.e. background and foreground[21]. In the context of plant disease identification, Otsu's thresholding segments the images of plant leaves or tissues and efficiently distinguishes healthy and unhealthy regions in the images. The mathematical Equation (ii) for Otsu's thresholding is as follows:

$$\sigma_b^2\,(t) = \ \omega_b\,(t)\,.\ \omega_f\,(t)\,.[\mu_b\,(t)\,.\ \mu_f\,(t)]^2 \tag{ii}$$

Here, $\sigma_b^2\,(t)$ is the inter class variance for a given threshold t, $\omega_b\,(t)\ \ and\ \ \omega_f\,(t)$are the probabilities of the background and foreground classes, respectively, and $\mu_b\,(t)\ \ and\ \ \mu_f\,(t)$ are the mean pixel intensities of the background and foreground classes, respectively.

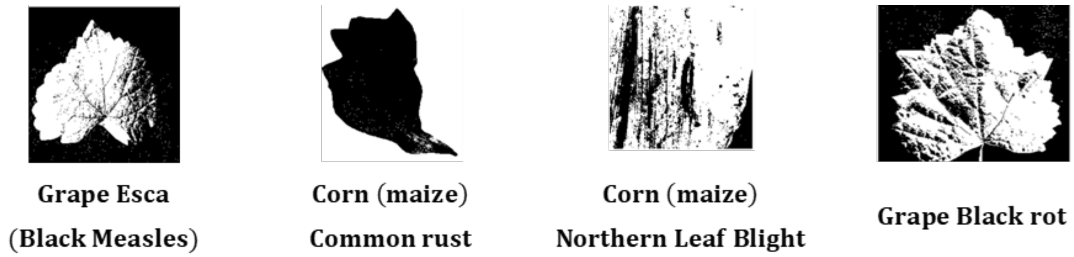

Fig 4. Enhanced the visualization of plant disease images through Otsu thresholding techniques

In the context of plant disease detection, **noise removal** is a crucial preprocessing step to enhance the accuracy of subsequent analyses. Image noise, such as random variations in pixel values, can adversely affect the performance of algorithms by introducing spurious information or obscuring meaningful features. Therefore, effective noise removal is essential for improving the overall reliability of plant disease detection systems[(21)]. One common method for noise removal is image smoothing or filtering. Hence, in this work, technique such as Gaussian smoothing has been employed to reduce high-frequency noise while preserving the essential structures of the image (Figure 5). This filter helps in creating a cleaner and more uniform representation of the plant tissues or leaves.

The mathematical equation for a 2D Gaussian filter is given by:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{iii}$$

Here, $G(x,y)$is the value of the Gaussian function at coordinates (x,y), π refers to the mathematical constant which represents the ratio of the circumference of a circle to its diameter, and σ refers to the standard deviation of the Gaussian distribution.

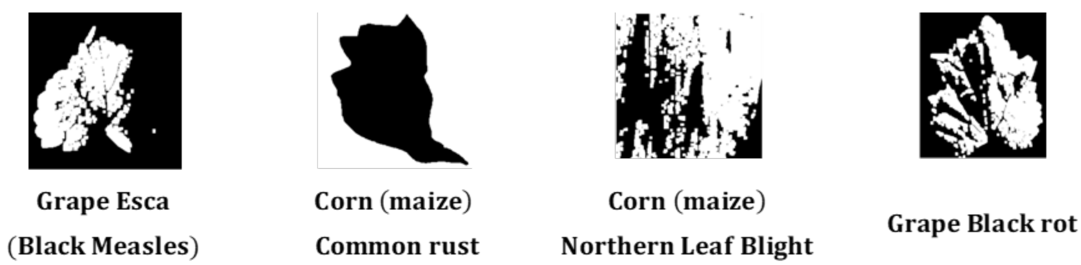

Fig 5. Removing noise in plant disease images

After removing noise, **distance transform technique** is applied to analyze and quantify the severity or extent of diseases affecting plant structures such as leaves. The distance transform computes the distance of each pixel in an image to the nearest boundary or edge[(21)]. In the context of plant images, the boundary could represent the outline of the plant structure or the contour of a diseased region (Figure 6). The Euclidean distance transform is a commonly used method, and its mathematical expression for a 2D image can be represented as follows:

Let $I(x,y)$ be the binary input image where $I(x,y)$ = 1 for foreground (object) pixels and $I(x,y)$ = 0 for background pixels. The distance transform D(x,y) is given by :

$$D(x,y) = \sqrt{\textstyle\sum_{i,j}}\,(i-x)^2 + (j-y)^2 \tag{iv}$$

Here, the sum is over all foreground pixels (i,j)in the binary image I(x,y). The distance D(x,y) represents the Euclidean distance from the pixel(x,y) to the nearest foreground pixel.

Grape Esca (Black Measles) | Corn (maize) Common rust | Corn (maize) Northern Leaf Blight | Grape Black rot

Fig 6. Distance transformation on plant disease images

The last technique used is a **watershed segmentation** which is useful in separately identifying the affected diseased areas in plants (Figure 7). It is able to accurately differentiate overlapping as well as adjacent regions which makes it more useful in instances where boundary delineation is crucial for accurately identifying and analyzing plant diseases[21].

The general equation for the watershed transformation can be expressed as follows:

Let I(x,y) be the input image, and $|\nabla I|$ be the gradient magnitude of the image. The watershed function W(x,y) is computed as the negative of the gradient magnitude:

$$W(x,y) = -|\nabla I| \quad \text{(v)}$$

Grape Esca (Black Measles) | Corn (maize) Common rust | Corn (maize) Northern Leaf Blight | Grape Black rot

Fig 7. Watershed technique on plant disease images

2.4 Feature Extraction

Various parameters such as area, perimeter, width, height, aspect ratio, etc, as shown in Table 1 are used to provide contour information to characterize as well as analyze diseased regions in plants for identification and interpretation[21].

Table 1. Characteristic values of images

Perimeter	Grape Esca (Black Measles)	Corn (maize) Common rust	Corn (maize) Northern Leaf Blight	Grape Black rot
Area	0.0	2.0	0.0	0.0
Perimeter	0.0	5.65	0.0	0.0
Epsilon	0.0	0.565	0.0	0.0
Width	1	3	1	1
Height	1	3	1	1
Equivalent Diameter	1.0	1	1.0	1.0
Extent	0.0	0.22	0.0	0.0
Aspect Ratio	0.0	1.59	0.0	0.0
Max Value	151.0	115.0	134.0	131.0

Continued on next page

Table 1 continued

Min Value	151.0	155.0	134.0	131.0
Min Value Loc	(231,255)	(239,249)	(43,255)	(66,255)
Max value loc	(231,255)	(238,249)	(43,255)	(66,255)
Mean color	(151.0)	(133.8)	134.0	(131.0)
Extreme Leftmost point	(231,255)	(238,249)	(43,255)	(66,255)
Extreme rightmost point	(231,255)	(240,249)	(43,255)	(66,255)
Extreme topmost point	(231,255)	(239,248)	(43,255)	(66,255)
Extreme bottommost point	(231,255)	(239,250)	(43,255)	(66,255)

2.5 Applied Classifiers

InceptionV3 uses inception modules with multiple filter sizes, batch normalization, factorized convolution, as well as auxiliary classifiers for capturing complex features and hierarchical representations. Likewise, the variant of DenseNet architecture, DenseNet169, has densely connected blocks which receives input from the previous layers, allows the reusing of plant disease image features, as well as mitigates the vanishing gradient problem [22]. Another classifier is Xception which is a derivative of Inception architecture. It is also useful in capturing the intricate features of images as it contains depth wise as well as point wise separable convolutions. The design of the network reduces the computational complexity and allows discerning fine details present in the image. A variant of ResNet architecture, ResNet50V2 has also showcased its effect in detecting diseases in plants. It contains residual blocks in stacked form that facilitates to preserve the information of the image via skip connections. At the end, a lightweight architecture, MobileNetV2, is used which has inverted residuals, linear bottlenecks as well as depth wise separable convolutions in its architecture. The network also contains shortcut and skip connections that enable the smooth flow of gradients during training and facilitate the learning of both local and global features [23]. The layered architectures of all the applied models are presented in Table 2.

Table 2. Parameters of the applied classifiers

Layer	Output Shape	Param#
Inception_V3	(None,2048)	21802784
Flatten_9	(None,2048)	0
Dense_45	(None,1024)	2098176
Dense_46	(None,512)	131328
Dropout_9	(None, 256)	0
Dense_48	(None, 128)	32896
Dense_49	(None,8)	1032
Total Parameters	**24591016**	
Trainable Parameters	**24556584**	
Non-Trainable Parameters	**34432**	
DenseNet169	(None,1664)	12642880
Flatten_1	(None,1664)	0
Dense_5	(None,1024)	1704968
Dense_6	(None,512)	524800
Dropout_1	(None, 256)	0
Dense_8	(None, 128)	32896
Dense_9	(None,8)	1032
Total Parameters	**15037896**	
Trainable Parameters	**14879496**	
Non-Trainable Parameters	**158400**	
Xception	(None,2048)	20861480
Flatten_2	(None,2048)	0
Dense_10	(None,1024)	2098176
Dense_11	(None,512)	524800
Dropout_2	(None,256)	0
Dense_13	(None,128)	32896
Dense_14	(None,8)	1032

Continued on next page

Table 2 continued

Total Parameters	**23649712**	
Trainable Parameters	**23595184**	
Non-Trainable Parameters	**54528**	
MobileNetV2	(None,1280)	2257984
Flatten_3	(None,1280)	0
Dense_15	(None, 1024)	1311744
Dense_16	(None,512)	524800
Dense_17	(None, 256)	131328
Drouput_3	(None, 256)	0
Dense_18	(None,128)	32896
Dense_19	(None,8)	1032
Total Parameters	**4259784**	
Trainable Parameters	**4225672**	
Non-Trainable Parameters	**34112**	
ResNet50V2	(None,2048)	23564800
Flatten_4	(None,2048)	0
Dense_20	(None,1024)	2098176
Dense_21	(None,512)	524800
Dense_22	(None,256)	131328
Dropout_4	(None,256)	0
Dense_23	(None,128)	32896
Dense_24	(None,8)	1032
Total Parameters	**26353032**	
Trainable Parameters	**26307592**	
Non-Trainable Parameters	**45440**	

2.6 Performance Metrics

When it comes to detecting plant diseases, there is several important performance metrics that help us evaluate how well a model is working. **Accuracy** is a fundamental metric which represents the proportion of correctly classified instances among the total samples. Loss, however, is a way to measure how much the predicted values differ from the actual values. Lower values indicate that the model is performing better[24].

$$Accuracy = \frac{True\ Negative + True\ Positive}{True\ Negative + True\ Positive + False\ Positive + False\ Negative} \tag{vi}$$

$$Loss = \frac{(Actual\ Value - Predicted\ Value)^2}{Number\ of\ observations} \tag{vii}$$

Precision measures the accuracy of positive predictions by measuring the proportion of true positives out of the total of true positives and false positives. **Recall,** or **sensitivity,** measures the model's capacity to correctly identify all relevant instances by computing the ratio of true positives to the sum of true positives and false negatives. **F1 score** represents the harmonic mean of precision and recall, providing a balanced assessment that is especially valuable when there is an imbalance between disease and non-disease instances[24].

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{viii}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{ix}$$

$$F1\ score = 2\frac{Precision * Recall}{Recall + Precision} \tag{x}$$

3 Results and Discussion

To predict and classify plant diseases, the performance metrics of five different architectures were assessed, namely DenseNet169, Xception, MobileNet V2, ResNet50 V2, and Inception V3 on the basis of training and validation accuracy and loss (Table 3).

Table 3. Analysis of the applied models for plant disease dataset

Models	Training		Validation	
	Accuracy	Loss	Accuracy	Loss
DenseNet 169	99.11	0.30	99.24	0.001
Xception	99.60	0.32	99.26	0.34
MobileNet V2	99.14	0.34	99.42	0.19
ResNet50 V2	99.49	0.59	99.42	0.49
Inception V3	99.60	0.59	98.49	0.46

The DenseNet169 model exhibited a commendable performance with a training accuracy of 99.11% and a negligible training loss of 0.30, while on the validation set, it achieved an impressive accuracy of 99.24% with an extremely low loss of 0.001. Similarly, the Xception model demonstrated a high level of accuracy in both training (99.60%) and validation (99.26%) sets, accompanied by relatively low losses (0.32 and 0.34, respectively). MobileNet V2 and ResNet50 V2 also performed well, with the training accuracy above 99% i.e. 99.14% and 99.49% respectively and relatively low losses. But these models computed the best accuracy at the validation phase with 99.42% each. On the other hand, the Inception V3 model showed a slightly lower validation accuracy of 98.49% compared to its training accuracy of 99.60%, suggesting a potential issue with generalization.

Table 4. Analyzing the execution of the models

Models	Precision	Recall	F1 Score
DenseNet169	0.99	0.99	0.99
Xception	0.99	0.99	0.99
MobileNet V2	0.97	0.97	0.97
ResNet50 V2	0.99	0.99	0.99
Inception V3	0.98	0.99	0.98

Likewise, as shown in Table 4, DenseNet169, ResNet50V2, and Xception indicated strong classification performance by obtaining the highest values of precision, recall, and F1 score of 0.99 followed by InceptionV3 with the best recall value of 0.99 but slightly lower value of precision and F1 score with 0.98. On the contrary, MobileNet V2 showed lower performance as compared to the other models in terms of precision, recall, and F1 score with 0.97.

As shown in Figure 8, for the classes "Grape___Esca_(Black_Measles)", "Corn_(maize)___Common_rust,"and "Grape___Black_rot," **DenseNet169** achieved perfect scores of 1.00 in precision, recall, and F1and showcase its ability to accurately identify instances of these diseases in grape and corn plants. On the contrary, for the class "Corn_(maize)___Northern_Leaf_Blight," the DenseNet 169 model exhibited little low precision (0.97), recall (0.99), and F1 score (0.98), which highlightes its effectiveness in distinguishing and classifying instances of Northern Leaf Blight in maize plants. Likewise, for "Grape___Esca_(Black_Measles)," **Xception** model achieved perfect precision (1.00), which indicate accurate positive predictions, along with high recall (0.98) and F1 score (0.99). In the case of "Corn_(maize)___Common_rust," the model shows flawless precision, recall, and F1 scores with 1.00. But regarding "Corn_(maize)___Northern_Leaf_Blight," the model obtained lower value of precision (0.96), recall (0.97), and an overall high F1 score (0.99). For "Grape___Black_rot," the Xception model demonstrates accurate classification with a balanced 0.97 as precision, 1.00 as recall, and 0.98 as F1 score. In the "Grape___Esca_(Black_Measles)" class, **MobileNetV2** shows high recall (1.00) but slightly lower precision (0.94) and results in a balanced F1 score of 0.97. For "Corn_(maize)___Common_rust," the model achieves flawless precision, recall, and F1 scores which indicates its precise identification of instances of common rust. In the case of "Corn_(maize)___Northern_Leaf_Blight," the model displays perfect precision but a lower recall i.e., 0.85 which leads to a slightly lower F1 score of 0.92. For "Grape___Black_rot," the model demonstrates perfect precision (1.00) but a somewhat lower recall of 0.93 but results in a balanced F1 score of 0.96. The **ResNet50V2** model exhibits robust and consistent performance in classifying various plant diseases. For the "Grape___Esca_(Black_Measles)" and "Grape___Black_rot" class, the model obtained 1.00 as precision, F1 score, and recall value respectively which thereby showcases its accuracy in identifying instances

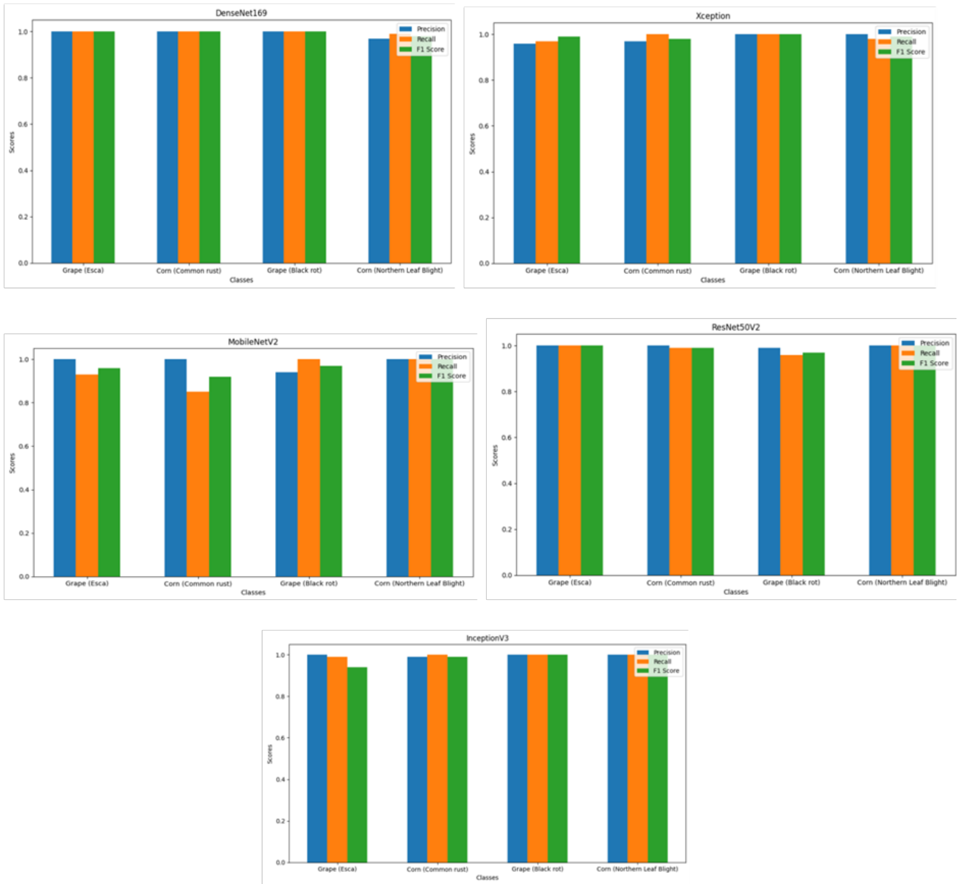

Fig 8. Performance evaluation of classifiers for different class of plant disease

of this disease in grape plants. In the "Corn_(maize)___Common_rust" class, the model maintains flawless precision, which indicates accurate positive predictions, but with a slightly lower recall of 0.99, resulting in a high F1 score of 0.99. Similarly, for "Corn_(maize)___Northern_Leaf_Blight," the model demonstrates a precise classification with a high precision of 0.99, though with a slightly lower recall of 0.96, thereby results in a commendable F1 score of 0.97. Similarly, the **InceptionV3** model demonstrates strong and precise performance in classifying specific plant diseases. For the "Grape___Esca_(Black_Measles)" and "Grape___Black_rot," class, the model obtains perfect precision, recall, and F1 score which indicates accurate identification and classification of instances of this disease in grape plants. In the "Corn_(maize)___Common_rust" class, the model maintains a high precision of 0.99, capturing the majority of true positives with perfect recall and resulting in a commendable F1 score of 0.99. For "Corn_(maize)___Northern_Leaf_Blight," the model exhibits perfect precision and a high recall of 0.99, though the F1 score is slightly lower at 0.94.

In addition to this, the performance of the applied models has been also compared with the existing ones in Table 5 through rigorous evaluation and analysis.

Table 5. Comparative Analysis

Ref	Dataset	Techniques	Accuracy	Remarks
[4]	Plant disease	GradCAM+MobileNetV2	96%	High processing time
[5]	Coffee plant data	CoffeeNet	98.54%	Limited dataset
[6]	Images of healthy and diseased plants	PlaNet	97.95%	Lack of generalizability

Continued on next page

Table 5 continued

(7)	Real time data	CNN+SVM	91.45%	Not reliable
(8)	Plant Village	SVM	98.97%	Class imbalance issue
(9)	Leaf dataset	RPN+CV	83.57%	Low detection accuracy
(15)	Plant Village Dataset	EfficientNetB5	99.1%	Fine tuning of model is required
Our Study	**New Plant Diseases Dataset**	**ResNet50V2 MobileNetV2**	**99.42% 99.42%**	**Improved accuracy and generalizability by using multiple plant diseases**

4 Conclusion

The paper presents that advanced CNN models has yielded significant quantitative observations and findings in plant disease detection. Through rigorous experimentation and evaluation, we observed that the ResNet50V2 and MobileNetV2 models achieved impressive validation accuracy scores of 99.42%. These high accuracy rates demonstrate the effectiveness of using the advanced deep learning architectures in accurately identifying and classifying various plant diseases. Furthermore, our research highlighted the importance of preprocessing plant images through operations such as converting to grayscale, applying Otsu thresholding, noise removal, distance transform, and watershed techniques along with the contour feature extraction. These preprocessing steps played a crucial role in improving the quality of the dataset and enhancing the performance of the applied deep learning models. Hence, by incorporating multiple image segmentation techniques and fine-tuning the parameters of advanced CNN models, we were able to optimize the results and achieve optimal scores for recall, precision, and F1 score. This novel approach not only enhanced the efficiency of disease detection but also provided valuable insights into the potential of AI-based systems in revolutionizing plant disease management efforts. However, there are also certain limitations and challenges like the risk of overfitting as well as use of small data. Addressing these issues through robust validation techniques, regularization methods, and data augmentation strategies in future will be crucial in ensuring the reliability and effectiveness of AI-based plant disease detection systems in practical agricultural settings. Apart from this, Explainable AI techniques should be also integrated to enhance the interpretability of model predictions and develop real-time plant disease monitoring systems for proactive management. By addressing these limitations and leveraging the future scope of research, the potential for AI technologies to transform plant health management and agricultural sustainability remains promising.

References

1) Kanna GP, Kumar SJKJ, Kumar YJ, Changela A, Woźniak M, Shafi J, et al. Advanced deep learning techniques for early disease prediction in cauliflower plants. *Scientific Reports*. 2023;13(1):1–21. Available from: https://doi.org/10.1038/s41598-023-45403-w.
2) Panchal AV, Patel SC, Bagyalakshmi K, Kumar P, Khan IR, Soni M. Image-based Plant Diseases Detection using Deep Learning. *Materials Today: Proceedings*. 2023;80(Part 3):3500–3506. Available from: https://dx.doi.org/10.1016/j.matpr.2021.07.281.
3) Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. *Plant Methods*. 2021;17(1):1–18. Available from: https://dx.doi.org/10.1186/s13007-021-00722-9.
4) Kumar Y, Singh R, Moudgil MR, Kamini. A Systematic Review of Different Categories of Plant Disease Detection Using Deep Learning-Based Approaches. *Archives of Computational Methods in Engineering*. 2023;30(8):4757–4779. Available from: https://dx.doi.org/10.1007/s11831-023-09958-1.
5) Naralasetti V, Bodapati JD. Enhancing Plant Leaf Disease Prediction Through Advanced Deep Feature Representations: A Transfer Learning Approach. *Journal of The Institution of Engineers (India): Series B*. 2024;10:1–4. Available from: https://dx.doi.org/10.1007/s40031-023-00966-0.
6) Shoaib M, Shah B, Ei-Sappagh S, Ali A, Ullah A, Alenezi FA, et al. An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*. 2023;14:1–22. Available from: https://doi.org/10.3389/fpls.2023.1158933.
7) Khalid MM, Karan O. Deep Learning for Plant Disease Detection. *International Journal of Mathematics, Statistics, and Computer Science*. 2023;2:75–84. Available from: https://dx.doi.org/10.59543/ijmscs.v2i.8343.
8) Nawaz M, Nazir T, Javed A, Amin ST, Jeribi F, Tahir A. CoffeeNet: A deep learning approach for coffee plant leaves diseases recognition. *Expert Systems with Applications*. 2024;237(Part A):121481. Available from: https://dx.doi.org/10.1016/j.eswa.2023.121481.
9) Khanna M, Singh LK, Thawkar S, Goyal M. PlaNet: a robust deep convolutional neural network model for plant leaves disease recognition. *Multimedia Tools and Applications*. 2024;83(2):4465–4517. Available from: https://dx.doi.org/10.1007/s11042-023-15809-9.
10) Haridasan A, Thomas J, Raj ED. Deep learning system for paddy plant disease detection and classification. *Environmental Monitoring and Assessment*. 2023;195. Available from: https://dx.doi.org/10.1007/s10661-022-10656-x.
11) Javidan SM, Banakar A, Vakilian KA, Ampatzidis Y. Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning. *Smart Agricultural Technology*. 2023;3:1–14. Available from: https://dx.doi.org/10.1016/j.atech.2022.100081.
12) Guo Y, Zhang J, Yin C, Hu X, Zou Y, Xue Z, et al. Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming. *Discrete Dynamics in Nature and Society*. 2020;2020:1–11. Available from: https://dx.doi.org/10.1155/2020/2479172.
13) Chen J, Chen J, Zhang D, Sun Y, Nanehkaran YA. Using deep transfer learning for image-based plant disease identification. *Computers and Electronics in Agriculture*. 2020;173:105393. Available from: https://dx.doi.org/10.1016/j.compag.2020.105393.
14) Chohan M, Khan A, Chohan R, Katpar SH, Mahar MS, , et al. Plant Disease Detection using Deep Learning. *International Journal of Recent Technology and Engineering (IJRTE)*. 2020;9(1):909–914. Available from: https://dx.doi.org/10.35940/ijrte.a2139.059120.
15) Ahmed I, Yadav PK. Plant disease detection using machine learning approaches. *Expert Systems*. 2023;40(5). Available from: https://dx.doi.org/10.1111/exsy.13136.

16) Panigrahi KP, Das H, Sahoo AK, Moharana SC. Maize Leaf Disease Detection and Classification Using Machine Learning Algorithms. In: Progress in Computing, Analytics and Networking;vol. 1119 of Advances in Intelligent Systems and Computing. Singapore. Springer. 2020;p. 659–669. Available from: https://doi.org/10.1007/978-981-15-2414-1_66.
17) Jasim MA, Al-Tuwaijari JM. Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques. In: 2020 International Conference on Computer Science and Software Engineering (CSASE). IEEE. 2020;p. 259–265. Available from: https://doi.org/10.1109/CSASE48920.2020.9142097.
18) Atila Ü, Uçar M, Akyol K, Uçar E. Plant leaf disease classification using EfficientNet deep learning model. *Ecological Informatics*. 2021;61:101182. Available from: https://dx.doi.org/10.1016/j.ecoinf.2020.101182.
19) Bhattarai S. New Plant Diseases Dataset. . Available from: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset.
20) Bansal K, Batla RK, Kumar Y, Shafi J. Artificial Intelligence Techniques in Health Informatics for Oral Cancer Detection. In: Connected e-Health;vol. 1021 of Studies in Computational Intelligence. Springer, Cham. 2022;p. 255–279. Available from: https://doi.org/10.1007/978-3-030-97929-4_11.
21) Koul A, Bawa RK, Kumar Y. An Analysis of Deep Transfer Learning-Based Approaches for Prediction and Prognosis of Multiple Respiratory Diseases Using Pulmonary Images. *Archives of Computational Methods in Engineering*. 2024;31(2):1023–1049. Available from: https://dx.doi.org/10.1007/s11831-023-10006-1.
22) Hammou DR, Boubaker M. Tomato Plant Disease Detection and Classification Using Convolutional Neural Network Architectures Technologies. In: Networking, Intelligent Systems and Security;vol. 237 of Smart Innovation, Systems and Technologies. Singapore. Springer. 2022;p. 33–44. Available from: https://doi.org/10.1007/978-981-16-3637-0_3.
23) De Silva M, Brown D. Plant disease detection using multispectral imaging. In: International Advanced Computing Conference: IACC 2022;vol. 1781 of Communications in Computer and Information Science. Springer, Cham. 2022;p. 290–308. Available from: https://doi.org/10.1007/978-3-031-35641-4_24.
24) Koul A, Bawa RK, Kumar Y. Enhancing the detection of airway disease by applying deep learning and explainable artificial intelligence. *Multimedia Tools and Applications*. 2024;p. 1–33. Available from: https://dx.doi.org/10.1007/s11042-024-18381-y.