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Performance Evaluation of Deep Learning Models for Multiclass Disease Detection in Pomegranate Fruits

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ABSTRACT

Background: Agriculture is a major driver of economic expansion and accounts for 17% of India's GDP. However, the loss of agricultural land is a major problem that affects the economy and farmers' livelihoods. Farmers use non-scientific techniques to detect pomegranate diseases, which takes time. A detection and classification system based on DL provides a quicker and more precise answer.

Methods: This paper presents a deep learning-based framework for the categorization and detection of pomegranate fruit diseases. For disease identification, five Deep CNN models are used: VGG16, MobileNetV2, ResNet50V2, DenseNet121 and the suggested PomeNetV2. 5,099 photos from five classes in a custom pomegranate fruit dataset are used. Pre-processing methods like data augmentation, resizing and rescaling are used to improve model performance and reduce overfitting. After that, the dataset is divided into 20% for testing and 80% for training.

Result: The confusion matrix, precision, recall, accuracy and F1-score were used to evaluate the performance of the suggested models. DenseNet201 did marginally better with 98% accuracy, according to the data, while VGG16, MobileNetV2 and ResNet50V2 all attained 97% accuracy. The PomeNetV2 model achieved the greatest accuracy of 99.02%, outperforming all other models.

Key words: Deep Learning, Detection and classification, Pomegranate fruit.

INTRODUCTION

A popular fruit in tropical and subtropical climates, pomegranates are grown extensively in the Mediterranean, India and other places. Being regarded as the "fruit of paradise," it is an important crop in dry regions (Jayalakshmi *et al.,* 2015). A fruit that is high in nutrients (Singh *et al.,* 2023) and has important therapeutic benefits is the pomegranate. Arid and semi-arid areas with less than 20 inches of annual rainfall are ideal for its growth. Well-known for their therapeutic properties, pomegranates are a powerful anti-parasitic and help (Gawade *et al.,* 2018) treat infertility and diarrhea (Kantale and Thakare *et al.,* 2020). The pomegranate's external characteristics such as color, lesions, black spots, weight and plant condition can be used to identify fruit illnesses. As described below, CNN has been used in several studies to detect diseases (Vasumathi *et al.,* 2021). A systematic review was discussed for pomegranate fruit disease using ML and DL Techniques (Pakruddin *et al.,* 2024). Fusarium Wilt disease also affects pomegranate plants (Pakruddin *et al.,* 2024). Using an effective method, (Naseer *et al.,* 2024) study seeks to identify pomegranate growth phases early. 5,857 photos from five different stages-bud, early-fruit, flower, mid-growth and Ripe-were utilized in the dataset. To extract spatial characteristics for precise categorization, a transfer learning model based on CRnets is suggested. A method that allows farmers to upload fruit photos for disease identification using a trained dataset is presented by Wakhare *et al.* (2023). To identify infection, the system uses image processing methods such as CNN-based clustering, SVM classification and feature extraction (color, morphology, CCV). Using features that have been extracted, an intent search method refines the results. The accuracy of the experimental evaluation in identifying diseases is 98.38%.

AgriDet, a system that combines INC-VGGN and Kohonen-based deep learning, is proposed by Pal Arunangshu *et al.* (2023) to identify plant diseases and categorize their severity levels. Khatawkar *et al.* (2023) Dataset preparation, picture pre-processing, segmentation, feature extraction and classification are all included in the suggested task. After segmenting the fruit image to identify any worrisome lesions, the GLCM approach is used to extract textural information. The lesions are then classified as either healthy or sick by an SVM classifier. There are

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1,000 photos in the dataset: 500 of healthy fruits, 250 of scabbed fruits and 250 of fruit rotted fruits. A confusion matrix was used to assess classification performance and 83% illness detection accuracy was attained. The machine learning-integrated approach provided by Nirmal *et al.,* (2023) achieves 95.54% accuracy in identifying healthy and diseased pomegranate leaves and 96.43% accuracy in classifying diseases. The 559 photos in the dataset, which comes from Mendeley Data, are divided 80:20 between training and testing (287 healthy, 272 diseased). An effective deep learning method for identifying the main pomegranate diseases-bacterial blight, anthracnose, fruit spot, wilt and fruit borer-is presented in the Nirgude and Rathi (2021) study. At a learning rate of 0.001, the optimized ResNet50 achieved 97.92% test accuracy, outperforming both ResNet18 (87.5%) and Inception-V3 (78.75%).

Javeriya (2021) uses specially trained deep-learning models to identify and categorize two diseases: Anthracnose and bacterial blight. Faster R-CNN outperforms conventional techniques in improving object detection. By uploading pictures of the fruit, Bhange Manisha *et al.* (2015) suggest a web-based tool that farmers can use to identify pomegranate infections. By using a pre-trained dataset, the system can identify diseases with 82% accuracy. To classify three soybean illnesses, Jadhav *et al.* (2021) trained the AlexNet and GoogleNet CNN models using photos of 649 infected and 550 healthy soybean leaves. GoogleNet obtained 96.25% accuracy and AlexNet scored 98.75% accuracy using a five-fold cross-validation approach. A CNN-based model with transfer learning is presented by Thorat *et al.* (2023) to help identify and detect agricultural diseases by classifying pomegranate fruit disorders. The goal of the Yan *et al.* (2023) study is to create a deep CNN with transfer learning for quick identification of Fusarium wilt in banana leaves. Madhavan *et al.* (2021) proposes a MATLAB-based framework for detecting and classifying pomegranate leaf diseases using image processing and machine learning. Key steps include image enhancement, segmentation using K-Means and classification via multi-class SVM. Using a hybrid dataset of healthy and infected leaves, including healthy and diseased samples (Alternaria Alternata, Anthracnose, Bacterial Blight and Cercospora Leaf Spot)-is used the system achieves 98.39% accuracy in detecting disease presence and 98.07% in classifying specific diseases. Nirgude and Rathi (2024) presents i-PomDiagnoser, a real-time system that uses drones, sensors and machine learning to identify, categorize and forecast pomegranate disorders. Using an Improved Ensemble Multilabel Classifier, the system obtained a classification accuracy of 95.82% by examining field data and micro-level climate factors. A hybrid LSTM-based forecasting model provided a dependable instrument for proactive disease management by accurately predicting illness states up to 45 days ahead of time.

Early and accurate detection of pomegranate fruit diseases is essential for reducing crop loss and enhancing productivity. Traditional disease detection methods are often manual, time-consuming and error-prone. This study aims to explore deep learning techniques to automate disease identification in pomegranate fruits, ensuring fast, accurate and scalable solutions for farmers and agricultural professionals. Although various deep learning models have been proposed, many focus on limited disease types, lack robust datasets, or fall short in real-time implementation. This study addresses these gaps by developing a transfer learning-based CNN model tailored for multiclass disease detection in pomegranate fruits. Using a curated dataset and optimized ResNet50 architecture, our model achieved high classification accuracy, enabling early detection of diseases such as alternaria fruit spot, bacterial blight, anthracnose, cercospora fruit spot and healthy.

The remainder of this paper is structured as follows: section 2 outlines the materials and methodology, section 3 details the experimental setup and results and Section 4 concludes with discussion and future research directions.

MATERIALS AND METHODS

Dataset used

Pakruddin *et al.* (2024) proposed a pomegranate fruit disease dataset. From places like Ballari, Bengaluru and Bagalakote, we gathered photos of five different pomegranate fruit states, including healthy ones. A Redmi 9 HD camera was used to take the pictures, which were then saved in JPG format with a 1:1 aspect ratio and 3120 × 3120 pixels. From July to October 2023, photographs were taken on farms in sunny, overcast weather from 9 AM to 4 PM. 5099 photos in all were divided into five categories: Alternaria Fruit Spot, Bacterial Blight, Anthracnose (Chavan *et al.*, 2017), Cercospora Fruit Spot and Healthy. The dataset was split into 80% for training and 20% for testing. Sample images are shown in (Fig 1).

Pre-processing and data augmentation

To ensure consistency and reduce computational overhead, all images were resized from their original resolution of 3120×3120 to 220×220 pixels during pre-processing. Pixel values were normalized by scaling them to a [0, 1] range through division by 255, which enhances model performance

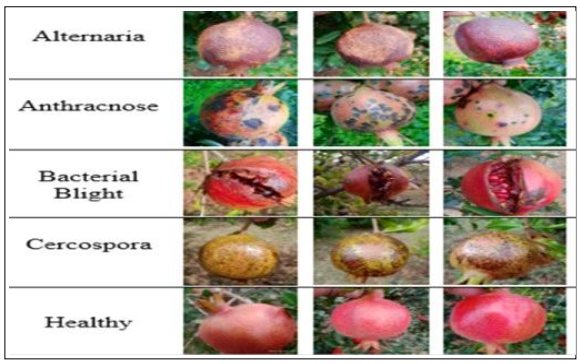


Fig 1: Sample images from the dataset.

and convergence. Noise reduction techniques such as Gaussian blur and median filtering were applied to remove irrelevant details while preserving critical features. To further improve generalization and mitigate overfitting, data augmentation techniques including random rotation (0.2), horizontal and vertical flips and rescaling (1.0/255) were applied. These transformations artificially expand the training dataset, enabling the model to learn more robust and invariant features.

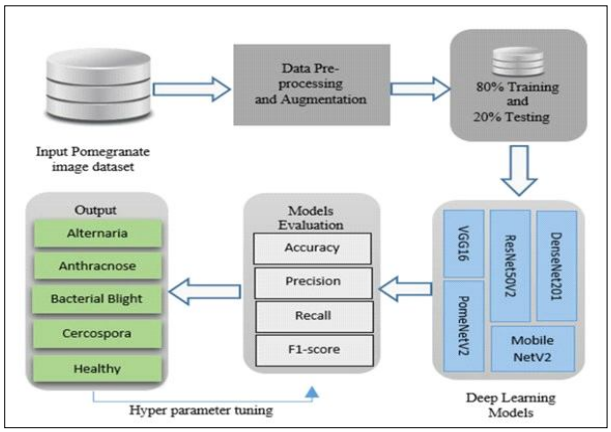


Fig 2: Proposed model architecture.

Table 1: Summary of the proposed model.

Component	Description
Model name	PomeNetV2
Architecture	15-layer CNN
Classification	Healthy + 4 disease categories
Transfer learning	Not used (trained from scratch)
Convolutional layers	6 (trainable weights and biases)
Max-pooling layers	6
Flattened layer	1
Fully-connected dense layers	2
Overfitting prevention	Reduced layers and fewer filters
Kernel size (Conv layers)	3×3
Pool size (Max-pooling Layers)	2×2
Filters per layer	64
Stride size	1
Padding	Valid
Feature extraction	First 12 layers
Classification layers	Final 3 layers

Proposed model architecture

The pomegranate disease diagnosis method based on deep learning is depicted in (Fig 2). Five classes-Alternaria (Aloi *et al.,* 2021), Anthracnose, Bacterial Blight, Cercospora (Ravichandra *et al.,* 2023) and Healthy are included in the initial input image dataset (Pakruddin *et al.,* 2024). Before being divided into 80% training and 20% testing, the images go through data pre-processing and augmentation. VGG16, ResNet50V2, DenseNet201 (Srivastava *et al.,* 2023), MobileNetV2 and the suggested PomeNetV2 are among the deep learning models that are trained for categorization. Accuracy, precision, recall and F1-score are used to assess the model's performance; hyperparameter adjustment improves classification accuracy. The projected disease category is provided by the final output, which helps with automated pomegranate crop disease diagnosis.

Description of the proposed model

The key hyperparameters used for training the PomeNetV2 model are summarized in (Table 1). The model was trained on images resized to 220×220×3 dimensions, using a batch size of 32 over 50 epochs. The Adam optimizer was employed with a learning rate of 0.001 and ReLU was used as the activation function. The loss function selected was Sparse Categorical Cross-Entropy, appropriate for multi-class classification tasks. These settings were optimized to ensure efficient learning and accurate classification performance (Pakruddin *et al.,* 2024).

Pre-trained models

This study explores pre-trained deep learning models for ImageNet using Keras. Table 2 summarizes their key characteristics.

Performance metrics

The performance of deep learning models is evaluated using metrics like Accuracy, Precision, Recall, F1 Score, Support and AUC. These metrics offer insights into various aspects of model effectiveness. Support indicates the frequency of each class in the dataset, while the confusion matrix True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN) helps assess classification accuracy. Precision reflects the proportion of correct positive predictions, Recall measures the ability to detect actual positives and the F1 Score balances both. AUC summarizes the model's class-separation ability,

Table 2: The summary of the main features of the several pre-trained models.

Model	Quantity (MB)	Top-rated precision	Highest five precision	Limits	Complexity	CPU time (ms) for each inference step	GPU inference step time (ms)
VGG16	528	71.30%	90.10%	138.4M	16	69.5	4.2
MobileNetV2	14	71.30%	90.10%	3.5M	105	25.9	3.8
ResNet50V2	98	76.00%	93.00%	25.6M	103	45.6	4.4
DenseNet201	80	77.30%	93.60%	20.2M	402	127.2	6.7

where 0.5 indicates poor, 0.7 good and 0.85 or above excellent performance (Pakruddin *et al.,* 2024).

$$\text{Precision} = \frac{TP}{TP + FP} \quad ...(1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad ...(2)$$

$$\text{F1 - score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad ...(3)$$

$$\text{Accuarcy} = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(4)$$

RESULTS AND DISCUSSION

The code for all experiments was implemented and executed in Google Colab, using the most recent versions of Keras and TensorFlow (Table 3). Provides a detailed account of the hardware specifications used during the trials.

Table 3: Hardware requirements for experiments.

Hardware component	Specification
GPU	Tesla T4, High RAM
System RAM	50.99 GB
Disk storage	238.68 GB

The efficacy of distinct architectures is demonstrated by the performance comparison of several deep learning models for multiclass illness detection in pomegranate fruits. With a 98% total accuracy, DenseNet201 outperformed the other pre-trained models. ResNet50V2, MobileNetV2 and VGG16 all came in second and third, respectively, with 97% accuracy. With an astounding 99% accuracy, the suggested PomeNetV2 model surpassed the others, showcasing its better categorization capabilities. PomeNetV2 demonstrated its good precision and recall balance by achieving F1-scores above 0.98 for every illness class. According to these findings, PomeNetV2 is a very effective pomegranate illness classification tool that offers improved accuracy and dependability over pre-trained models as shown in (Table 4).

With 100% training accuracy, 99.02% validation accuracy and the lowest validation loss (0.0344), the suggested PomeNetV2 model performs exceptionally well in the categorization of pomegranate diseases, guaranteeing outstanding generalization. With a validation accuracy of 98.34% and a validation loss of 0.0658, DenseNet201 comes in second. Although they have greater validation losses, VGG16, MobileNetV2 and ResNet50V2 all perform well (97% accuracy). These findings support PomeNetV2's ability to accurately classify diseases with

Table 4: Performance analysis of proposed models.

Models	Classes	Precision	Recall	F1-score	Accuracy
VGG16	Alternaria	0.97	0.94	0.96	97%
	Anthracnose	0.99	0.94	0.96	
	Bacterial_Blight	0.92	0.99	0.95	
	Cercospora	0.94	0.94	0.94	
	Healthy	0.99	0.99	0.99	
MoileNetV2	Alternaria	0.94	0.97	0.96	97%
	Anthracnose	0.96	1.00	0.98	
	Bacterial_Blight	0.97	0.95	0.96	
	Cercospora	0.99	0.90	0.94	
	Healthy	0.98	0.99	0.99	
ResNet50V2	Alternaria	0.98	0.96	0.97	97%
	Anthracnose	0.98	0.96	0.97	
	Bacterial_Blight	0.97	0.98	0.97	
	Cercospora	0.96	0.94	0.95	
	Healthy	0.97	1.00	0.98	
DenseNet201	Alternaria	0.98	0.98	0.98	98%
	Anthracnose	1.00	0.95	0.97	
	Bacterial_Blight	0.99	0.99	0.99	
	Cercospora	0.93	1.00	0.96	
	Healthy	1.00	1.00	1.00	
Proposed PomeNetV2 Model	Alternaria	0.98	0.99	0.99	99%
	Anthracnose	0.99	0.99	0.99	
	Bacterial_Blight	1.00	0.98	0.99	
	Cercospora	0.97	0.99	0.98	
	Healthy	1.00	1.00	1.00	

little overfitting as shown in Table 5. Training and validation accuracy-loss curves are shown in Fig 3. A comparison between the current and earlier work Table 6.

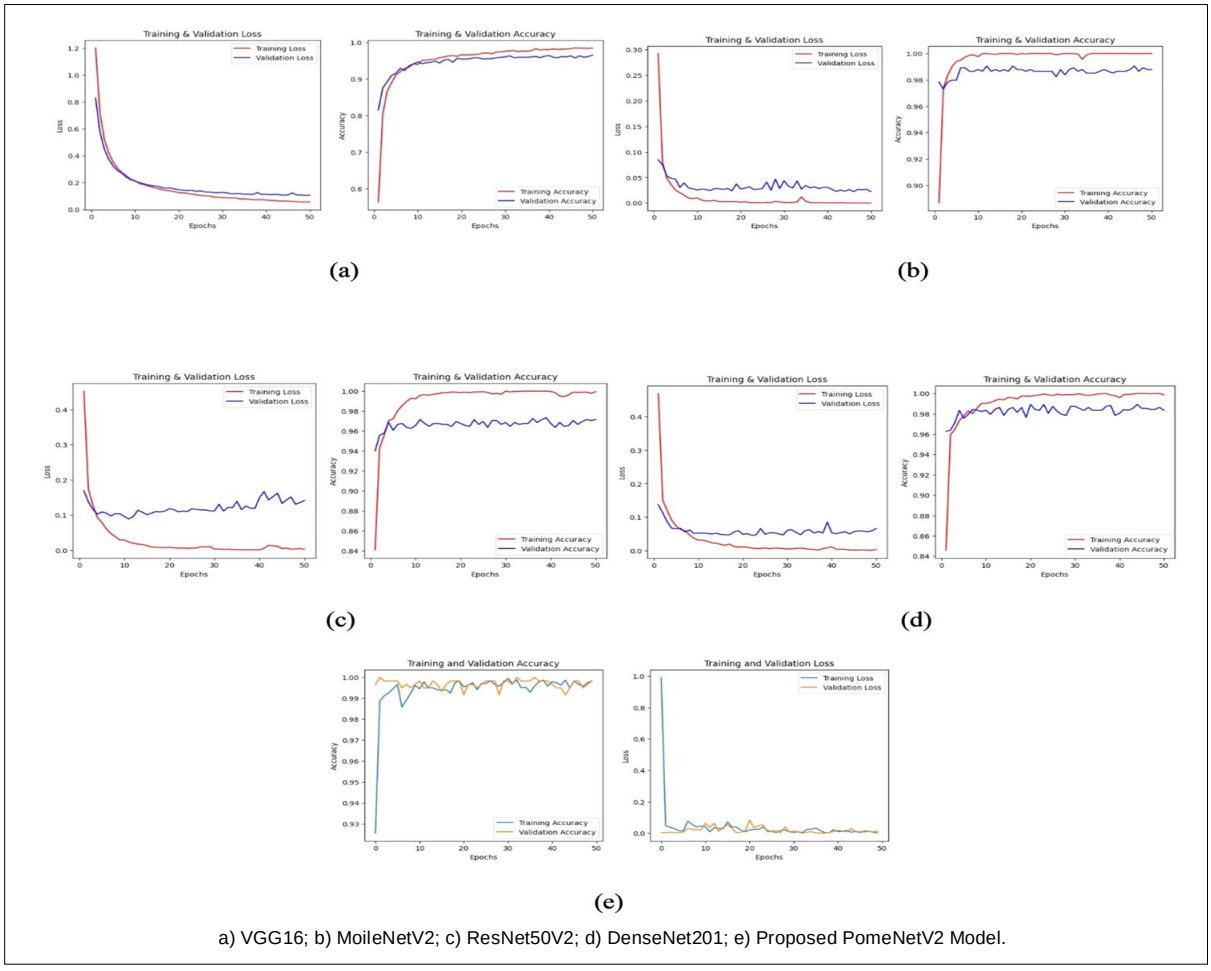
The classification performance of different deep learning models for pomegranate illness is highlighted by their confusion matrices as shown in (Fig 4). While Alternaria, Anthracnose and Bacterial Blight are occasionally confused with similar classes, VGG16, MobileNetV2, ResNet50V2 and DenseNet201 show high true positive numbers with just minimal misclassifications. While ResNet50V2 and MobileNetV2 maintain dependable precision and recall across all classes, DenseNet201 achieves strong accuracy, especially in Cercospora classification. PomeNetV2 is the most reliable model for pomegranate illness detection,

Table 5: Performance comparison of different models.

Model	Training loss	Training accuracy	Validation loss	Validation accuracy
VGG16	0.0585	0.9847	0.1073	0.9658
MobileNetV2	0.0012	0.9996	0.1169	0.9716
ResNet50V2	0.0025	0.9997	0.1411	0.9716
DenseNet201	0.0012	0.9998	0.0658	0.9834
PomeNetV2 proposed model	0.0000	100.0	0.0344	0.9902

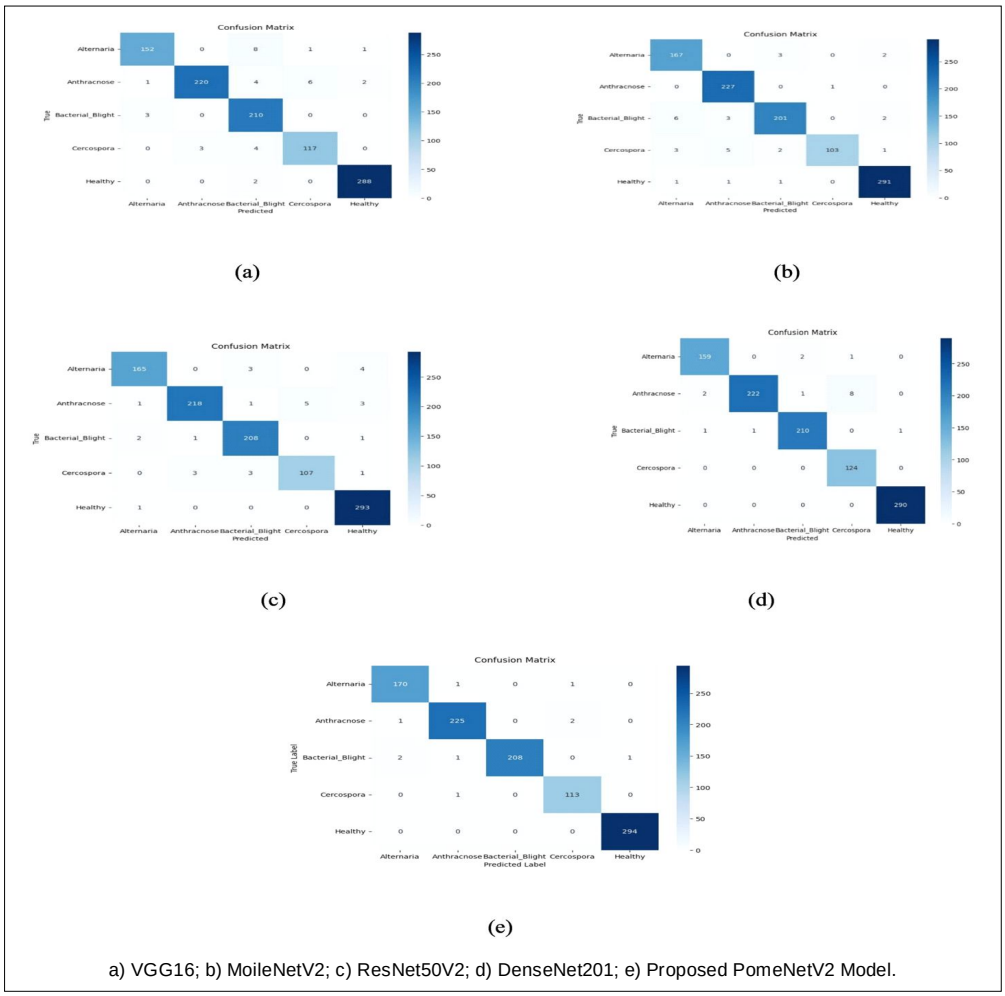
Table 6: A comparison between the current and earlier work.

Reference	Diseases detected	Method	Accuracy
Proposed work	5	PomeNetV2 CNN model	99.02%
Mangena *et al.* 2021	5	K- means, SVM	98.07%
Nirgude and Rathi 2024	5	LSTM and i-Ensemble-MLC	95.82%



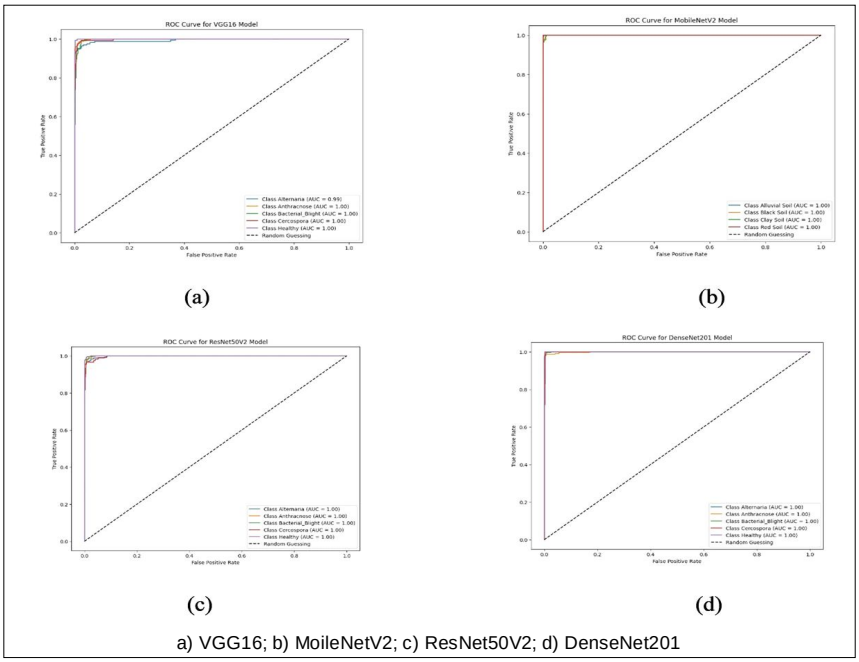
a) VGG16; b) MoileNetV2; c) ResNet50V2; d) DenseNet201; e) Proposed PomeNetV2 Model.

Fig 3: Accuracy and loss curves for all proposed models.



a) VGG16; b) MoileNetV2; c) ResNet50V2; d) DenseNet201; e) Proposed PomeNetV2 Model.

Fig 4: Confusion matrix of all proposed models.



a) VGG16; b) MoileNetV2; c) ResNet50V2; d) DenseNet201

Fig 5: ROC curve of proposed models.

outperforming the others with nearly flawless classification, low mistakes and the best accuracy. Proposed models ROC curves are shown in (Fig 5).

CONCLUSION

PomeNetV2 showed promise as a reliable and effective method for automated disease identification in agriculture by outperforming four cutting-edge CNN models in the classification of pomegranate leaf diseases with an accuracy of 99.02%. The model's dependence on a single dataset and flawless training accuracy, however, suggest possible overfitting and constrained generalizability. Robustness will be increased by addressing class imbalance, using regularization, external validation and a variety of field images. More research is needed in the areas of misclassification among related disease kinds and a lack of analysis on architectural efficiency. Drone-based real-time detection is a promising avenue for the future, but it needs to take environmental unpredictability, edge computing and latency into account. The system must also prioritize farmer accessibility through user-friendly mobile interfaces, data protection and transparent AI decision-making in order to be practically adopted.

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Conflict of interest

All athors declared that there is no conflict of interest.

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