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Performance Analysis of Various Deep Transfer Learning Models for Bacterial Blight Disease Detection and Classification in Pomegranate Fruits

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ABSTRACT

Background: Detecting and classifying diseases in pomegranate fruit using computer vision remains a challenging task due to the presence of numerous diseases. Recent research findings suggest that models based on Convolutional Neural Networks (CNNs) have shown significant enhancements in accuracy when it comes to classifying images of fruits and leaves. The fungal infection responsible for the disease swiftly propagates through the soil, infiltrating the roots of pomegranate plants. Presently, the sole method to halt its spread entails farmers conducting thorough inspections and promptly eliminating infected plants, an uphill task.

Methods: The present study introduces a classification PomeNetV1 model for identifying pomegranate fruit diseases employing CNN and transfer learning techniques. For executing this system, the dataset is created by taking the images directly from the farms in Ballari, Bengaluru, Bagalakote, *etc.* The proposed pomegranate fruit disease dataset contains 5099 images of five categories: Alternaria, Anthracnose, Bacterial Blight, Cercospora and Healthy. The system under consideration utilizes TensorFlow as its framework for developing deep learning models.

Result: This paper evaluates ten different pre-trained models using a transfer learning approach and a proposed novel PomeNetV1 model for classification. All pre-trained models achieved over 99% classification accuracy. However, the PomeNetV1 model stands out with an impressive 99.80% accuracy, making it the most efficient for detecting healthy and bacterial blight diseases compared to others. Surpassing existing models like Vasumathi *et al.*, 2021 deep CNN model with at least 1.63% accuracy, the PomeNetV1 model offers a feasible solution for detecting bacterial blight in pomegranate crops.

Key words: Agriculture, Bacterial blight, Detection and classification, Pomegranate diseases, Transfer learning.

INTRODUCTION

Agriculture remains a vital pillar of the Indian economy, according to the FAO (Food and Agriculture Organization of the United Nations) in their 2020 report, around 40% of the global population relies on agriculture for their livelihoods. However, fruit diseases pose significant threats to food security (Rehman *et al.,* 2021), with 40% of fruit loss attributed to pests and diseases and 25-30% lost during post-harvest stages (Technology Information, Forecasting and Assessment Council). The spread of diseases throughout farms can result in substantial losses in both quality and quantity of fruits. Tragically, crop failure contributes to 11.2% of all suicides in India (Hossain *et al.,* 2020), emphasizing the urgent need for effective disease detection and prevention methods. Precise and prompt identification of fruit diseases is crucial for farmers, consumers and policymakers to develop strategies for trade-offs, pricing, storage and addressing food shortages. Pomegranate fruit production is widespread globally, with several countries contributing significantly to its cultivation (Singh *et al.,* 2023). Iran is the world's leading producer of pomegranates. Pomegranates are deeply rooted in Persian culture and Iran's climate is well-suited for their cultivation. India is another major producer of pomegranates, with states like Maharashtra Andhra Pradesh and Karnataka leading the production (Naseer *et al.,* 2024). Indian pomegranates are known for their sweet taste and vibrant color (Gawade *et al*., 2018). When pomegranate fruit is attacked by diseases, it can have various effects on the fruit itself, the plant and the overall yield of the orchard. Diseases can directly impact the yield of pomegranate orchards by causing premature fruit drop, quality decline, increased susceptibility to pests, spread to other trees, reducing fruit size, or even killing the fruit before it reaches maturity (Wakhare *et al.,* 2023). There are several diseases,

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like Anthracnose (Jayalakshmi *et al.,* 2015), Alternaria (Aloi *et al.,* 2021), Fruit Rot, Bacterial Blight (Sharath *et al.,* 2019), Cercospora (Ravichandra *et al.,* 2023), Fusarium wilt (AlZubi *et al.,* 2024) *etc*., which can have various effects on their appearance, quality and marketability.

However, current manual detection methods are time-consuming and costly, requiring continuous expert monitoring. Laboratory testing, while effective, demands optimal conditions and specialized knowledge. Hence, prioritizing automatic early detection and prevention measures is crucial to mitigate disease spread, safeguard food security and bolster economic development. This approach not only saves resources but also protects food donors and enhances the nation's prosperity. This research aims to evaluate different CNN-based architectures to improve the accuracy of pomegranate disease detection and reduce losses. The proposed system aids farmers in identifying diseases and suggests suitable treatments and preventive actions to mitigate losses.

Review of literature

Pal and kumar (2023) presented AgriD *et al.* framework for plant disease detection and severity classification. AgriDet outperforms previous models in accuracy and is validated through statistical analysis for metrics including accuracy, specificity and sensitivity. Khatawkar *et al.* (2023), provide a system that utilizes a machine-learning approach to identify and categorize two major diseases affecting pomegranates, namely Fruit Rot and Scab, during their early stages. The dataset comprises 1000 images, including 250 each of Fruit rot and Scab diseases and 500 healthy fruit images. Classifier accuracy, evaluated via confusion matrix, reaches 83% for disease detection. Nirmal *et al.* (2022) suggested a framework utilizing a Support Vector Machine to classify healthy and diseased leaf images. The dataset collected from the Mendeley portal contains a total of 559 images, with obtained accuracy of 95.53%.

Nirgude *et al.* (2021) employed pre-trained models ResNet50, ResNet18 and InceptionV3 for detecting and classifying pomegranate diseases. The dataset created by the authors contains 1493 images. ResNet50 achieved 97.92% accuracy, ResNet18 achieved 87.5% accuracy and Inception-V3 achieved 78.75% accuracy. Javeriya Syeda *et al.* (2021) utilized the Faster R-CNN deep learning model for detecting and classifying pomegranate fruit diseases. Bhange *et al.* (2015), introduced a web-based application facilitating farmers in identifying fruit diseases via image uploads. Specifically targeting pomegranate fruit, the system utilizes a pre-existing dataset for comparison. Authors continuously expand the dataset to enhance system accuracy, achieving an 82% detection accuracy for Bacterial Blight in pomegranates. Jadhav *et al.* (2021) employed pre-trained CNN models to identify plant diseases. Their dataset comprised 649 images of healthy and diseased plants, focusing on three soybean diseases: Frogeye leaf spot, Bacterial blight and Septoria brown spot. Achieving accuracies of 98.75% and 96.25% for the respective CNN models. Thorat *et al.* (2023) introduced a pomegranate fruit disease classification system employing a pre-trained VGG16 model in conjunction with a transfer learning approach.

In the research outlined in Yan *et al.* (2023), a deep learning model employing a transfer learning approach was introduced to detect Fusarium wilt disease in banana crop leaves. Their model achieved an accuracy of 98% and an F-1 score of 98% when evaluated on a dataset comprising 600 samples of both diseased and healthy banana leaf images. Geetharamani *et al.* (2019) suggested that transfer learning has been applied in a variety of fields, including software defect prediction, sentiment analysis and plant classification. In essence, transfer learning operates by incorporating the expertise of an earlier trained CNN model into a newly created CNN model intended for a particular task Shaha *et al.* (2018). In a transfer learning-based plant disease detection task Mukti *et al.* (2019) the authors assessed the four previously trained models. ResNet-50 was discovered to be the most accurate model, achieving an accuracy of 99.80%. Srivastava *et al.* (2023) present a deep learning framework for detecting and classifying plant leaf diseases, employing five DCNN models. MobileNetV2 achieves the highest accuracy of 98.9% for dataset1, while DenseNet121 achieves 99.9% accuracy for the Cherry Dataset. Pakruddin *et al.* (2024) concluded that various techniques for pomegranate fruit disease detection and classification using machine learning and deep learning have been effectively consolidated.

MATERIALS AND METHODS

All the experiments were conducted at the research center named Rashtreeya Vidyalaya College of Engineering Bangalore in the academic year 2023-2024.

Dataset used

The proposed pomegranate fruit disease dataset contains 5099 images of five categories Alternaria, Anthracnose (Chavan and Dhutraj, 2017), Bacterial Blight (Sharath *et al.,* 2019), Cercospora and Healthy images. In the current study, a total of 2400 images portraying both healthy and bacterial blight diseases were utilized. These images were partitioned into training and testing sets, with 80% allocated for training purposes and 20% for testing. The dataset consists of five folders named by related medical conditions. The original images were captured in JPG format, featuring a 1:1 aspect ratio and dimensions of 3120×3120 pixels. These pomegranate images were obtained within both sunny and cloudy environments on a farm (Pakruddin *et al.,* 2024). Fig 1 showcases a selection of images from the dataset put forth in this study.

Proposed model architecture

The author created the proposed PomeNetV1 model, a lightweight, straightforward 12-layer CNN model, to

categorize the health and diseases in the proposed dataset images. The suggested model does not make use of transfer learning, in contrast to other models that are put out in this study. Just 6 layers 2 fully-connected dense layers and 4 convolutional layers have trainable weights and biases. The proposed model was created specifically to battle overfitting by including a smaller number of layers, in each layer less number of filters. There are 3 dropout layers are also added for not recognizing insignificant patterns. Each convolutional layer uses a 3×3 kernel size, while each max-pooling layer employs a 2×2 pool size. Feature extraction is conducted from the initial 8 layers of the model, while the final 4 layers are utilized for generating classification results. The model is trained from scratch since no transfer learning is used.

The 1st layer receives the input images of size 220× 220 and applies 64 3×3 filters to them. A ReLU activation function is then applied to this layer's output. The output of the 1st layer is fed into the 2nd layer, which uses a ReLU activation function and 64 filters with a 3×3 size. The 2nd layer's output is sent into a max-pooling layer with a 2×2 filter size to reduce the dimensions of the data, 108×108 image size and to extract important features from the input. For regularization, the output of the max-pooling layer is fed into the dropout layer with a probability of 0.2 per cent. The 3rd layer receives the input images of size 106×106 and applies 128 3×3 filters to them. A ReLU activation function is then applied to this layer's output. The output of the 3rd layer is fed into the 4th layer, which uses a ReLU activation function and 128 filters with a 3×3 size. The 4th layer's output is sent into a max-pooling layer with a 2×2 filter size to reduce the dimensions of the data, 52×52 image size and to extract important features from the input. For regularization, the output of the max-pooling layer is fed into the dropout layer with a probability of 0.2 per cent. After being flattened into a vector, the dropout layer's output is passed into two fully connected layers, each containing 512 and 2 neurons. A ReLU activation function and a dropout layer for regularization with a learning rate of 0.001 come after the first fully connected layer. A probability distribution across the 2 potential classes is produced by the softmax layer, which is the last layer.

Transfer learning and fine tuning

The tensor flow open-source platform provides 38 pre-trained deep-learning models based on Keras. These models can be used for various applications, including transfer learning, optimization, forecasting, feature extraction, image recognition, natural language processing and handwriting recognition. This technique, widely used in deep learning, leverages pre-trained models' weights (initially trained on ImageNet for image classification) as a starting point and fine-tunes them on new data. This approach greatly reduces the computational resources and time needed for training, particularly when labeled data is scarce. Fine-tuning involves unfreezing some or all layers of a pre-trained model and retraining it with new data (Yan *et al.,* 2023). In our study, we froze the top layers of all pre-trained models and applied transfer learning only to the fully connected layers. We then modified the architecture by replacing the 1000 neurons in the output layer with two neurons to suit our health and disease classification objective.

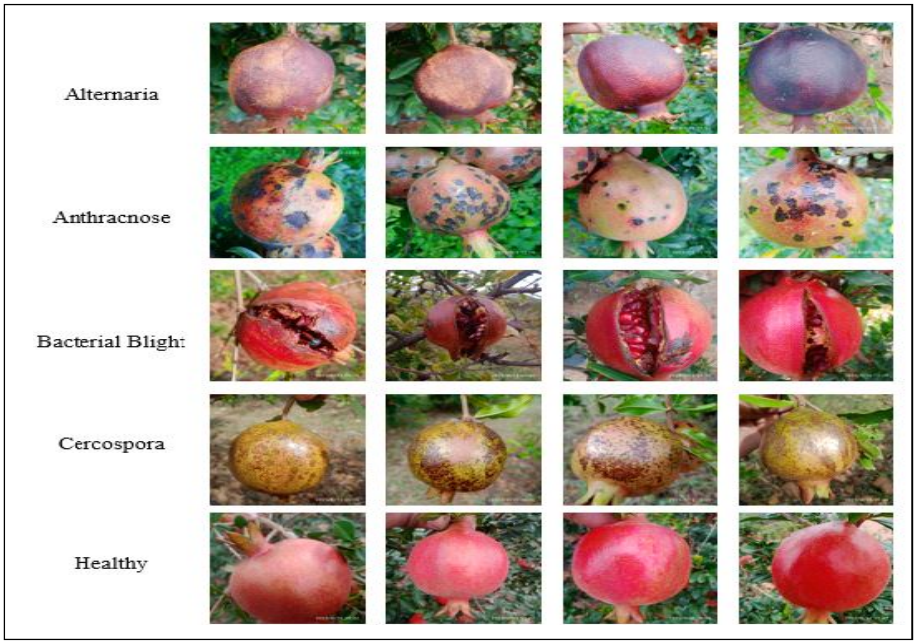

Fig 1: Several sample images from the proposed dataset.

Table 1: The summary of the main features of the several pre-trained models.

Model	Quantity (MB)	Top-rated precision	Highest five precision	Limits	Comp lexity	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
ResNet50V2	98	76.00%	93.00%	25.6M	103	45.6	4.4
InceptionV3	92	77.90%	93.70%	23.9M	189	42.2	6.9
DenseNet201	80	77.30%	93.60%	20.2M	402	127.2	6.7
Xception	88	79.00%	94.50%	22.9M	81	109.4	8.1
MobileNetV2	14	71.30%	90.10%	3.5M	105	25.9	3.8
NASNetLarge	343	82.50%	96.00%	88.9M	533	344.5	20
ResNet101V2	171	77.20%	93.80%	44.7M	205	72.7	5.4
InceptionResNetV2	215	80.30%	95.30%	55.9M	449	130.2	10
MobileNet	16	70.40%	89.50%	4.3M	55	22.6	3.4

Table 2: Hardware requirement for the trials.

Hardware Component	Specification
CPU	Disk space: 107.7 GB, System RAM: 12.7 GB
GPU	Tesla T4, System RAM - 12.67GB, Disk - 78.19 GB

Table 3: Hyper parameter setting for the experiments.

Hyper parameters	Values
Image input size	220×220×3
Epoch count	50
Size of batch	32
Learning rate	0.001
Activation function	ReLU
Optimizer	Adam
Loss function	Categorical Cross-Entropy

Table 4: Data augmentation for the proposed dataset for all models.

Parameters	Values
Rescale	1.0/255
Shear range	0.5
Zoom range	0.7
Horizontal flip	True
Vertical flip	True

Pre- trained models

This work presents pre-trained deep-learning models for ImageNet based on Keras. Table 1 summarizes the essential characteristics of the pre-trained models.

Experimental Setup

For all tests, Tensor Flow version 2.14.0 and Keras version 2.14.0 are utilized. All of the code is written and executed using Google Colab. Table 2 provides particular hardware parameters for the experiment.

An essential part of training deep learning models is optimizing hyperparameters. Hyperparameters are predefined configuration settings crucial for training, not derived from the data itself. Optimizing these parameters can substantially influence the performance of our deep-learning model Table 3. Summarizes some common hyperparameters used for pre-trained models and proposed models.

In deep learning, data augmentation is frequently utilized as a strategy to improve the performance and generalization of models, especially when datasets are constrained. The primary objective of data augmentation is to apply several transformations to the existing data, artificially enlarging the size of the training dataset. Rotation, flipping, zooming, cropping and other basic data augmentation techniques are used in deep learning use

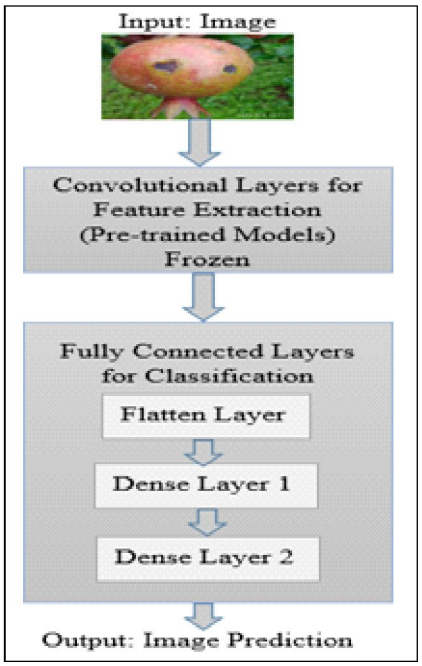

Fig 2: The pre-trained model's network architecture is based on transfer learning or fine-tuning.

cases. A few of the methods for pre-trained models and the proposed model are shown in Table 4.

The network architecture utilized in all pre-trained models except the proposed PomeNetV1 model where transfer learning or fine-tuning is applied is shown in Fig 2 and Fig 3 describes the proposed PomeNetV1 model architecture. The two primary components of the network architecture consist of the fully connected layers and the convolutional layers. Two dense layers and a flattened layer make up the classifier. With 25 nodes, the first dense layer has "ReLU" as its activation function. With 2 nodes, the second dense layer has "softmax" as its activation function. However, section 4.1 provides the network architecture for the proposed model.

Due to the unavailability of a standard benchmark pomegranate fruit disease dataset, we have collected images in different places from real fields for dataset preparation, based on the symptoms of the pomegranate

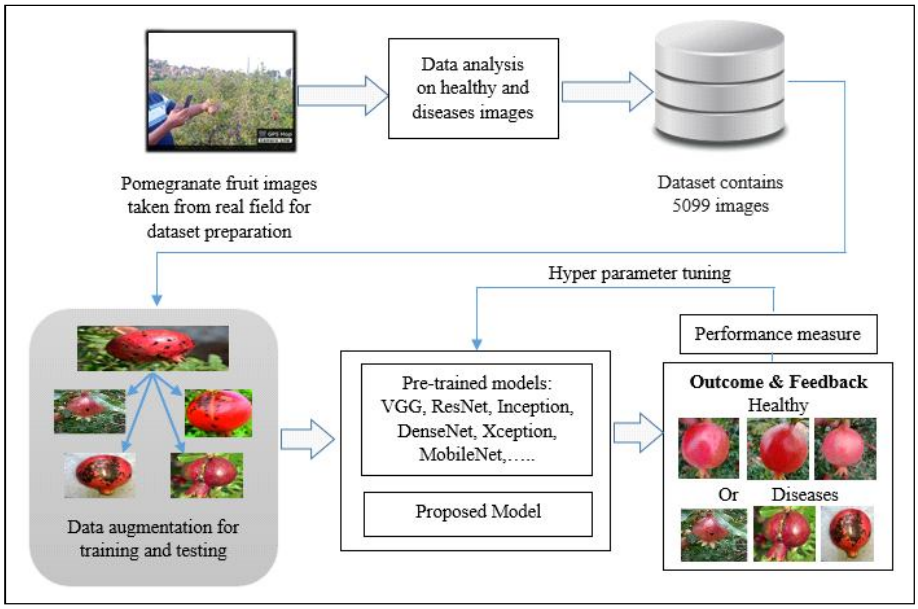

Fig 3: Proposed PomeNetV1 model architecture for pomegranate fruit health and disease classification.

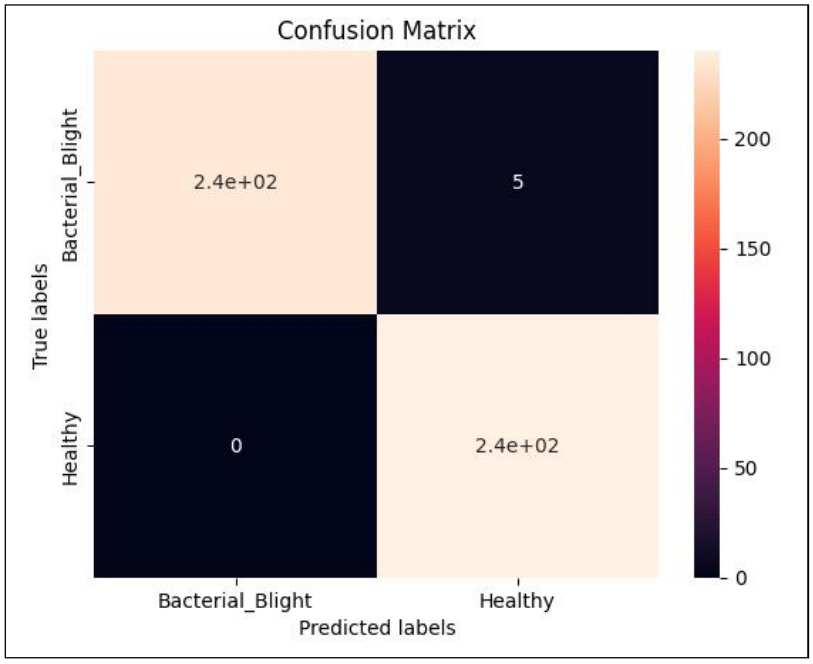

Fig 4: Confusion matrix for proposed PomeNetV1 model.

fruit it is categorized into five different diseases including healthy. A total of 5099 images were collected for experimentation. The data augmentation technique is used for training and testing deep learning models with different parameters. The training process involved the following steps.

1. Pre-trained models being loaded.
2. Rebuilding the final three layers using the transfer learning technique to complete a new recognition task.
3. With the proposed dataset, train the model.
4. Verifying the outcome of the performance.

Fig 3 describe the proposed system architecture. Table 5 illustrates the comparative study of various models in pomegranate fruit disease classification.

RESULTS AND DISCUSSION

The accuracy and loss given in Table 6, are the performance of the ten pre-trained models using the transfer learning approach and the proposed PomeNetV1 model without the transfer learning approach. The Confusion Matrix and ROC curve for the Proposed PomeNetV1 Model are depicted in Fig 4 and 5, respectively. From Fig 4, it's evident that the proposed model correctly classified a total of 235 and 245 images, with only 5 images being misclassified. Fig 6, 7 and 8 depict training curves for the proposed PomeNetV1 model alongside two other models. To provide a general understanding of the training process, these three models have been chosen because the proposed PomeNetV1 model is trained entirely from scratch, its initial training and validation losses started at relatively higher values, gradually decreased and eventually stabilized over the subsequent epochs. In contrast, because the VGG16 and ResNet50V2-based models already had a trained convolutional base, they both started with substantially lower loss values. The classification

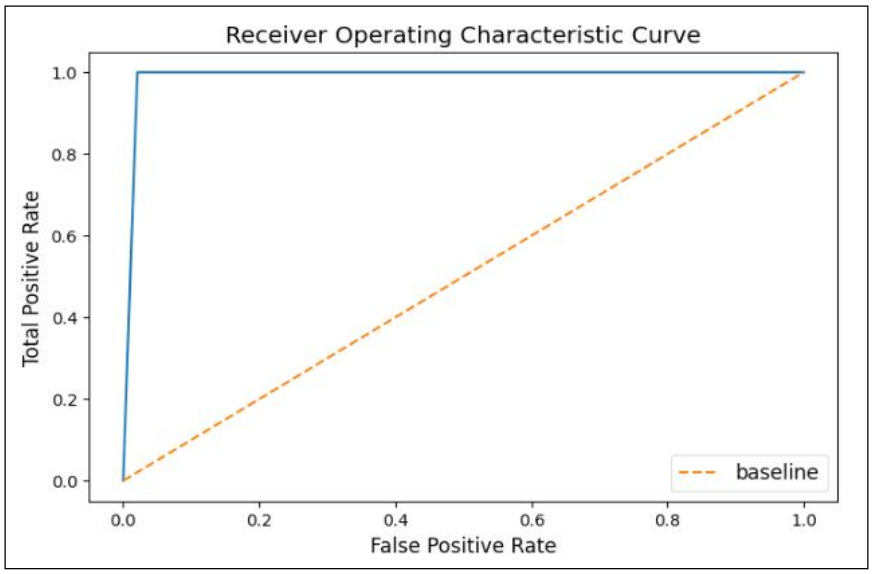

Fig 5: ROC curve for the proposed PomeNetV1 model.

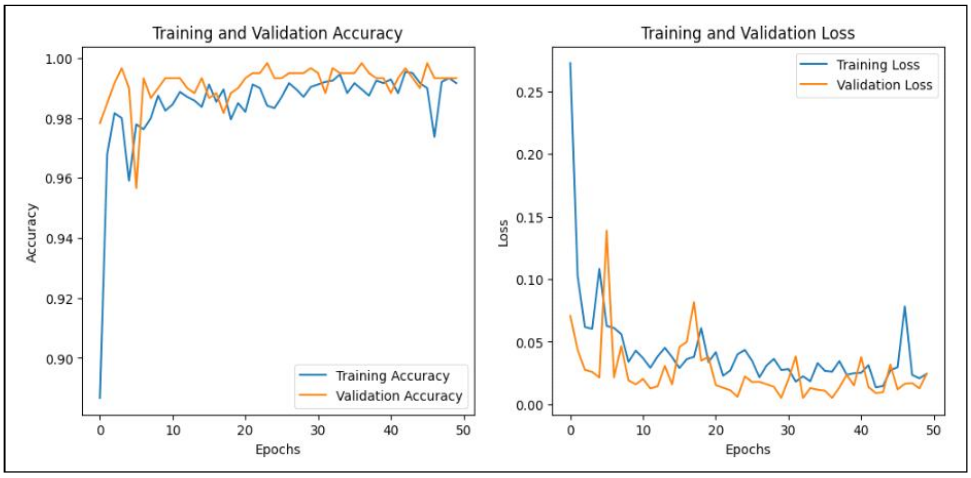

Fig 6: Accuracy and loss comparison Curves for VGG16 Model.

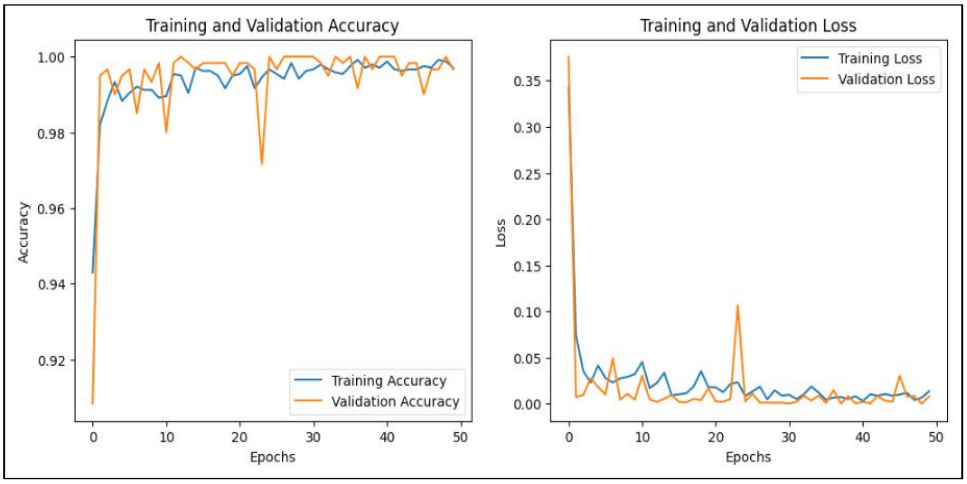

Fig 7: Accuracy and Loss comparison curves for ResNet50V2 Model.

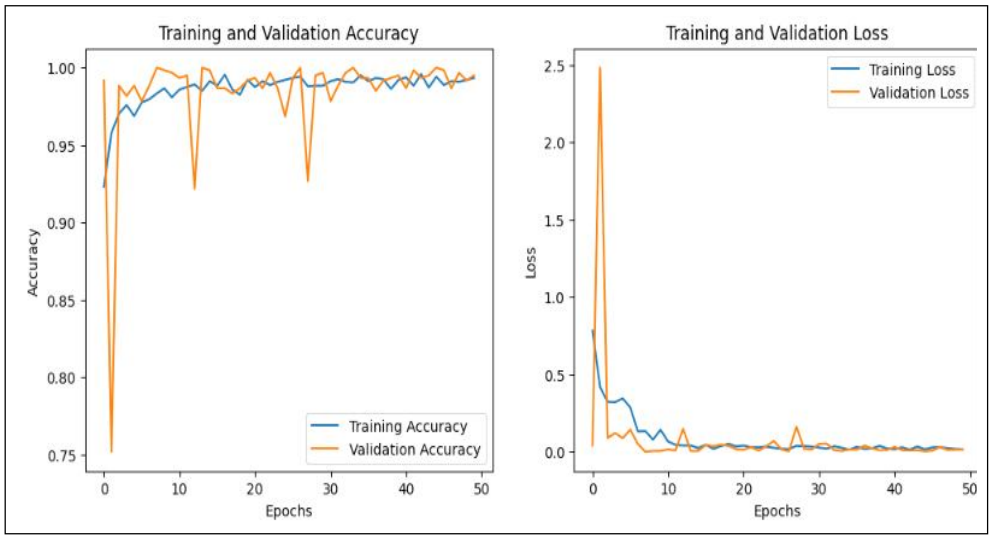

Fig 8: Accuracy and loss comparison curves for proposed model.

Table 5: Comparative analysis of different classifier models employed for disease classification.

References	Research study	Classifier	Dataset used	Accuracy
Proposed work	Pomegranate fruit disease classification	PomeNetV1 CNN Model	Healthy 1450 images Bacterial Blight 966 images	99.80%
Vasumathi *et al.* (2021)	Pomegranate fruit disease classification	CNN-LSTM	Normal 3706 images Abnormal 2813 images	98.17%
Kantale Pooja *et al.* (2020)	Pomegranate fruit disease classification	SVM	190 images	92.09%
Dhakate *et al.* (2015)	Pomegranate fruit quality assessment	ANN	The number of images in the dataset is unspecified.	90%
Sharath *et al.* (2020)	Pomegranate fruit disease detection	Neural Networks	The number of images in the dataset is unspecified.	85%
Bhange *et al.* (2015)	Pomegranate fruit disease detection	SVM	Healthy 170 images Bacterial Blight 440 images	82%

Table 6: Comparative performance of various models.

Model	Training loss	Training accuracy	Validation loss	Validation accuracy
VGG16	0.0243	99.08%	0.0243	99.33%
ResNet50V2	0.0136	99.83%	0.0078	99.66%
InceptionV3	0.0166	99.37%	0.0152	99.50%
DenseNet201	0.0029	99.75%	0.0141	99.33%
Xception	0.0095	99.62%	0.0572	98.33%
MobileNetV2	0.0079	99.45%	0.0127	99.33%
NASNetLarge	0.053	97.70%	0.2661	88.66%
ResNet101V2	0.0599	98.87%	0.0783	96.17%
InceptionResNetV2	0.2644	97.54%	0.2967	93.00%
MobileNet	0.018	99.66%	0.0024	99.23%
PomeNetV1 Proposed Model	0.0166	99.33%	0.0152	99.80%

Table 7: Classification report for proposed PomeNetV1 model.

Classes	TP	TN	FP	FN	Precision	Recall	F1-score	Accuracy
Bacterial_blight	235	240	5	0	1.00	0.98	0.99	0.99
Healthy	240	235	0	5	0.98	1.00	0.99	0.99

report for the proposed PomeNetV1 model with precision, recall, f1 score and accuracy is described in Table 7.

CONCLUSION

To classify pomegranate fruit diseases based on images, this research offered 10 different pre-trained deep learning-based models as well as a PomeNetV1 model. Except for the suggested model, which uses a pre-trained feature extractor for feature extraction and a modified classifier for final classification, Transfer learning or fine-tuning is beneficial for each of these models. In addition to these ten models, a straightforward sequential 12-layer PomeNetV1 model has been offered. The studies have been conducted using a publicly available proposed dataset of images related to pomegranate fruit disease. There are five classes in the dataset. Such a huge number of pomegranate fruit disease classifications was not the basis of any prior research. A novel assignment for identifying pomegranate fruit surface flaws is the classification of 2 types in this article. Prior studies have categorized them into more manageable categories, such as normal and abnormal but not with specific diseases. All pre-trained models produced the best classification accuracy of 99% for 50 epochs with transfer learning for pomegranate fruit health and disease image classification. Conversely, the proposed PomeNetV1 model exhibited outstanding performance with an accuracy of 99.80% over 50 epochs, despite its simple structure and compact size. This is mostly because of its feature extractor, which is made up of just four convolutional layers and is incredibly lightweight. Our future work is to evaluate a PomeNetV2 model on a proposed dataset for each disease detection and classification of the pomegranate fruits.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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