ConvNeXt-based Mango Leaf Disease Detection: Differentiating Pathogens and Pests for Improved Accuracy

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***Abstract*—Mango farming is a key economic activity in several locations across the world. Mango trees are prone to various diseases caused by viruses and pests, which can substantially impair crops and have an effect on farmers' revenue. To stop the spread of these illnesses and to lessen the crop damage they cause, early diagnosis of these diseases is essential. Growing interest has been shown in employing deep learning models to create automated disease detection systems for crops because of recent developments in machine learning. This research article includes a study on the application of ConvNeXt models for the diagnosis of pathogen and pest caused illnesses in mango plants. The study intends to investigate the variety in how these illnesses emerge on mango leaves and assess the efficiency of ConvNeXt models in identifying and categorizing them. Images of healthy mango leaves as well as the leaves with a variety of illnesses brought on by pathogens and pests are included in the dataset used in the study. In the study, deep learning models were applied to classify mango pests and pathogens. The models achieved high accuracy on both datasets, with better performance on the pathogen dataset. Larger models consistently outperformed smaller ones, indicating their ability to learn complex features. The ConvNeXtXLarge model showed the highest accuracy: 98.79% for mango pests, 100% for mango pathogens, and 99.17% for the combined dataset. This work holds significance for mango disease detection, aiding in efficient management and potential economic benefits for farmers. However, the models' performance can be influenced by dataset quality, preprocessing techniques, and hyperparameter selection.**

Keywords—Mango disease; pest; pathogens; machine learning; deep learning; convnext models

I. Introduction

Mangoes, scientifically known as Mangifera indica L. (Family: Anacardiaceae), are tropical and subtropical fruits that are native to Indo-Burma. India boasts the largest variety of mangoes, with more than a thousand identified types [1]. India is a major mango-producing nation.

With 2.5 million hectares producing 18.0 million tonnes of mangoes per year, India takes the top spot and produces almost 50% of the world's mangoes. A significant barrier to mango cultivars producing their maximum production potential is insect infestations. Mangoes are reported to be infested by 400 distinct kinds of insect pests worldwide [2]. The pest complex and the structures of the pest community have undergone substantial change because of commercial mango agriculture, which is defined by the area expansion, altered cropping patterns, varietal replacements and increasing chemical interventions. Moreover, climate change has unintentionally encouraged invading species or caused the creation of new pests. Formerly regarded as a minor or secondary pests, thrips, mealybugs, mites, leaf webbers, scales, stem borer, etc., have recently developed into a major concern. Mangoes are reported to be infested by 400 distinct kinds of insect pests worldwide [3].

The fruit mango is full of nutrients and has a distinct flavour, aroma and taste. With flavonoids like beta-carotene, alpha-carotene and beta-cryptoxanthin, it is a fantastic source of vitamin A. According to research findings, eating natural fruits that are high in carotenes can help prevent lung and mouth cancer. Mango fruit also contains a wealth of vitamins, minerals, fibre, prebiotic dietary substances and antioxidant components, all of which are good for human health. Consuming mango fruit guards against colon, breast leukaemia and prostate cancer, according to the recent studies [4].

One of the earliest illnesses associated with mango was powdery mildew, which is extensively present around the globe. One of the most dangerous diseases in the world is mango malformation sickness. The export market, which demands great fruit quality, is particularly concerned about mango bacterial canker, also known as bacterial black spot. Stem-end rot and mango dieback are two of the most significant diseases influencing mango yield and post-harvest losses internationally [5]. Mango wilt is a harmful disease that destroys plants.

Mango crops are commonly affected by various pests, including white scale and red wax scale, which consume the mango's leaves and fruit, causing damage and reduced quality. Other common pests include the mango leaf beetle, which can cause defoliation and the mango seed weevil, which infests the mango fruit and causes premature fruit drops [6]. Fruit flies, mealybugs, felt scales, long tailed mealybugs, shoot borers and stone weevils are also commonly found in mango crops and can cause various types of damage to the leaves and fruit. Mango shoot caterpillars, gall midges and stone bugs are also known to infest mango crops and cause stunted growth, reduced yield and fruit drop [7].

Image processing may identify plant diseases. The fruit, leaves and stems are frequently affected by disease signs. The ability to automatically detect plant disease from raw photos using Artificial Intelligence.

An efficient image-learning system for isolating plant diseases is the deep learning approach that uses neural networks. While neural networks learn how to obtain attributes to train, it can automatically extract properties from photos [8]. These methods rely on Deep Learning (DL) and conventional Machine Learning (ML) techniques.

Having a solid dataset to work with is essential for effective machine learning. The models are built or trained using the hidden patterns that these algorithms extract from the dataset and future occurrences are predicted using these learned patterns [9]. As a result, there is a strong relationship between a machine learning system's performance and the dataset's quality. Size, intra-class integrity, interclass dissimilarity and label quality, such as noise in the labels, are a few factors that may determine a dataset's quality [10].

II. Literature Survey

Shripad Veling et al. [11] utilized the MATLAB function "Imadjust" to enhance contrast in photographs of diseased mangoes. The improved contrast aided in the extraction of essential characteristics such as Energy, Correlation, Entropy, Cluster prominence, Homogeneity, Cluster shadow, Variance, and Dissimilarity. Their system achieved an accuracy of 90% with 92 tested samples, employing Support Vector Machines (SVM) as a classifier. The segmentation process took three seconds, while classification only required 0.1 seconds.

Faye, D et al. [12] evaluated the effectiveness of DL algorithms for predicting mango illnesses, highlighting shortcomings in their solutions. The identified issues included problems with leaf segmentation, a lack of real-time diagnosis, and insufficient training data. These challenges are crucial for researchers working on automatic detection of mango illnesses.

In their work, Kusrini et al. [13] augmented the pre-trained VGG-16 deep learning model with a fully connected network consisting of two additional layers. They took into account practical operational challenges faced by Indonesian farmers in gathering and analyzing visual data. By incorporating contrast and affine transforms, the supplemented data process achieved an overall accuracy of 76%. However, when classification was performed without augmentation on a combination of all three datasets, the accuracy dropped to 67%.

Md. Rasel Mia et al. [14] collected a training dataset comprising various photos of mango leaves with different illnesses. They developed a machine learning method using an SVM classifier that could automatically recognize symptoms of mango leaf diseases by uploading and matching fresh photos with the learned data. Their approach achieved an average detection and classification score of 80% for four different illness types.

The approach proposed by Ritika et al. [15], which utilizes a python-based webpage, offers considerable benefits to farmers in terms of pest control and pesticide application. Although SVM had low accuracy of approximately 43%, investigating the RGB values improved the results. By implementing XGBoost and CatBoost, a higher accuracy was achieved compared to SVM. Furthermore, their custom-built CNN system provided a respectable accuracy of 72.05%.

Sarder Iftekhar Ahmed et al. [16] obtained photographs from four mango orchards in Bangladesh, resulting in a collection of 4000 images representing seven illnesses found on approximately 1800 different leaves. To minimize sample bias, diverse locales in Bangladesh were selected. The images were meticulously labeled by human specialists, noise was removed, and the images were scaled to standard forms for machine learning analysis.

Arun Malik et al. [17] employed the transfer learning models VGG-16 and MobileNet for mango classification. They combined these models using the stacking ensemble learning approach to create a hybrid model. The authors constructed a dataset of 329 sunflower images obtained from Google Images, which were divided into five categories. The proposed hybrid model was compared to several contemporary deep learning models based on accuracy using the same dataset.

Inchara R et al. [18] have two objectives: first, to review the latest advancements in mango fruit evaluation prior to market delivery, and second, to explore untapped areas in post-harvest mango fruit handling. Their technology simplifies illness identification by automating the process and alerting users to any afflicted ailments. Aspects such as color, size, and shape influence the grade of the fruits and the satisfaction of the buyers.

Soleha Kousar et al. [19] present a unique technique that combines the Kuwahara filter for edge enhancement with histogram equalization to enhance image clarity and contrast. The Local Binary Pattern (LBP) feature extraction approach is used to recover significant features, enabling training of the Multi-layer Convolutionary Neural Network (MCNN) classifier. This method achieves an impressive 99% accuracy.

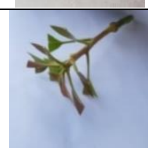
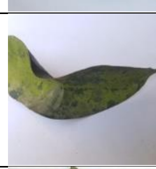
A standard, open-access collection of 4000 images of mango leaves with around 1800 distinct leaves is created by Sarder Iftekhar Ahmed et al., [20]. A categorical cross-entropy is used as the loss function in the CNN and ResNet50 models to handle the multi-class classification issue. The squared hinge loss is used in the CNN-SVM model.

III. Methodology

A. *Dataset Description*

1) Mango pathogen dataset: This dataset consists of 4000 JPEG images of mango leaves with a resolution of 240x320 pixels. Around 1800 images are unique, while the rest were generated by zooming and rotating the original images. The dataset includes a category for healthy leaves and seven categories of mango leaf diseases, including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould [21]. Every one of the eight categories has 500 photos, ensuring a fairly even distribution of examples. Using machine learning and computer vision techniques, this dataset may be used to distinguish between healthy and sick leaves (two-class prediction) and to detect various illnesses (multi-class prediction). Researchers and practitioners can use this dataset for crop disease detection and diagnosis, as well as for the development and evaluation of machine learning models for automated identification and classification of mango diseases. Details of the classes of Mango Pathogen dataset is shown in Table I.

TABLE I. MANGO PATHOGEN DATASET DETAILS

Mango Pathogen Dataset		
Class Name	**Image Details**	
Anthracnose	500	
Bacterial Canker	500	
Cutting Weevil	500	
Die Back	500	
Gall Midge	500	
Healthy	500	
Powdery Mildew	500	
Sooty Mould	500	

2) Mango pest dataset: This dataset focuses on detecting pests that harm mango farming, which have a large economic impact on the country. It features photographs taken in mango farms where 15 types of pests, which result in structural and aesthetic defects in mango leaves, are present. The dataset comprises of 510 unique photos, encompassing the 15 pest categories plus the original mango leaf look, creating 16 classes [22]. The dataset was enhanced to increase its size and replicate the extensive data collecting method used by farmers. A total of 62,047 picture samples from the data augmentation procedure were employed to train the network. Annotations for both the original and enhanced picture samples are included in the dataset, which was divided into training, validation and testing sets. Using variable quantities of pictures for training, validation and testing. Pictures in JPEG format are provided in every version of the dataset. Details of Mango Pest Dataset are shown in Table II.

TABLE II. MANGO PEST DATASET DETAILS

Mango Pest Dataset		
Class Name	**Image Details**	
Apoderus_javanicus	100	
Aulacaspis_tubercularis	100	
Ceroplastes_rubens	100	
Cisaberoptus_kenyae	100	
Dappula_tertia	100	
Dialeuropora_decempuncta	100	
Erosomyia_sp	100	
Icerya_seychellarum	100	
Ischnaspis_longirostris	100	
Mictis_longicornis	100	
Neomelicharia_sparsa	100	
Normal	100	
Orthaga_euadrusalis	100	
Procontarinia_matteiana	100	
Procontarinia_rubus	100	
Valanga_nigricornis	100	

TABLE III. CONVNEXT MODELS' ARCHITECTURAL DETAILS

Model	Number of Layers	Number of Parameters	Architecture	Batch normalization	Dropout	Top-1 Accuracy	Top-5 Accuracy
ConvNeXtTiny	23	8.6 million	2 layers with 64 channels and 3x3 filters	Yes	Yes	66.90%	88.80%
ConvNeXtSmall	29	17.1 million	4 layers with 128 channels and 3x3 filters	Yes	Yes	73.90%	93.30%
ConvNeXtBase	56	44.2 million	8 layers with 256 channels and 3x3 filters	Yes	Yes	77.50%	94.80%
ConvNeXtLarge	98	136.1 million	16 layers with 512 channels and 3x3 filters	Yes	Yes	79.30%	95.60%
ConvNeXtXLarge	164	366.4 million	32 layers with 1024 channels and 3x3 filters	Yes	Yes	80.20%	95.90%

TABLE IV. CONVNEXT MODELS' EVALUATION DETAILS

Model	Computational Complexity	FLOPs	Activation Function	Regularization	Residual connections	Image augmentation	Transfer learning	Fine-tuning
ConvNeXtTiny	1.46 GMac	0.37B	ReLU	L2 regularization	No	Yes	Yes	Yes
ConvNeXtSmall	3.07 GMac	0.77B	ReLU	L2 regularization	No	Yes	Yes	Yes
ConvNeXtBase	14.34 GMac	3.59B	ReLU	L2 regularization	Yes	Yes	Yes	Yes
ConvNeXtLarge	41.34 GMac	10.34B	ReLU	L2 regularization	Yes	Yes	Yes	Yes
ConvNeXtXLarge	150.27 GMac	37.57B	Swish	DropBlock	Yes	Yes	Yes	Yes

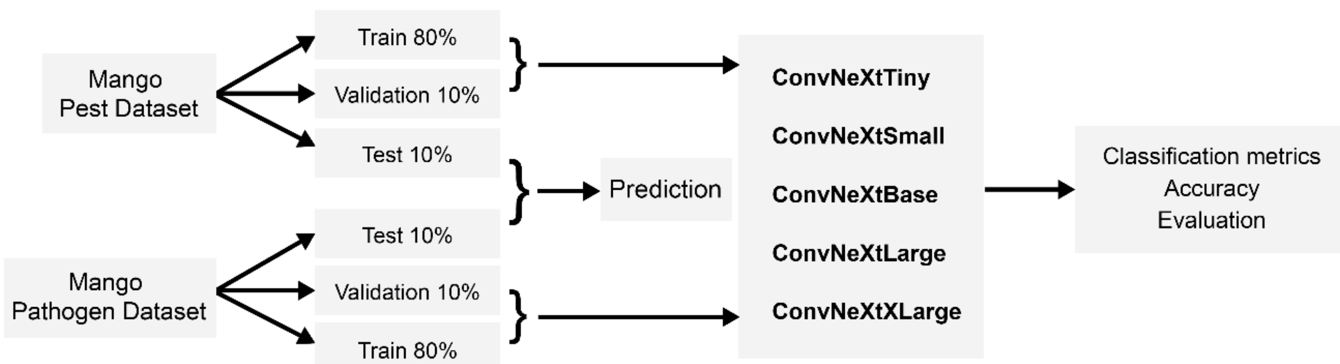


Fig. 1. Proposed methodology.

B. Procedure Used

The training process for a Transfer Learning model used for the mango leaf disease dataset involves feeding the model with labelled images and adjusting the weights to minimize the loss function. The accuracy of the model is evaluated using a separate set of labelled images during the testing process, while the validation process fine-tunes the model to prevent overfitting by testing it on a set of labelled images not used in training. A diagram illustrating the procedure is shown in the Fig. 1. The study involved two datasets, namely the pathogen and pest dataset of mango leaves. ConvNeXt models were trained separately for both datasets and also combined and trained.

C. Transfer Learning Models Used ConvNeXt Models

ConvNeXt was developed as an extension of the transformer architecture, which was originally designed for natural language processing tasks [23]. The transformer architecture consists of a series of encoder and decoder layers, which learn to encode and decode sequential data.

ConvNeXt extends the transformer architecture to image recognition tasks by incorporating convolutional layers into the encoder and decoder layers. This allows ConvNeXt to learn spatially localized features of an image, while also leveraging the attention mechanism of the transformer.

In contrast to traditional convolutional neural networks, which typically comprise of a series of convolutional layers followed by fully connected layers, ConvNeXt uses a parallel convolutional structure that allows for increased model capacity and improved performance on image recognition tasks [24].

In Table III and Table IV parameters [25] used are

1) Number of Layers: The number of layers refers to the depth of a neural network, where each layer performs a set of computations on the input data before passing it to the next layer.

2) Number of Parameters: The number of parameters refers to the total number of learnable parameters in a neural network, which includes weights and biases.

3) Architecture: The architecture refers to the design and organization of a neural network, including the number of layers, the size of each layer and the connections between them.

4) Batch normalization: Batch normalization is a technique used to normalize the input data to each layer of a neural network, improving the overall stability and convergence of the model.

5) Dropout: Dropout is a regularization technique used to prevent overfitting in neural networks by randomly dropping out some of the neurons during training.

6) Top-1 Accuracy: Top-1 accuracy is a metric used to evaluate the performance of a neural network on a classification task, measuring the percentage of predictions that match the correct label.

7) Top-5 Accuracy: Top-5 accuracy is similar to top-1 accuracy, but measures the percentage of predictions that include the correct label within the top 5 predictions.

8) Computational Complexity: Computational complexity refers to the amount of time and resources required to perform computations in a neural network.

9) FLOPs: FLOPs (FLoating-point Operations Per second) is a measure of the number of floating-point arithmetic operations a neural network can perform per second[26].

10) Activation Function: The activation function is a mathematical function used to introduce non-linearity into the output of a neural network layer [27].

11) Regularization: Regularization refers to techniques used to prevent overfitting in neural networks, such as dropout and weight decay [28].

12) Residual connections: Residual connections are connections between layers that bypass intermediate layers, allowing the input to flow directly to the output and improving the flow of gradients during training [29].

13) Image augmentation: Image augmentation is a technique used to increase the amount of training data by randomly transforming images, such as rotating, scaling or flipping.

ConvNeXts have several advantages over traditional transformers for image recognition tasks [30]. They are

1) Spatial information: Transformers were originally designed for sequence tasks such as natural language processing where spatial information is not as important as the order of the tokens. However, for image recognition tasks, the spatial information of the pixels is crucial. ConvNeXts include convolutional layers that can capture spatial information, enabling the model to learn local features in the image.

2) Parameter efficiency: Transformers have a high number of parameters due to the large attention matrices, which can limit their scalability. ConvNeXts use a parallel convolutional structure which allows for increased model capacity without a large increase in parameters, making them more efficient in terms of memory and computation.

3) Robustness to object scale: ConvNeXts are better able to handle object scales than transformers. In transformer-based models, the receptive field of the model is fixed and cannot change. In contrast, ConvNeXts use convolutional layers which have a varying receptive field size, enabling them to capture features at different scales.

4) Improved accuracy: ConvNeXts have achieved state-of-the-art performance on several benchmark image recognition datasets, including ImageNet and CIFAR-10. They have shown improved accuracy compared to traditional convolutional neural networks and transformer-based models.

Overall, the incorporation of convolutional layers in ConvNeXts provides a more efficient and effective approach to leveraging the power of transformers for image recognition tasks [31].

TABLE V. MANGO PEST DATASET IMPLEMENTATION RESULTS FOR CONVNEXT MODELS

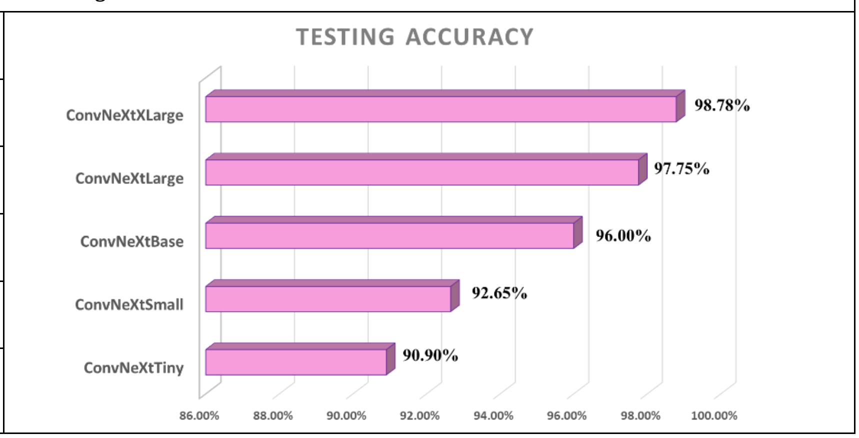
Mango Pest Dataset				
Model	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**	
ConvNeXtTiny	100 %	100 %	90.90 %	
ConvNeXtSmall	100 %	100 %	92.65 %	
ConvNeXtBase	100 %	100 %	96.00 %	
ConvNeXtLarge	100 %	100 %	97.75 %	
ConvNeXtXLarge	100 %	100 %	98.78 %	

TABLE VI. MANGO PATHOGEN DATASET IMPLEMENTATION RESULTS FOR CONVNEXT MODELS

Mango Pathogen Dataset			
Model	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**
ConvNeXtTiny	100 %	99.88 %	99.75 %
ConvNeXtSmall	100 %	99.875 %	99.5 %
ConvNeXtBase	100 %	100 %	99.375 %
ConvNeXtLarge	100 %	99.875 %	99.875 %
ConvNeXtXLarge	100 %	100 %	100 %

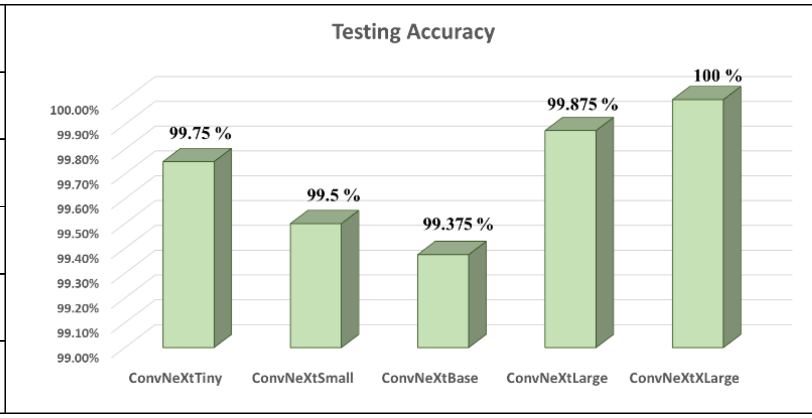
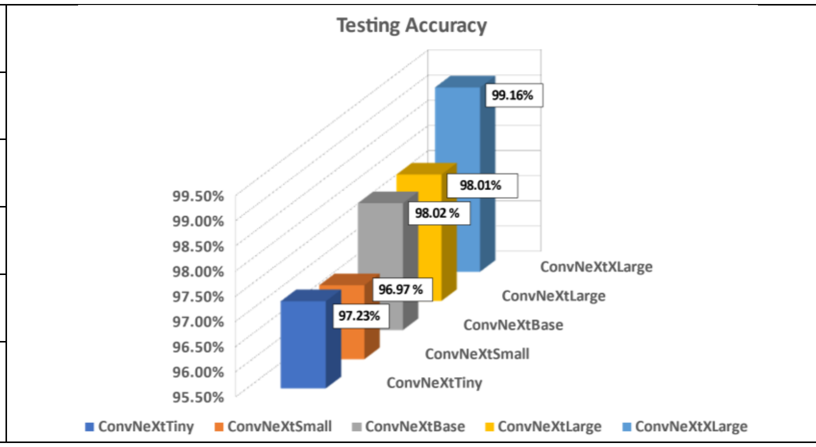


TABLE VII. COMBINATION OF BOTH MANGO PEST AND MANGO PATHOGEN DATASET IMPLEMENTATION RESULTS FOR CONVNEXT MODELS

Combination of Both Mango Pest and Mango Pathogen Dataset			
Model	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**
ConvNeXtTiny	100 %	97.237%	97.23%
ConvNeXtSmall	99.53%	97.237 %	96.97 %
ConvNeXtBase	99.60 %	98.816 %	98.02 %
ConvNeXtLarge	100 %	98.947 %	98.01%
ConvNeXtXLarge	100 %	100 %	99.16%



IV. IMPLEMENTATION RESULT

The Table V provides the training accuracy, validation accuracy and testing accuracy for five different models (ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, ConvNeXtLarge and ConvNeXtXLarge) trained on a Mango Pest Dataset.

The accuracy of the model over the training set throughout the training process is referred to as training accuracy. The accuracy of the model on a different validation set is referred to as validation accuracy, and this accuracy is used to assess the performance of the model during training and adjust its hyperparameters. The accuracy of the model under test is its performance on a brand-new test set that it has never seen or used before.

All five models had 100% accuracy on the training set, demonstrating that they had flawless memorization of the training data. Achieving 100% training accuracy, however, is not necessarily a desirable thing because it may signify overfitting, in which the model matches the training data too well and may not generalise well to new data.

The validation accuracies of the models vary, with the larger models generally achieving higher accuracy than the smaller ones. However, the difference in validation accuracy between the models is relatively small, which suggests that the models are not overfitting to the training data.

Overall, the ConvNeXtXLarge model achieved the highest testing accuracy of 98.786747%, indicating that it is the best performing model on this Mango Pest Dataset.

The Table VI provides the training accuracy, validation accuracy, and testing accuracy for five different models (ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, ConvNeXtLarge, and ConvNeXtXLarge) trained on a Mango Pathogen dataset.

The testing accuracies of the models are high, with all five models achieving above 99% accuracy. The ConvNeXtXLarge model achieved the highest testing accuracy of 100%, showing that it is the best performing model on this Mango Pathogen dataset. However, the difference in testing accuracy between the models is relatively small, which suggests that they are all performing well on this task. Overall, the results suggest that all five models are effective at identifying pathogenic infections in mangoes, with larger models performing slightly better than smaller ones.

Comparing the Table III and Table IV, it is seen that the performance of the ConvNeXt models on the Mango Pathogen dataset is better than on the Mango Pest dataset. All models achieved 100% training accuracy on both datasets, indicating that they could fit the training data perfectly. However, the testing accuracy of the models on the Mango Pathogen dataset is higher than on the Mango Pest dataset, suggesting that the models are better able to generalize to unseen data in the pathogen classification task.

The architecture of the ConvNeXt models may have contributed to their performance on these datasets. In both tables, the models have increasing accuracy as the model size increases, with the largest model, ConvNeXtXLarge, achieving the highest accuracy on both datasets. This suggests that increasing the model size and complexity can improve the model's ability to learn and classify patterns in the data.

The ConvNeXt models combine convolution layer, pooling layers, & fully linked layers in terms of their technical features. These models use the concept of grouped convolutions to capture both local and global dependencies in an image. The key idea behind ConvNeXt models is to create a network architecture that balances computational efficiency and modeling capacity. By using grouped convolutions, the number of parameters and computations required in each convolutional layer is reduced compared to fully connected convolutions. This enables deeper models with a large receptive field without significantly increasing the computational cost. The number of filters, the size of the filters, the number of groups, as well as the number of layers are some of the hyperparameters for the models. The algorithms' performance on the datasets may have also been influenced by the selection of hyperparameters. The selection of these hyperparameters can significantly affect the performance of ConvNeXt models based on different datasets.

In Table V to VI, the implementation results of ConvNeXT models for mango pest and mango pathogen datasets are presented separately. In contrast, Table VII shows the implementation results of ConvNeXT models for a combination of both mango pest and mango pathogen datasets.

The results of Table V shows that all models performed well on the mango pest dataset, with the ConvNeXtXLarge model achieving the highest testing accuracy of 98.79%. The results of Table VI demonstrate that all models also performed well on the mango pathogen dataset, with the ConvNeXtXLarge model achieving perfect testing accuracy of 100%.

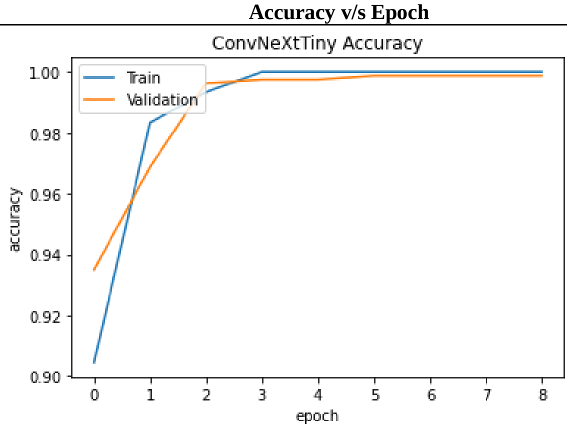
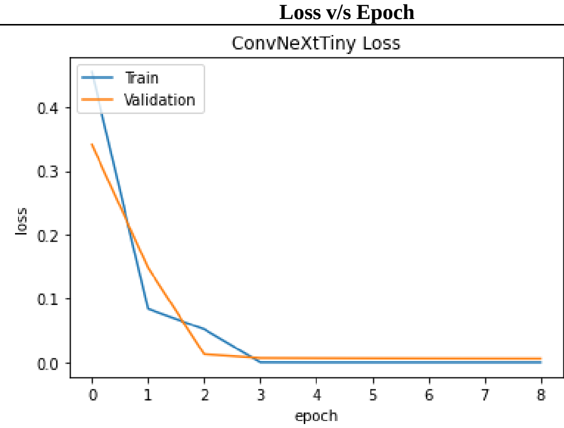
In Table VII, which shows the results for a combination of both mango pest and mango pathogen datasets, the testing accuracy of all models decreased compared to their performance in Table V and VI. This decrease in accuracy is likely due to the increased complexity of the combined dataset. However, the ConvNeXtXLarge model still achieved the highest testing accuracy of 99.17%, indicating its effectiveness in handling the combined dataset.

Overall, the results of Table VII suggests that using a combination of both mango pest and mango pathogen datasets can provide more comprehensive information about the health of mango leaves. While the accuracy of the models decreased slightly when using the combined dataset, the ConvNeXT models were still effective in detecting both pests and pathogens on mango leaves.

Table VIII shows Accuracy V/s Epoch and Loss V/s Epoch Graph for various ConvNeXt Models.

The effectiveness of the ConvNeXtTiny model upon the Mango Pathogen dataset is as shown in the confusion matrix in Fig. 2. The columns of the confusion matrix represent the anticipated labels, while the rows represent the genuine labels. Each cell of the matrix represents the count of cases where the predicted class (column) aligns with the actual class (row).

TABLE VIII. ACCURACY V/S EPOCH AND LOSS V/S EPOCH GRAPH FOR VARIOUS CONVNEXT MODELS

Accuracy v/s Epoch	**Loss v/s Epoch**
	
The accuracy starts at 0.9046 in the first epoch and steadily increases with each epoch. It reaches its highest value of 1.0 in the fourth epoch and remains consistently high from there onwards. *This indicates that the model quickly learns from the training data and achieves near-perfect accuracy in classifying the images.*	The loss starts at 0.4548 in the first epoch and decreases significantly in the subsequent epochs. It reaches its lowest value of 7.1631e-06 in the ninth epoch. *The decreasing loss indicates that the model is effectively minimizing errors and improving its predictive capabilities.*

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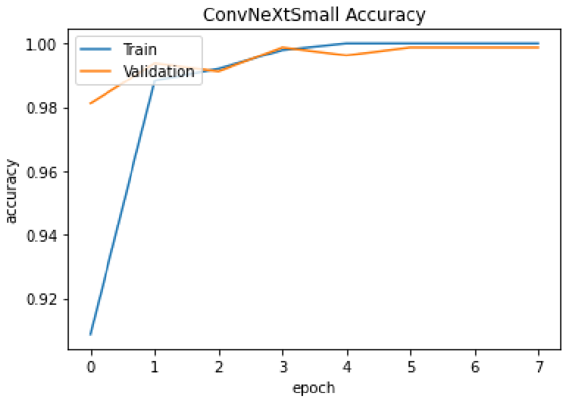

The accuracy steadily increases with each epoch until the fourth epoch, where it reaches its highest value of 0.9979. After that, the accuracy remains consistently high at 1.0 from the fifth epoch onwards. *This indicates that the model quickly learns from the training data and achieves near-perfect accuracy in classifying the images.*
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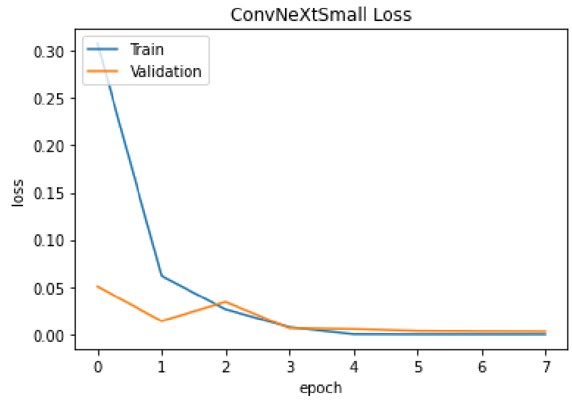

The loss starts at 0.3075 in the first epoch and decreases significantly in the subsequent epochs. It reaches its lowest value of 1.2019e-05 in the eighth epoch. *The decreasing loss indicates that the model is effectively minimizing errors and improving its predictive capabilities.*
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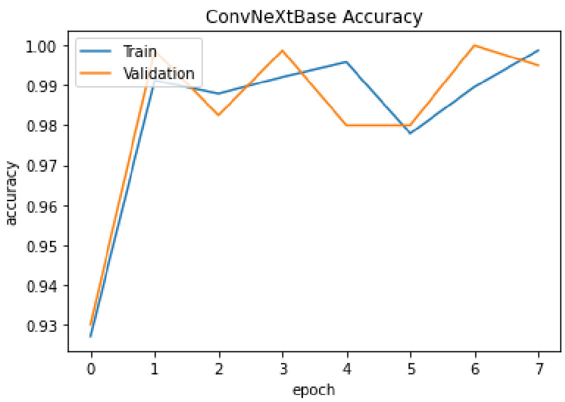

The accuracy steadily increases with each epoch until the seventh epoch, where it reaches its highest value of 0.9896. However, in the last epoch, the accuracy drops slightly to 0.9987. *Overall, the model achieves high accuracy throughout the training process, indicating its ability to correctly classify images.*
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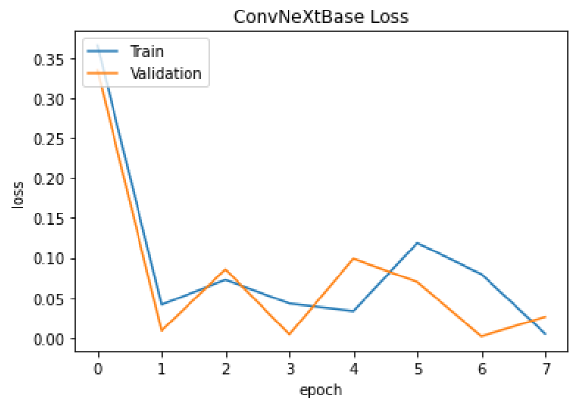

The loss starts at 0.3656 in the first epoch and decreases significantly in the subsequent epochs. It reaches its lowest value of 0.0017 in the seventh epoch. However, in the last epoch, the loss increases slightly to 0.0049. *The decreasing loss indicates that the model is effectively minimizing errors and improving its predictive capabilities.*
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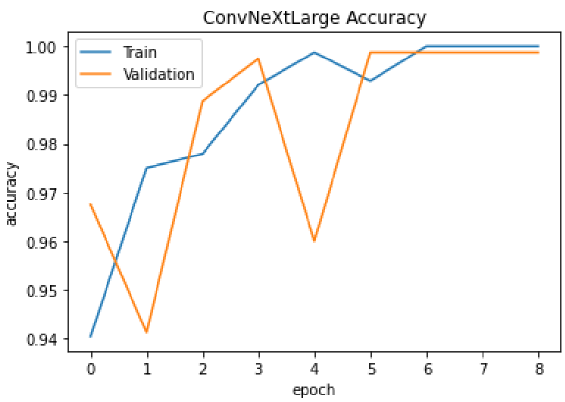
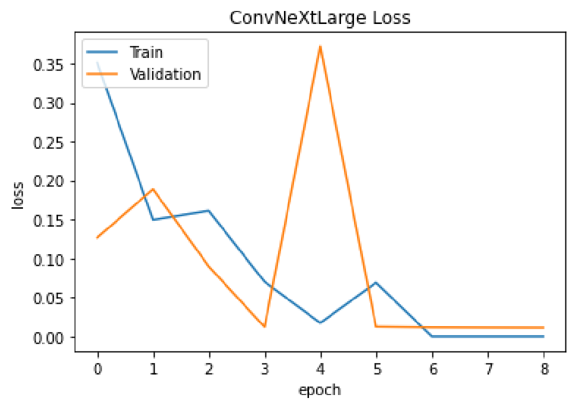
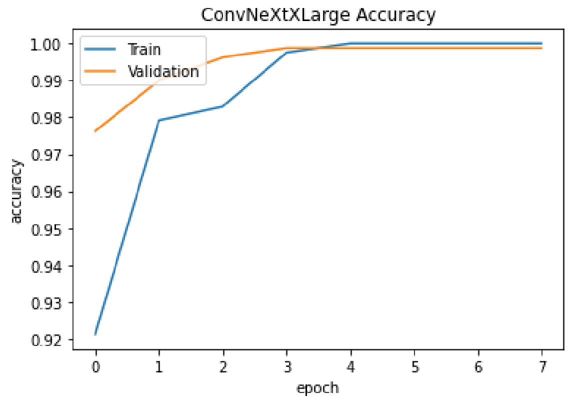
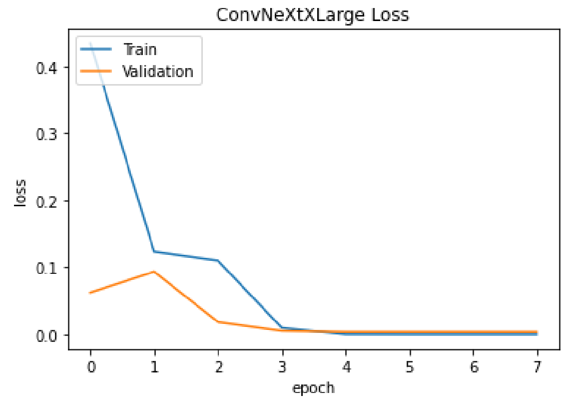
<td>


The accuracy steadily increases with each epoch, reaching a high value of 1.0 (100%) for the training dataset. *On the validation dataset, the accuracy also shows a steady improvement, reaching a peak value of 0.99875 (99.875%) before the model stopped training due to early stopping.*
</td>
<td>


The loss decreases significantly in the initial epochs, indicating that the model is learning and improving its predictions. *After reaching a minimum value of 6.7500e-07, the loss plateaus and remains constant until the end of training.*
</td>
</tr>
</table>



The accuracy steadily increases with each epoch. It starts at 0.9212 in the first epoch and gradually improves to 1.0000 in later epochs. *This indicates that the model's ability to correctly classify images improves over time as it learns from the training data.*



The loss decreases significantly as the epochs progress. It starts at 0.4345 in the first epoch and steadily decreases to 5.3854e-07 in the eighth epoch. *The decreasing loss indicates that the model is effectively minimizing errors during training, resulting in better performance.*

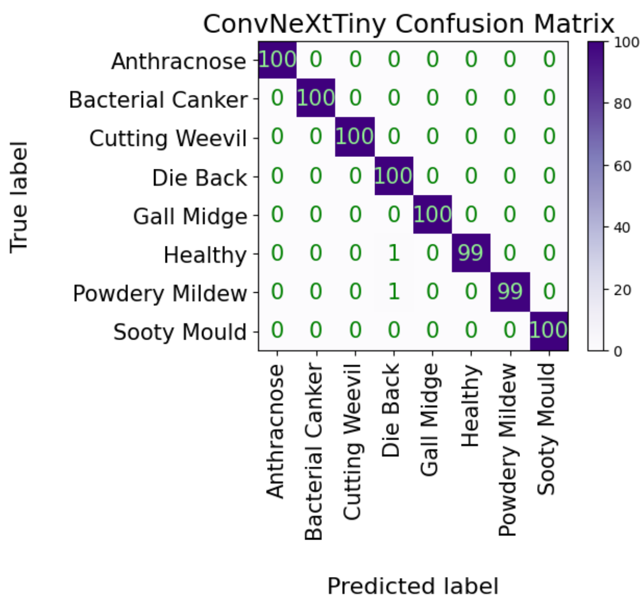


Fig. 2. ConvNeXtTiny confusion matrix for mango pathogen dataset.

Looking at the matrix, we can see that the model performed very well, with perfect accuracy in most of the classes (classes 0 to 5 and class 7). The only class where the model made mistakes is class 6 (Powdery Mildew), where it misclassified 1 instance as class 7 (Sooty Mould). The confusion matrix indicates that the ConvNeXtTiny model achieved high accuracy on the Mango Pathogen dataset, with only a single misclassification out of 800 instances.

V. Conclusion

It can be concluded that all the models have performed well on both the mango pest and pathogen datasets. However, the accuracy of the models on the mango pathogen dataset is higher compared to the mango pest dataset. This is because the pathogen dataset contains images that are more distinct and easier to classify compared to the pest dataset.

In terms of the model architecture, it is seen that larger models, i.e., ConvNeXtBase, ConvNeXtLarge, and ConvNeXtXLarge, have consistently higher accuracy than the smaller models, i.e., ConvNeXtTiny and ConvNeXtSmall. This suggests that the larger models have more capacity to learn complex features and patterns in the images, which results in better accuracy.

ConvNeXtXLarge Model giving its highest accuracy of 98.786747% for Mango Pest Dataset, 100% for Mango Pathogen Dataset and 99.16654% for Combination of Both Mango Pest and Mango Pathogen Dataset is the best model for Mango Disease Detection.

ConvNeXtTiny Model giving its accuracy of 90.908746% for Mango Pest Dataset, ConvNeXtSmall Model giving 96.97368% for Combination of Both Mango Pest and Mango Pathogen Dataset can be considered as Baseline models for Mango Disease Detection.

The models consistently improve their accuracy with each epoch, reaching near-perfect or perfect accuracy in classifying the mango pests and pathogens. The decreasing loss throughout the epochs demonstrates the models' ability to effectively minimize errors and improve their predictive capabilities.

This work is important in Mango Disease detection using transfer learning and ConvNeXT. The results show the potential of using deep learning models to accurately classify mango diseases, which can lead to more efficient and effective management of mango plantations. This can ultimately help farmers reduce crop losses and increase yields, leading to economic benefits for the agriculture industry.

Overall, the results show that deep learning models can be effective in classifying images of mango pests and pathogens with high accuracy, and larger models tend to outperform the smaller ones. However, it is important to note that the models' performance may depend on factors such as the quality of the dataset, pre-processing techniques and the choice of hyper parameters.

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