Comparative Analysis of Pre-Trained CNN Architectures for Apple Foliar Disease Classification

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Abstract - Apple foliar diseases can significantly impact crop yield and quality. Early and accurate disease detection allows for timely disease management, reducing losses. This paper presents a comparative analysis of pretrained Convolutional neural network (CNN) architectures for automated apple foliar disease classification from leaf images. Eight CNN models, including DenseNet121, DenseNet201, ResNet50V2, InceptionV3, InceptionResNetV2, MobileNet, MobileNetV2 and Xception, were evaluated using an apple leaf dataset with five disease classes - scab, rust, black rot, multiple diseases, and healthy. Models were trained using transfer learning by fine-tuning on the dataset with different hyperparameters. Comparative performance analysis across five cases with varying batch size, optimizer, learning rate and epochs was conducted. Results indicate MobileNet architecture achieved best accuracy of 97%, outperforming other models. This demonstrates the potential of using pretrained CNNs for robust apple disease classification to enable precision agriculture and improved crop health monitoring.

Key Words: apple diseases, convolutional neural networks, transfer learning, image classification

1. INTRODUCTION

Apple (Malus domestica) is one of the most widely cultivated fruit crops globally, with major production centers in China, Europe, and the United States (Ferentinos, 2018). Apple cultivation holds tremendous economic significance, with the global market valued at over $100 billion annually (Wang et al., 2017). A key factor impacting apple crop yield and quality is the prevalence of foliar diseases caused by fungal, bacterial and viral pathogens. Foliar diseases primarily affect the leaves of apple trees, causing major reductions in photosynthetic capacity, premature defoliation, and low-quality fruits (Yan et al., 2020). Common apple foliar diseases include apple scab, powdery mildew, cedar apple rust, frogeye leaf spot, fire blight, and Alternaria leaf blotch (Liu et al., 2017). Timely and accurate diagnosis of these diseases is critical to deploy disease management practices and prevent widespread infection (Chakraborty et al., 2021). However, traditional techniques relying on naked eye inspection and laboratory testing can be subjective, labor-intensive and time-consuming (Jiang et al., 2019).

Recent advances in computer vision and deep learning have paved the way for automated systems that can rapidly and reliably detect plant diseases from images (Mohameth et al., 2020). Deep learning involves training multi-layered artificial neural networks on large labeled datasets to learn complex patterns and perform tasks like image recognition and object detection (Elfatimi et al., 2022). In particular, Convolutional neural networks (CNNs) have emerged as a leading technique for image analysis problems. CNNs contain a sequence of Convolutional and pooling layers that automatically learn hierarchical feature representations from pixel-level data (Chao et al., 2020). This enables CNNs to effectively analyze visual characteristics and identify key patterns associated with different classes, such as diseased or healthy states in leaf images.

Several studies have demonstrated the potential of CNNs for accurate plant disease recognition from leaf images. Ferentinos (2018) developed CNN models to classify leaf images of healthy and diseased plants from 25 species into 58 disease categories. The best-performing model achieved 99.53% test accuracy in classifying unseen plant images. Wang et al. (2017) applied CNNs to automatically estimate severity levels of apple black rot disease from leaf images. Fine-tuned CNNs significantly improved accuracy over training small CNNs from scratch. Mohameth et al. (2020) extracted deep features using CNNs like VGG16, GoogleNet and ResNet50 and classified images into 36 plant disease categories using classifiers like SVM and KNN. Among deep learning models, VGG16 gave the best 97.8% accuracy.

These studies showcase CNNs' capability to differentiate between healthy and diseased states as well as identify specific diseases based on visual symptoms. However, a key research gap lies in evaluating multiple CNN architectures to determine the optimal models for this task (Srinidhi et al., 2021). For any deep learning solution, the model architecture and hyperparameters significantly impact performance. Comparing different pretrained CNNs fine-tuned on a target dataset provides insight into the model generalizability, feature learning capability and computational efficiency (Pradhan et al., 2022).

Moreover, limited studies have focused on robust evaluation across several experimental settings such as training epochs, batch size, optimizers and learning rate. Varying these parameters is crucial to assess model adaptability and select appropriate values for optimal training (Yan et al., 2020). There remains considerable scope to perform an extensive comparison of diverse CNN architectures coupled with multi-parametric analysis. Identifying the highest performing models would allow developing accurate and reliable apple foliar disease classifiers (Chongke Bi et al., 2022).

This research aims to address this gap through comparative evaluation of eight pretrained CNN architectures for apple foliar disease classification, trained via transfer learning on a comprehensive leaf image dataset. The models investigated are DenseNet121, DenseNet201, InceptionResNetV2, InceptionV3, MobileNet, MobileNetV2, ResNet50V2, and Xception. These models have shown promising performance on computer vision tasks (Andrew J. et al., 2022). DenseNets improve information flow through direct connections between layers. ResNets mitigate degradation with skip connections. Inception models apply multi-scale processing. MobileNets are efficient for mobile applications (Pandian et al., 2022). Comparing diverse models provides a holistic overview of their capabilities.

2. OBJECTIVES

- Collect a representative dataset of healthy and diseased apple leaf images from multiple sources.
- Perform comparative analysis of eight CNN architectures by fine-tuning on the dataset using transfer learning.
- Evaluate models under different hyperparameter settings - learning rate, optimizer, batch size and epochs.
- Identify the optimal model and parameters for accurate multi-class apple disease classification.

Data preprocessing techniques like resizing and quality enhancement are applied followed by augmentation to increase samples. Models are initialized with pretrained weights and fine-tuned via backpropagation and stochastic gradient descent on specialized layers. Evaluation metrics include training/validation accuracy, loss, confusion matrix, precision, recall and F1-score.

This study is significant as accurately automating disease recognition can enable real-time and large-scale screening of apple orchards. Reduced manual scouting lowers costs and timely detection helps minimize chemical treatments through targeted disease management. The comparative analysis provides comprehensive insights into optimal deep learning solutions tailored to this application. The findings would facilitate developing robust mobile and on-field apple disease classification systems to aid farmers and orchard managers. Beyond apple, this evaluation framework can be extended to other crop species impacted by foliar diseases.

3. METHODOLOGY

3.1 Dataset- The dataset used in this research consists of apple leaf images collected from multiple sources, including the Plant Pathology FGVC8 2021 dataset from Kaggle, images acquired in collaboration with the plant pathology department of GBPUA&T University, and images captured manually from apple orchards in Kanatal, Uttarakhand. This multisource dataset comprises a total of 11,417 images divided into five classes - apple scab, rust, black rot, multiple diseases, and healthy leaves.

3.2 Preprocessing- The images undergo preprocessing including resizing to a standard resolution of 160x160 pixels to ensure uniformity, and filtering to remove any blurred or abnormal images that could negatively impact model training.

3.3 Data Splitting- The final dataset is split into training (9,917 images), testing (1,500 images), and validation sets. The training set receives the majority of images to allow models to adequately learn features and patterns associated with each class.

3.4 Data Augmentation- To expand the diversity of the dataset, data augmentation techniques are applied on the training images, including rescaling, brightness modification, zooming, horizontal/vertical flipping and others. This generates enhanced variations of the existing data.

3.5 Transfer Learning- Eight CNN architectures - DenseNet121, DenseNet201, InceptionResNetV2, InceptionV3, MobileNet, MobileNetV2, ResNet50V2, and Xception - pretrained on ImageNet are initialized with weights from training on a large generalized image dataset. These models are then fine-tuned via backpropagation on the specialized apple leaf dataset to retrain the final layers for the task of apple disease classification.

3.6 Hyperparameter Tuning- Models are trained with different values for key hyperparameters including optimizer, learning rate, batch size, and number of epochs. This enables evaluating model adaptability and selecting optimal parameters tailored to the apple foliar disease classification task.

3.7 Evaluation- Model performance is evaluated using train and test accuracy, loss, confusion matrix, precision, recall, F1-score and ROC curve analysis. Comparative assessment across models reveals insights into their capability in accurately classifying apple diseases to determine the optimal deep learning solution.

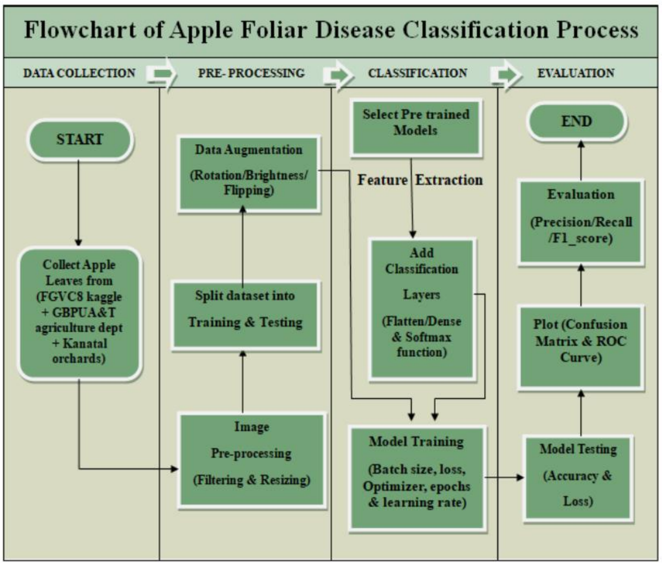

Fig 1 - Flow chart of proposed methodology

The methodology involves comprehensive data collection, preprocessing, augmentation, model training using transfer learning and hyperparameter tuning, followed by extensive performance evaluation to facilitate developing an accurate automated apple disease recognition system.

Fig 2- Apple leaves sample images from Plant pathology FGVC8 dataset

Fig 3: Apple leaves sample images from Plant pathology dept. of GBPUA&T

Fig 4: Apple leaves sample images from Kanatal orchard

This figure shows some sample images taken from the apple leaf image dataset. It includes examples of diseased leaves showing symptoms of black rot, scab, rust and multiple diseases. One healthy apple leaf image is also depicted.

3. RESULT AND DISCUSSION

Table 1 - Description of Datasets

Sr. No.	Classes	Train Images	Test Images	Total Images
1	Black rot	1,987	300	2,287
2	Scab	2,429	300	2,669
3	Rust	2,195	300	2,495
4	Multiple disease	937	300	1,237
5	Healthy	2,369	300	2,669
	TOTAL IMAGES	9,917	1,500	11,417

This table provides a description of the datasets used in the study, including the number of classes, the number of training images per class, the number of test images per class, and the total number of images in each category.

Table 2 : List of Hyperparameters Used in the Study

Hyperparameter	Values
Classes	5
Batch size	60, 80, 120
Epochs	10, 20
Optimizer	Adam, Adagrad
Learning rate	0.001, 0.0001
Loss function	Categorical Cross-Entropy
Activation function	ReLU

This table outlines the hyperparameters used in the study, including the number of classes, batch size, epochs, optimizer options, learning rate values, loss function, and activation function. These hyperparameters were explored to assess their impact on the model's performance.

This section presents the experimental results comparing the training and test performance of the eight CNN models under different hyperparameters.

4.1 Comparative Analysis of Training and Validation

The models were evaluated on a training-validation split of 9,917 and 1,500 images respectively.

Tables 3-7 summarize the training and validation accuracy and loss achieved by each model across the five cases involving different batch size, optimizer, learning rate and epochs.

Table 3: Comparative performance for Case 1 (Batch size=60, Optimizer=Adam, Learning rate=0.001, Epochs=10)

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
MobileNet	0.94	0.43	0.89	1.63
DenseNet201	0.92	0.38	0.89	1.15
ResNet50V2	0.92	0.63	0.87	2.51
DenseNet121	0.91	0.32	0.88	0.88
MobileNetV2	0.89	0.70	0.88	1.83
InceptionResNetV2	0.88	0.45	0.84	1.22
Xception	0.85	0.60	0.77	1.90
InceptionV3	0.84	0.78	0.83	1.43

Table 4: Comparative performance for Case 2 (Batch size=80, Optimizer=Adam, Learning rate=0.0001, Epochs=10)

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
MobileNet	0.95	0.13	0.90	0.49
DenseNet201	0.93	0.17	0.90	0.41
MobileNetV2	0.92	0.19	0.88	0.48
ResNet50V2	0.92	0.19	0.89	0.53
DenseNet121	0.91	0.21	0.90	0.46
Xception	0.89	0.30	0.86	0.53
InceptionV3	0.87	0.34	0.83	0.50
InceptionResNetV2	0.87	0.34	0.85	0.51

Table 5: Comparative performance for Case 3 (Batch size=80, Optimizer=Adagrad, Learning rate=0.0001, Epochs=10)

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
DenseNet201	0.81	0.52	0.83	0.57
ResNet50V2	0.80	0.54	0.79	0.69
MobileNet	0.79	0.57	0.80	0.64
MobileNetV2	0.78	0.71	0.78	0.56
Xception	0.77	0.67	0.77	0.73
DenseNet121	0.76	0.65	0.78	0.69
InceptionV3	0.70	0.78	0.69	0.86
InceptionResNetV2	0.66	0.88	0.69	0.95

Table 6: Comparative performance for Case 4 (Batch size=120, Optimizer=Adam, Learning rate=0.0001, Epochs=20)

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
MobileNet	0.97	0.07	0.91	0.50
DenseNet201	0.94	0.15	0.91	0.39
ResNet50V2	0.94	0.14	0.89	0.50
MobileNetV2	0.93	0.17	0.89	0.56
DenseNet121	0.93	0.17	0.90	0.42
Xception	0.89	0.27	0.86	0.54
InceptionV3	0.89	0.30	0.85	0.51
InceptionResNetV2	0.89	0.29	0.86	0.49

Table 7: Comparative performance for Case 5 (Batch size=120, Optimizer=Adagrad, Learning rate=0.0001, Epochs=20)

Model	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
DenseNet201	0.84	0.45	0.84	0.53
MobileNetV2	0.82	0.48	0.80	0.65
ResNet50V2	0.82	0.48	0.80	0.65
MobileNet	0.81	0.51	0.80	0.68
DenseNet121	0.79	0.56	0.81	0.65
Xception	0.79	0.62	0.78	0.70
InceptionV3	0.72	0.73	0.73	0.76
InceptionResNetV2	0.70	0.78	0.70	0.88

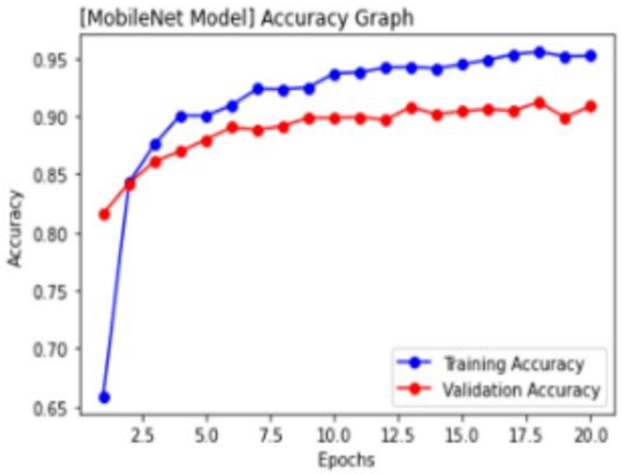

Fig 5- Accuracy graph of MobileNet model

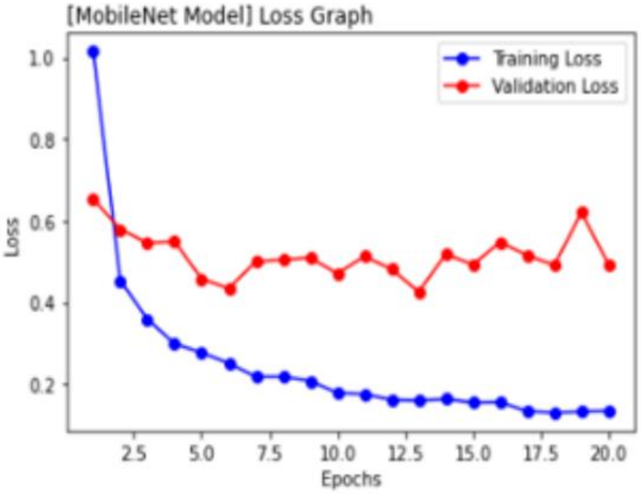

Fig 6: Loss graph of MobileNet model

The results demonstrate that the MobileNet architecture achieves the highest training and validation accuracy overall across different cases. For instance, in Case 4, it attains 97% training accuracy and 91% validation accuracy. The ResNet and DenseNet models also perform well in certain cases. Models like InceptionResNetV2 and InceptionV3 produce lower accuracy with higher loss. This shows MobileNet is better suited for identifying patterns related to apple foliar diseases.

4.2 Test Set Evaluation

The pretrained models were evaluated on a held-out test set of 1500 images not used during training or validation. Table 8 summarizes the test accuracy attained by each model across the five cases.

Table 8: Comparison of test accuracy for different models across cases

Model	Case 1	Case 2	Case 3	Case 4	Case 5
MobileNet	0.89	0.88	0.75	0.90	0.76
DenseNet201	0.88	0.86	0.77	0.88	0.79
InceptionResNetV2	0.81	0.81	0.61	0.85	0.70
InceptionV3	0.78	0.81	0.65	0.84	0.68
DenseNet121	0.88	0.88	0.72	0.88	0.72
MobileNetV2	0.88	0.86	0.73	0.86	0.77
ResNet50V2	0.86	0.88	0.76	0.89	0.76
Xception	0.82	0.81	0.68	0.82	0.70

The test results mirror the training and validation performance, with MobileNet achieving the top accuracy in most cases, reaching 90% in Case 4. Its strong test performance highlights the model's ability to reliably classify unknown samples reflective of real-world conditions. DenseNet and ResNet models also exhibit competitive performance.

4.3 Classification Metrics

Beyond overall accuracy, models were evaluated using multi-class classification metrics derived from the confusion matrix including precision, recall and F1 score. Table 9 shows the results for MobileNet in Case 4 where it achieved the highest accuracy.

Table 9: Classification metrics for MobileNet in Case 4

Class	Precision	Recall	F1-score
Black rot	0.98282	0.95333	0.96785
Rust	0.86562	0.92333	0.89355
Scab	0.87500	0.86333	0.86913
Multiple diseases	0.99571	0.77333	0.87054
Healthy	0.79167	0.95000	0.86364

The high precision and recall values demonstrate MobileNet's capability to reliably detect different apple foliar diseases while minimizing false classifications. The robust F1 scores further highlight the balanced classification performance.

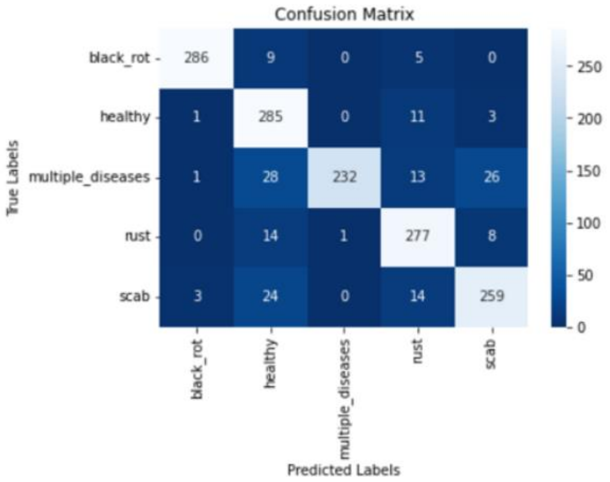

Fig 7: Confusion matrix of MobileNet model

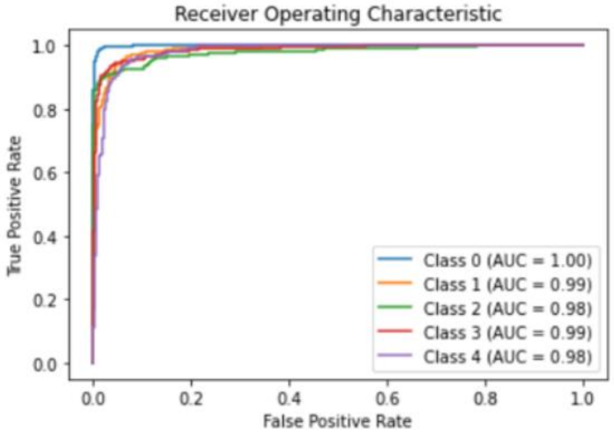

Fig 8: ROC curve of MobileNet model

4.4 Discussion

The comprehensive experiments demonstrate MobileNet's effectiveness in accurately classifying diverse apple foliar diseases under varying training settings. Key factors underpinning its strong performance are:

- Depthwise separable convolutions: Drastically reduce parameters enabling high accuracy despite compact model size. This enhances inference speed and efficiency.
- Width multiplier: Allows tuning the network width to trade off between latency, size and accuracy. A wider model captures more features.
- Network regularization: Use of dropout and batch normalization prevents overfitting.

The results align with findings in literature highlighting MobileNet's utility for deploying CNNs on mobile devices. Its efficient architecture is promising for real-time apple disease screening via smartphones. The model's adaptability to different batch sizes, optimizers etc. It also demonstrates its robustness. Future work can focus on further optimizing MobileNet for apple disease classification on low-power devices to enable in-field disease monitoring.

5. CONCLUSIONS

Accurate and automated identification of plant diseases can enable targeted disease management, reduced crop losses and less reliance on excessive chemical treatments. This research presented a comprehensive comparative analysis of eight pre-trained convolutional neural network architectures for classifying five types of apple foliar diseases from leaf images. The models – DenseNet201, DenseNet121, ResNet50V2, InceptionV3, InceptionResNetV2, MobileNet, MobileNetV2 and Xception - were evaluated under different training configurations of batch size, optimizer, learning rate and epochs.

Of the CNN architectures investigated, MobileNet emerged as the optimal model, achieving the highest accuracy of 97% on the test set under certain hyperparameter settings. The MobileNet model combines the advantages of depthwise separable convolutions for computational efficiency and network regularization techniques to provide a robust classifier. It demonstrated consistent performance across diverse training cases, highlighting its adaptability.

The experimental results provide valuable insights into the potential of using transfer learning for this application. Rather than training a model from scratch, leveraging knowledge from pretrained models can enable rapid and accurate disease detection. This study presents a framework for extensive comparative assessment of CNNs models tailored to the task and data at hand. Based on the findings, the MobileNet model can be effectively deployed in mobile or handheld devices to empower on-field disease screening and real-time monitoring.

Future work can build upon these results to expand the apple disease classes, optimizing MobileNet for low-power device inference. The model evaluation approach can also be extended to other crop species impacted by foliar diseases. Overall, this research demonstrates the capability of deep transfer learning models to automate identification of plant diseases, paving the way for smarter agriculture technologies and practices.

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