J. Integr. Sci. Technol.2024, 12(4), 799

Journal of Integrated
SCIENCE& TECHNOLOGY

Orchard Guard: Deep Learning powered apple leaf disease detection with MobileNetV2 model

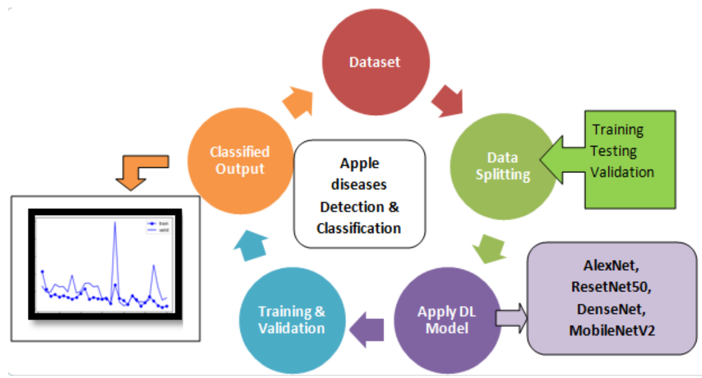
Snehal J. Banarase,* Suresh Shirbahadurkar

Electronics and Telecommunication Engineering department, ZEAL College of Engineering & Research, Narhe, Pune, 411041 Maharashtra, India.

Received on: 29-Nov-2023, Accepted and Published on: 25-Jan-2024

Article

ABSTRACT



The apple crops are susceptible to various diseases that can substantially reduce quality and yield, emphasizing the need for an accurate and automated detection system. The designed model can efficiently detect four different classes of an apple leaf viz. Apple Scab, Black Rot, Cedar rust, and Healthy. The detection has been carried out using a transfer learning approach with different models such as AlexNet, DenseNet121, ResNet-50, and MobileNetV2 as the primary ones. With hyperparameter tuning and by using different optimizer combinations we trained the MobileNetV2 model to achieve the best accuracy. The selected model is trained and fine-tuned on an Apple dataset of 3175 images, leveraging transfer learning from pre-trained models on large-scale image datasets. The designed 'Orchard Guard' model has achieved an accuracy of 99.36%. The research findings can help in the selection of a useful model for actual use in orchards and can aid in the creation of effective and precise disease management systems.

Keywords: Apple Leaf Disease Detection, Convolutional Neural Network, Deep Learning, MobileNetV2.

INTRODUCTION

Apple is a vital source of nutrition and income for millions of people worldwide, cultivation of an apple is a cornerstone of the global agricultural industry. However, a variety of diseases are constantly hampering the successful cultivation of an apple which can reduce yields and compromise fruit quality. To ensure the productivity and sustainability of apple orchards, timely detection and effective management of these diseases are paramount. Traditional disease detection methods are time-consuming and often labor-intensive, making them impractical for large-scale agricultural operations. In recent years, Deep Learning (DL), a subset of Artificial Intelligence (AI), has created new avenues for automating disease detection in plants. Deep learning models, particularly Convolutional Neural Networks (CNNs),[1] have demonstrated remarkable capabilities in image-processing tasks, including the detection of diseases in crops. Transfer learning has further accelerated progress in this field, it is a method that leverages the knowledge acquired by pre-trained deep learning models on large datasets. By fine-tuning pre-trained models on specific tasks, such as apple leaf disease detection, researchers can achieve impressive results even with limited labeled data.

This study delves into the application of deep learning-powered apple leaf disease detection[2-6] using four prominent CNN architectures: ResNet-50, AlexNet, DenseNet, and particular focused on mobileNetV2. MobileNet is a lightweight CNN model that is well known for its computational efficiency. We explore their suitability for automating the identification of common apple leaf diseases, such as apple scab, apple black rot, cedar apple rust, and healthy leaf. Transfer learning approach is adopted to get more precise results which enhance model performances in the specific domain of apple disease detection. The primary objective of this study is to explore and evaluate the application of MobileNet in the context of apple leaf disease detection.The research involves a dataset consisting of images of both healthy and diseased apple leaves. Various data preprocessing techniques like image preprocessing, and image augmentation are employed to improve

*CorrespondingAuthor: Snehal J. Banarase, Narhe, Pune
Tel: 7722031109
Email: snehal.banarase1@gmail.con

Cite as: *J. Integr. Sci. Technol., 2024, 12(4), 799.*
URN:NBN:sciencein.jist.2024.v12.799

model generalization. Subsequently, the selected deep learning models are fine-tuned on this dataset, adapting their pre-trained knowledge to get apple leaf disease recognition.

In addition to evaluating the model's accuracy and performance, we assess their computational efficiency to determine their suitability. The findings of this research hold the promise of revolutionizing apple orchard management by providing a reliable, automated, and efficient means of disease detection. As we navigate the challenges of sustaining global food production, harnessing the power of deep learning and transfer learning in agriculture becomes increasingly critical. This study aims to contribute to this evolving field, bridging the gap between cutting-edge technology and the agricultural sector's pressing needs for precision and sustainability.

Overview of Literature

Apple cultivation is a prime component of the global agricultural field, providing a valuable source of fresh produce and economic stability. However, the persistent threat of apple leaf diseases presents a significant challenge to sustainable apple farming. To address this challenge, researchers and technologists have explored to detect and manage these diseases. In this literature overview, we examine the state-of-the-art techniques and technologies based on traditional inspection methods, improved CNN, and lightweight CNN.

Traditional disease detection method

Disease detection in apple orchards is majorly relied on visual inspections by agronomists and farmers. These methods are often time-consuming and subject to human error, making them less prone than ideal for large-scale orchards. It is very difficult to inspect each leaf of an apple tree. Only experts from this field can do such a tedious job; even experts will be tired after continuous monitoring of the leaf diseases. Such kind of method is not at all reliable. So, it is necessary to replace this system with some low-cost, stable, and highly efficient automatic system. So, the Deep Learning model is the best solution for this problem since it has been developed well in recent years.

Deep CNN detection method

Improved CNN is used to detect five common types of apple leaf diseases rust, alternaria leaf spot, mosaic, and grey spot. The deep learning model is developed using Rainbow concatenation and GoogleNet Inception structure which is named as INAR-SSD model. This model is incorporated with the ResNet model.[1] Deep CNN based on AlexNet is used to detect four common types of apple leaf diseases which are mosaic, rust, brown spot, and alternaria leaf. This model has achieved 97.62% accuracy. Apple pathological image dataset of 13,689 images is used for training purposes. AlexNet model is used by adding a pooling layer and has removed partially fully connected layers.[2] The work is focused on plant disease identification with fine-tuned DL models. The models are evaluated by using Inception V4, VGG16, ResNet Series, and DenseNet.[3] The focus of the paper is on convolutional layer optimization. SA-GAUSS i.e., simulated annealing with Gaussian CNN is proposed in order to solve noise interference in feature extraction. A diverse dataset of cats, deer, birds, sheep, frogs, dogs, airplanes, etc. is considered for sampling. Image classification with improved CNN is proposed here.[4] A systematic review is important for plant leaf disease detection. The study of different DL techniques is mentioned; which allow future researcher to learn high capabilities of improved DL a technique. This paper has given a good overview of all existing deep-learning models.[5] Diagnosis using simple leaves of diseased and healthy plants is taken into consideration through DL methodologies. The model has achieved an accuracy of 99.53%. Different fruits like apples, bananas, blueberries, cherries, cucumber, oranges, peach, grapes, tomato, strawberry, etc. image dataset is collected for identification purposes. CNN models like AlexNet, GoogleNet, VGG, and Overfeat are used.[6] Nine-layer Deep CNN is proposed for plant leaf disease identification. The dataset consists of apple, cherry, orange, peach, tomato, blueberry, squash, and strawberry images. Accuracy found is 96.46%.[7]

A review of different Machine Learning (ML) and DL techniques is presented for plant leaf disease detection. All DL classifiers computation comparison is presented here. This study includes various segmentation techniques, and feature extraction techniques along with this overall study of ML and DL classifiers along with its advantages and limitations are presented.[8] The study is based on several factors that influence the use of deep learning for plant disease recognition and classification. Image dataset composed of common leaf disease spreading of an apple, tomato, rice, corn, olive tree, potato, etc. Depth-wise analysis of DL along with shortcomings and advantages are highlighted.[9]

Lightweight convolutional neural networks

MobileNet model is used to identify apple leaf diseases. Two common types of apple diseases rust and alternaria leaf blotch are inspected here. The ResNet152 and InceptionV3 model's comparison is presented over a dataset of 334 images. The model accuracy found for MobileNet, InceptionV3, and ResNet 152 is 73.50%, 73.59%, 77.65% resp.[10] Deep Lab V3+ model with ASPP i.e., actors spatial pyramid pool module is proposed for apple leaf lesion detection. The study is based on semantic segmentation; two disease datasets rust and ring rot were calibrated with this model. These models are again combined with PSPNet, DeepLabV3+, and GCNet for precise diagnosis.[11] Several studies have been conducted to recognize the versatile use of MobileNet and mobile computing devices along with a CNN for optical character recognition, palm print recognition, acoustic scene classification, garbage classification, and skin lesion classification.[12-16]

Utilization of CNN with hardware implementation for mobile vision application is presented for image recognition with the help of embedded devices and a biometric person recognizing system which is able to capture 19 different movements like sitting, standing, exercise; right side, etc. can be identified by using MobileNet.[17-19] The ECA-DCNet MobileNet model is Designed for the detection of apple leaf diseases which is based on the MobileNet V2 model.[20]

Similar Work in disease detection

Apple leaf disease detection with a genetic algorithm is used to extract different 38 features of shape, texture, color, etc. using a correlation-based feature selection method. Support Vector Machine (SVM) is used for classification purposes.[21] An empirical study of apple cultivation is carried out in Jammu and Kashmir region to improve farmer's income through automation. A detailed survey of apple cultivation, region-wise apple growth rate, and production scenario in India is presented in a good manner.[22] The ensemble model is developed using DenseNet121 and EfficientNet pre-trained model for apple leaf disease detection. The dataset includes four classes of 3642 apple leaves. The model has achieved an accuracy of 96.25% on the validation dataset.[23] Papaya fruit leaf disease detection and papaya maturity status detection using a transfer learning approach are included. Experimentation is carried out with the help of different CNN models.[24-25]

Bacterial foraging optimization is used efficiently to findout disease regions on plant leaves. A good survey of common fungal disease classification along with symptoms and their effect is presented.[26] Grape leaf disease identification[27] with multiple convolutional neural network approaches is presented based on AlexNet, GoogleNet, DenseNet, and ResNet.[28]

Cucumber disease identification based on deep CNN[29] and with a global pooling view is also carried out.[30] Ensemble classifier based on ML and DL has shown a remarkable approach todisease detection.[32-34] In the medical field too, CNN has provided the best results for Alzheimer's classification, prediction of antiviral peptides, and cancer cell detection.[35-37] The power of CNN is found in different areas like malware detection and classification.[38-39]

This review underscores the significance of combining cutting-edge technology with agricultural needs to enhance the production of apple orchards by analyzing disease threats. We examine the state-of-the-art techniques and technologies that leverage CNN-based deep learning models for empowering farmers with different leaf disease recognition.

METHODS

Data Acquisition and Preprocessing

The CNN models were evaluated and trained on apple leaves with the aim of identifying and classifying diseases. A total of 3175 images are used for a healthy and diseased category of apple leaf. The dataset used here is openly and freely available, which is created by referring to images from a plant village dataset. To evaluate the model performance 75% of the dataset is used for training and the remaining 25% is used for testing.

To avoid overfitting training dataset is again divided into a train set and a validation set; the ratio of the training dataset to that of the validation dataset is 4:1. Table 1. Shows image distribution among four classes.

Table 1: Apple leaf dataset

Leaf Class	No. of Training/ Testing Images	Total Images
Apple Scab	504/123	627
Black Rot	497/124	621
Cedar Apple Rust	225/55	280
Healthy	1319/328	1647
Total Number of Images		3175

Data preprocessing and augmentation are applied using Image DataGenerator. All input images are resized to 224×224.

The designed model has been evaluated on four different classes of an apple leaf i.e., Apple Scab, Apple Black Rot, Cedar Rust, and Healthy leaf. Referred images are shown in Figure 1.

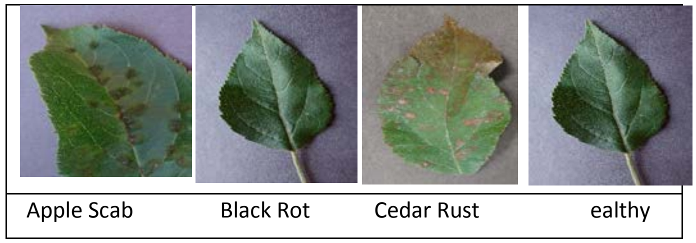


Figure 1. Images of four Apple Leaf Classes

CNN Models

To form an automated plant leaf diagnosis system different CNN architectures are trained and assessed. In this work,the basic four architectures of CNN were tested to get more precise results for apple leaf disease management. The models are AlexNet, ResNet50, DenseNet121 and MobileNetV2. AlexNet is a CNN network[20] used primarily for image classification and image recognition.

1. AlexNet

AlexNet is the first major CNN architecture thathas used GPUs for training purposes. It is always good to start with the basic version, so we have used this AlexNet for experimentation where we can train our dataset efficiently. AlexNet contains a total of 8 layers, which is better to extract features. AlexNet uses ReLu (Rectified Linear Unit) as its activation function.

2. ResNet50

In 2015 ResNet50 was introduced by Microsoft Research, isa 50-layer deep CNN architecture.[31] ResNet stands for residual network, which uses residual connection or skip connection. Residual networksbypass the information to certain layers in the network. ResNet is very useful for object detection and image classification. ResNet helps in reducing vanishing gradient problems that may occur while working with huge datasets or training very deep neural networks.

3. DenseNet121

It is a dense convolutional neural network that is 121 layers deep, where each layer takes input from backend layers and forwards its own feature map to all subsequent layers.[23] In traditional CNN, input passes sequentially through all layers while in DenseNet every layer contains information of each proceeding layer in the feed-forward mechanism. We have referred to pre-trained weights from ImageNet.

4. MobileNetV2

In 2017 Google proposed a lightweight convolutional neural network i.e., MobileNet, which is specifically designed for embedded device interfacing.[20] In 2019 a new version of MobileNetV2 was proposed with a reduced number of parameters. This model is trained on 1.4 million images of 1000 diverse classes. MobileNet architecture splits convolution into pointwise and depthwise convolution. Pointwise convolution performs a linear combination of input images to generate a new feature map, whereas depthwise convolution performs the calculation of a single channel of an input image.

Table 2: Performance Comparison of Different Models

Name	Accuracy (%)	Recall (%)	Number of Parameter / M
AlexNet	89.67	92.1	105
ResNet50	91.25	93.28	25.6
DenseNet	93.63	93.36	7.1
MobileNetV2	98.50	98.60	4.2

MobileNet based on a depthwise separable convolution model[19] is designed using a width multiplier and resolution multiplier. These models are trained using the DL computation framework and tested on an apple leaf dataset of 3526 images of healthy and diseased categories. The results are represented in Table 2.

Transfer learning with a pre-trained model saves a lot of computational power and also helps to identify best suitable model to implement. For experimentation and comparison purposes all standard CNN architectures are used without any hyperparatunning. Performance comparison with popular transfer learning approaches such as AlexNet, ResNet50, DenseNet121, and MobileNetV2 is carried out. Figure 2 represents accuracies among different transfer learning models. It is observed that MobileNetV2 is performing well. So, we have built our Designed model with a primary focus on MobileNetV2 with some hyperparatunning.

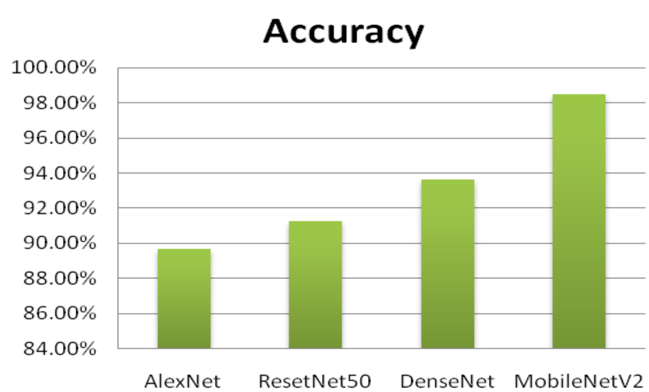


Figure 2. Accuracy Comparison of CNN models

DESIGNED ORCHARD GUARD MODEL ARCHITECTURE

To form an automated plant leaf diagnosis system, CNN architecture is trained and analyzed. MobileNetV2 model is chosen as a primary model to design our orchard guard, because of its suitability, accuracy, and efficiency. To build a lightweight network, we have used depth-wise separable convolutions. To train a deep neural network with our modified MobileNetV2 model we have replaced some layers of classical MobileNet, along with this we have done some hyperparatuning. In our modified orchard guard model, the initial input layer is followed by 13 convolutional layers. These convolutional layers efficiently extract all features from the input images. After each depthwise convolutional layer, subsequent pointwise convolutional layers are there. Batch normalization is applied followed by activation function ReLU (Rectified Linear Unit).

To reduce the size of extracted features global average pooling layer is inserted in between. The classical MobileNetV2 model has a reshape layer, dropout layer, convolutional layer, and activation function layer. In the Designed modified 'Orchard Guard' model, we have replaced all the last five layers of the classical MobileNet model with two layers i.e., the dropout layer and reshape layer as shown in Figure 3.

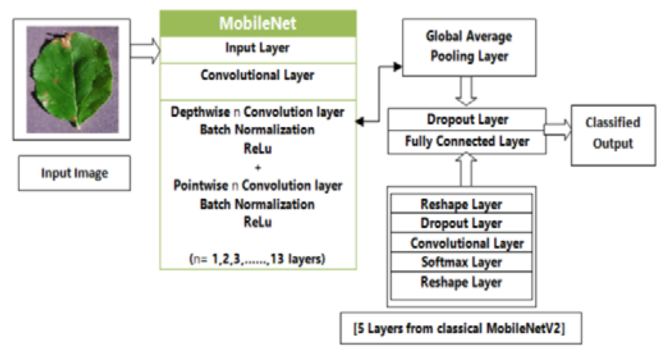


Figure 3. Designed 'Orchard Guard' for apple leaf diseases classification

With this reduced version overfitting problem is resolved which occurs in classical MobileNetV2 model. The designed version can solve this issue while working on a huge dataset. The total number of trainable parameters are also reduced from 4,264,664 to 3,228,864, which ultimately reduces computation time.

Model Training

The Designed Orchard Guard is trained on a dataset of 3175 apple leaf diseased and healthy leaf images by using the deep learning model MobileNetV2. Training of the model is carried out with two different optimizers SGD (Stochastic Gradient Descent) and Adam (Adaptive Moment Estimation) which are discussed in this section.

1. Training with SGD

SGD is a fundamental optimization algorithm that is widely used in training machine learning and deep learning models. SGD is easy to understand and implement. During the training process, SGD iteratively updates the model's parameters like weights and biases to minimize the loss function.

To compute the gradient of the loss function, SGD randomly selects a data subset from training data. This helps to compare the model's predicted value and the true target values. So, we can identify closed values of model parameters. SGD performs better with large and diverse data. For training purposes, we have selected momentum value as 0.9 with two different learning rates of 0.001 and 0.000.

As we are working on a multiclass classification problem, 'categorical_crossentropy' is used as a loss function and 30 numbers of epochs are chosen for training purpose. For performance evaluation 'Accuracy' is used as a metric.

2. Training with Adam

Now a days, Adam is the most popular optimization algorithm due to its efficiency and effectiveness in practice. In the field of deep learning, Adam is a widely used optimization algorithm. So, we have trained our model with Adam to improve accuracy. Based on historical gradient information, Adam computes individual learning rate for each parameter and stabilize the training. Due to this Adam runs faster and more robustly with diverse data. For training purposes, we have selected numbers of epochs as 30 and two different learning rates. As we identify four different classes of apple leaf disease, we have used 'categorical_crossentropy' as a loss function for training.

Table 3 shows the performance comparison of the MobileNetV2 model with different learning rates and different optimizer combinations.

Table 3: Performance of MobileNetV2 model with hyperparatuning

Model	Optimizer	Learning Rate	Accuracy (%)
MobileNetV2	SGD	0.001	97.34
MobileNetV2	SGD	0.0001	98.73
MobileNetV2	Adam	0.001	98.11
MobileNetV2	Adam	0.0001	99.36

As can be seen from Table 3, MobileNetV2 is working well with both the optimizer with different learning rates. There is a slight change in accuracy concerning changes in learning rates with the same optimizer. MobilenetV2 with SGD and a learning rate of 0.0001 gives an accuracy of 98.73%. MobileNetV2 with Adam and a learning rate of 0.001 gives an accuracy of 98.11%. This means lowering the learning rate will reduce the model's accuracy. MoobileNetV2 with SGD and a higher learning rate performs better than that of MoobileNetV2 with Adam and a lower learning rate. However, we can see a significant difference of 2.02% in the first value and last value of MobileNetV2 model accuracy with the change in the optimizer and learning rate. Based on the above analysis we can say that MobileNetV2 with Adam as an optimizer and a higher learning rate of 0.0001 predicts the best accuracy among all combinations.

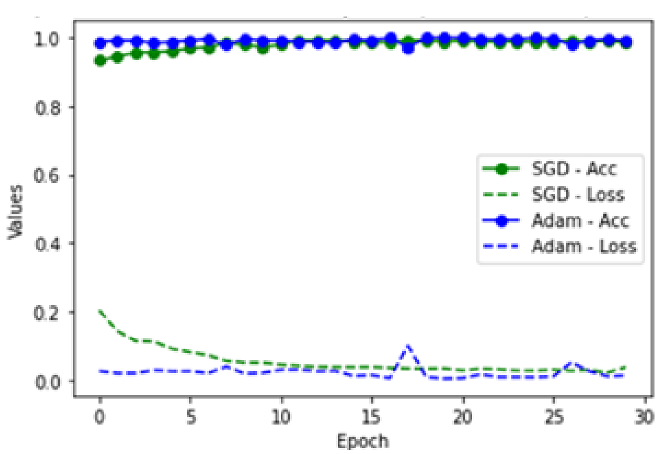


Figure 4. Relationship between validation accuracy and epochs across two optimizers

For training purposes, we have taken 30 epochs. The relationship between validation accuracy and number of epochs across two optimizers is shown in Figure 4. We can see that, from 5 to 10 epochs, validation accuracy is less. In between 15-20 model has achieved the best validation accuracy while it is reducing from 20-25.

EXPERIMENTAL RESULT AND ANALYSIS

In this section, the experimental setup is introduced along with performance metrics. The details of experimentation and benchmark are provided. Finally, experimental results are analyzed.

Experimental Setup

All these deep learning models are trained and tested on a system D4A50CDE-A6BC-452F-8696-07951E7A7BF0 using Scitkit-learn, Keras, and openCV libraries. Python is used as a programming language. The training and testing of all models were implemented using the TensorFlow framework. All experimentation is carried out on a system with Intel core i5-1235 U, 64-bit operating system, x64-based processor 16GB RAM.

Performance Metrics

To analyze the model performance, we have trained individual CNN models by providing an apple leaf train, test, and validate dataset. Statistical parameters play an important role in evaluating the model performance. The performance metrics we have used here are Accuracy, Precision, Recall, and F1-score. These parameters are mentioned in equation (1) to (4). Accuracy finds correctly classified values based on true positive and true negative values. Precision clarifies how often the model is right based on all positive values. Recall gives models predicted frequency; i.e., how the model predicts the correct positive values. The F1 Score is a harmonic mean of recall and precision.

$$\text{Accuracy: } A = (TP + TN) / TP+TN+FP+FN \quad (1)$$

$$\text{Precision: } P = TP / (TP + FP) \quad (2)$$

$$\text{Recall: } R = TP / (TP + FN) \quad (3)$$

$$\text{F1 Score: } F1 = 2*P*R / (P+R) \quad (4)$$

Where; TP, FP, TN, and FN are true positive, false positive, true negative and false negative resp.

RESULTS AND DISCUSSION

The Designed 'Orchard Guard' model can efficiently classify the four different classes of an apple leaf diseases. The model is trained by using the MobileNetV2 model with some hyperparatunning and different combinations of an optimizers such as SGD and Adam. To improve model performance, slight variation is done with learning rate, the results are discussed in earlier section as shown in Table 3. The transfer learning approach helps to find out best suitable CNN model to train the Designed architecture. We got the best results for the MobileNet V2 model with Adam as an optimizer and a learning rate of 0.0001. This model has achieved an accuracy of 99.36%. Again, the number of trainable parameters are also reduced from 4.2 M to 3.2 M.

The Designed system is trained with a modified MobileNetV2 model to do the multiclass classification of an apple leaf disease. The model is trained on a diverse dataset of an apple-diseased leaf and a healthy leaf. Table 4 & 5 represents the model performance based on precision, recall, and F1- score for the validation dataset and test dataset resp.

It is seen that precision and recall are perfect 1 for black rot and cedar rust. For the healthy class, precision is perfect 1 in the validation set but recall is 0.98 on the other hand in the test dataset, recall is perfect 1 but precision is 0.99. A similar case is observed in apple scab too.

Table 4: Apple leaf disease detection in the validation set

Class	Precision	Recall	F1-Score
Apple Scab	0.96	1.00	0.98
Black Rot	1.00	1.00	1.00
Cedar Rust	1.00	1.00	1.00
Healthy	1.00	0.98	0.99

Table 5: Apple leaf disease detection in test set

Class	Precision	Recall	F1-Score
Apple Scab	1.00	0.98	0.98
Black Rot	1.00	1.00	1.00
Cedar Rust	1.00	1.00	1.00
Healthy	0.99	1.00	0.99

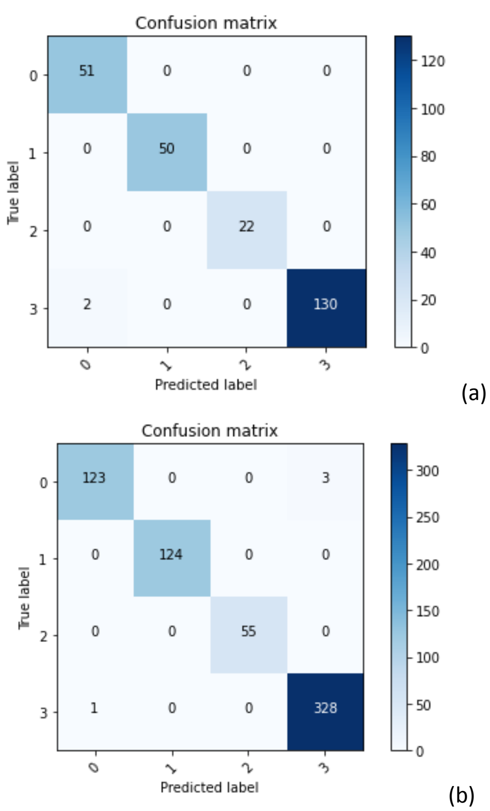


Figure 5. Confusion matrix: (a) Validation dataset (b) Test dataset

These results are also incorporated by the confusion matrix. The confusion matrix represents visual estimates of the modified MobileNetV2 model as shown in Figure 5. The results are pretty good for all four classes. Sometimes classifiers may get confused with multiclass classification problems because of similar shapes. To improve model performance these accuracies enable us to avoid confusion between different classes.

The Designed model is trained with two different combinations of an optimizer such as SGD and Adam to achieve the best accuracy and minimum loss. Figure 6 and 7 shows accuracy and loss comparison between these optimizers for training and validation dataset. The accuracies seen here are calculated for the learning rate of 0.0001, where we have achieved good results for both optimizers. MobileNetV2 with SGD as an optimizer has given an accuracy of 98.73%. MobileNetV2 with Adam as an optimizer has given an accuracy of 99.36%. There is a significant difference between these accuracies.

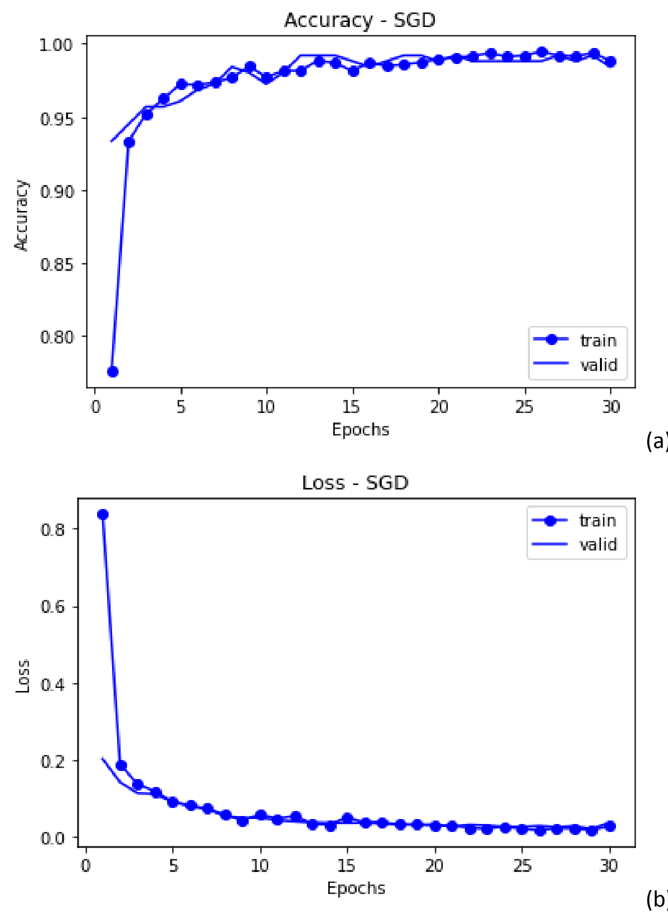
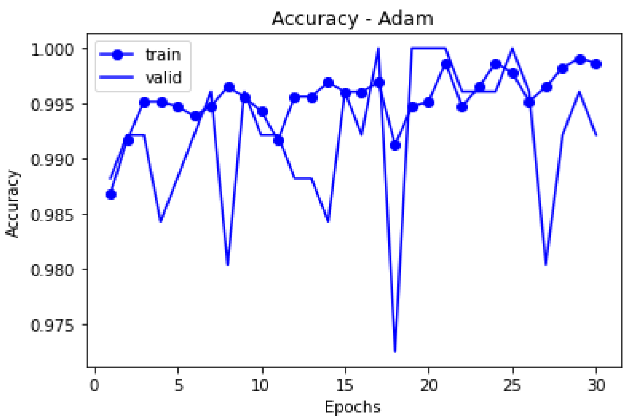
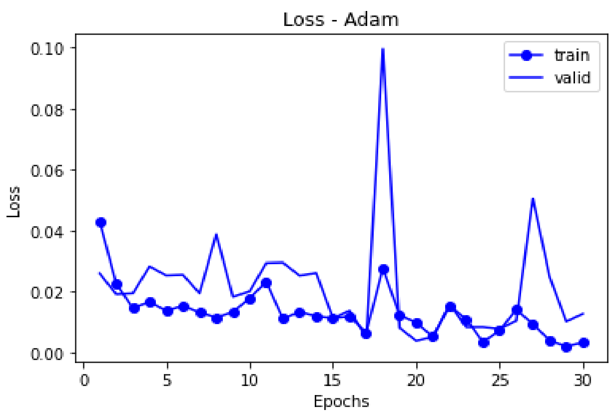


Figure 6 (a) and (b). Performance Comparison of SGD Optimizer

It is observed that minimum loss is there during the training and validation phase for two different optimizers. As expected, we have had very minimal loss during training and validation.



(a)



(b)

Figure 7 (a) and (b). Performance Comparison of Adam Optimizer

Our model has provided high accuracy and fast computation speed compared with the existing model. According to studies[2] developed AlexNet model-based DL environment, which can efficiently detect four common types of apple leaf diseases. The overall accuracy for the model was 97.62%. The model based on ResNet, DenseNet, VGG, and Inception-V4[3] has given the best accuracy in detecting apple leaf diseases. The transfer learning model is implemented on a huge dataset of various fruit categories and has received an accuracy of 96.46%,[7] the study is based on six different data augmentation methods. Two major categories of apple leaf diseases such as Alternaria leaf and Rust are detected with three different CNN models[10] MobileNet, Inception V3, and ResNet-50, and accuracy received is 73.50%, 75.59%, and 77.65% resp. Three different semantic segmentation models are utilized on a small sample dataset of apple leaves,[11] which has given a good accuracy of 97.26%. An improved apple leaf disease detection algorithm is designed to safeguard apple food safety.[20] The algorithm is based on MobiNetV2 and ECA-Net is also included with this to achieve an accuracy of 96.23%. A new approach like apple leaf disease detection based on a genetic algorithm with SVM predicts more than 90% detection accuracy.[20] CNN-based MobileNet model has provided an accuracy of 92.4% which has used depthwise convolution.[17] A novel ensemble deep CNN model with a transfer learning approach based on various augmentation techniques has been reported.[23] This model uses DenseNet and EfficientNet and gives an accuracy of 96.25%.

The use of the MobileNetV2 model is not limited to disease detection only but it is found that this model has given more than 90% of accuracies in different areas. The MobileNetV2 is widely used in research areas like handwritten character recognition, palmprint recognition, acoustic scene classification, common garbage classification, skin lesion detection, and person recognition based on different movements.[12-18]

CONCLUSIONS

We Designed a modified MobileNetV2 model called ‘Orchard Guard’ for the classification of apple leaf disease. This model can efficiently classify four different classes of an apple such as Apple Scab, Black Rot, Cedar Rust, and Healthy. The improved convolutional neural network models can automatically extract discriminative features of an apple leaf. Training and fine-tuning of the deep learning architecture is done with a transfer learning approach along with AlexNet, ResNet-50, DenseNet121, and MobileNetV2. All models have achieved better performance when using hyperparatuning. To train the model, SGD and Adam as an optimizer are used. Among these two optimizers, MobileNetV2 with Adam as an optimizer has achieved the best accuracy of 99.36% followed by MobileNetV2 with SGD which has provided an accuracy of 98.73%. Total trainable parameters for the modified MobileNetV2 model are also reduced from 4.2M to 3.2 M.

ACKNOWLEDGMENTS

Authors thank MAHAJYOTI, Nagpur for providing the required environment and material for this research.

CONFLICT OF INTEREST STATEMENT

Authors don’t have any competing interests.

REFERENCES AND NOTES

1. P. Jiang, Y. Chen, B. Liu, D. He, C. Liang. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. *IEEE Access* **2019**, 7, 59069–59080.
2. B. Liu, Y. Zhang, D. He, Y. Li. Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks. *Symmetry.* **2017**, 10 (1), 11.
3. E.C. Too, L. Yujian, S. Njuki, L. Yingchun. A comparative study of fine-tuning deep learning models for plant disease identification. *Comput. Electron. Agric.* **2019**, 161, 272–279.
4. Z. tao Hu, L. Zhou, B. Jin, H. jiang Liu. Applying Improved Convolutional Neural Network in Image Classification. *Mob. Networks Appl.* **2020**, 25 (1), 133–141.
5. M. Nagaraju, P. Chawla. Systematic review of deep learning techniques in plant disease detection. *Int. J. Syst. Assur. Eng. Manag.* **2020**, 11 (3), 547–560.
6. K.P. Ferentinos. Deep learning models for plant disease detection and diagnosis. *Comput. Electron. Agric.* **2018**, 145, 311–318.
7. G. Geetharamani, A.P. J. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Comput. Electr. Eng.* **2019**, 76, 323–338.
8. M. Snehal, J. Banarase, S.D. Shirbhadurkar. A Review on Plant Leaf Diseases Detection and Classification. *International Journal of All Research Education and Scientific Methods (IJARESM)*. 2021, pp 2455–6211.
9. J.G.A. Barbedo. Factors influencing the use of deep learning for plant disease recognition. *Biosyst. Eng.* **2018**, 172, 84–91.
10. C. Bi, J. Wang, Y. Duan, et al. MobileNet Based Apple Leaf Diseases Identification. *Mob. Networks Appl.* **2022**, 27 (1), 172–180.

11. L. Li, B. Wang, Y. Li, H. Yang. Diagnosis and Mobile Application of Apple Leaf Disease Degree Based on a Small-Sample Dataset. *Plants* **2023**, 12 (4), 786.
12. Y. Weng, C. Xia. A New Deep Learning-Based Handwritten Character Recognition System on Mobile Computing Devices. *Mob. Networks Appl.* **2020**, 25 (2), 402–411.
13. M. Izadpanahkakhk, S.M. Razavi, M. Taghipour-Gorjikolaie, S.H. Zahiri, A. Uncini. Deep region of interest and feature extraction models for palmprint verification using convolutional neural networks transfer learning. *Appl. Sci.* **2018**, 8 (7), 1210– 1230.
14. D. Wei, J. Li, P. Pham, S. Das, S. Qu. Acoustic Scene Recognition with Deep Neural Networks. *DCASE2016 Chall.* **2016**, No. September.
15. S.G. Paulraj, S. Hait, A. Thakur. Automated municipal solid waste sorting for recycling using a mobile manipulator. *Proc. ASME Des. Eng. Tech. Conf.* **2016**, 5A-2016.
16. B. Harangi. Skin lesion classification with ensembles of deep convolutional neural networks. *J. Biomed. Inform.* **2018**, 86, 25–32.
17. B. Khasoggi, Ermatita, Samsuryadi. Efficient mobilenet architecture as image recognition on mobile and embedded devices. *Indones. J. Electr. Eng. Comput. Sci.* **2019**, 16 (1), 389–394.
18. Ş. Kılıç, Y. Kaya, İ. Askerbeyli. A New Approach for Human Recognition Through Wearable Sensor Signals. *Arab. J. Sci. Eng.* **2021**, 46 (4), 4175–4189.
19. A.G. Howard, M. Zhu, B. Chen, et al. MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *Comput. Sci. Apr* **2017**.
20. S. Liu, H. Bai, F. Li, et al. An apple leaf disease identification model for safeguarding apple food safety. *Food Sci. Technol.* **2023**, 43.
21. Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui, C. Jia. Apple leaf disease identification using genetic algorithm and correlation based feature selection method. *Int. J. Agric. Biol. Eng.* **2017**, 10 (2), 74–83.
22. S.A. Wani, S. Kumar, F. Naqash, et al. Potential of apple cultivation in doubling farmer's income through technological and market interventions: An empirical study in Jammu & Kashmir. *Indian J. Agric. Econ.* **2021**, 76 (2), 278–291.
23. P. Bansal, R. Kumar, S. Kumar. Disease detection in apple leaves using deep convolutional neural network. *Agric.* **2021**, 11 (7), 617.
24. S.K. Behera, A.K. Rath, P.K. Sethy. Maturity status classification of papaya fruits based on machine learning and transfer learning approach. *Inf. Process. Agric.* **2021**, 8 (2), 244–250.
25. S.J. Banarase, S.D. Shirbahadurkar. Papaya Diseases Detection Using GLCM Feature Extraction and Hyperparatuning of Machine Learning Approach. *Lecture Notes in Networks and Systems*. 2023, pp 145–158.
26. S.S. Chouhan, A. Kaul, U.P. Singh, S. Jain. Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology. *IEEE Access* **2018**, 6, 8852–8863
27. M. Ji, L. Zhang, Q. Wu. Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks. *Inf. Process. Agric.* **2020**, 7 (3), 418–426.
28. V. Bodhwani, D.P. Acharjya, U. Bodhwani. Deep Residual Networks for Plant Identification. *Procedia Comput. Sci.* **2019**, 152, 186–194.
29. J. Ma, K. Du, F. Zheng, et al. A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. *Comput. Electron. Agric.* **2018**, 154, 18–24.
30. S. Zhang, S. Zhang, C. Zhang, X. Wang, Y. Shi. Cucumber leaf disease identification with global pooling dilated convolutional neural network. *Comput. Electron. Agric.* **2019**, 162, 422–430.
31. D. Rajpal, A.R. Garg. Ensemble of deep learning and machine learning approach for classification of handwritten Hindi numerals. *J. Eng. Appl. Sci.* **2023**, 70 (1).
32. J. Bonam, S.S. Kondapalli, N.L.V. Prasad, K. Marlapalli. Lightweight CNN Models for Product Defect Detection with Edge Computing in Manufacturing Industries. *J. Sci. Ind. Res. (India).* **2023**, 82 (4), 418–425.
33. A. Yousuf, U. Khan. Ensemble Classifier for Plant Disease Detection. *Int. J. Comput. Sci. Mob. Comput.* **2021**, 10 (1), 14–22.
34. K. Nagasubramanian, S. Jones, A.K. Singh, et al. Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant Methods* **2019**, 15 (1), 98.
35. S.S. Bamber, T. Vishvakarma. Medical image classification for Alzheimer's using a deep learning approach. *J. Eng. Appl. Sci.* **2023**, 70 (1), 54.
36. F. Ali, H. Kumar, W. Alghamdi, F.A. Kateb, F.K. Alarfaj. Recent Advances in Machine Learning-Based Models for Prediction of Antiviral Peptides. *Arch. Comput. Methods Eng.* **2023**, 30 (7), 4033–4044.
37. D.B. Hoang, S. Hoang. Deep Learning-Cancer Genetics and Application of Deep Learning To Cancer Oncology. *Vietnam J. Sci. Technol.* **2022**, 60 (6), 885–928.
38. S. Kumar, B. Janet. DTMIC: Deep transfer learning for malware image classification. *J. Inf. Secur. Appl.* **2022**, 64.
39. Z. Wu, J. Zheng, J. Liu, C. Lin, H.D. Li. DeepRetention: A Deep Learning Approach for Intron Retention Detection. *Big Data Min. Anal.* **2023**, 6 (2), 115–126.
40. M.H. Saleem, J. Potgieter, K.M. Arif. Plant disease detection and classification by deep learning. *Plants* **2019**, 8 (11).
41. A.F. Fuentes, S. Yoon, J. Lee, D.S. Park. High-performance deep neural network-based tomato plant diseases and pests diagnosis system with refinement filter bank. *Front. Plant Sci.* **2018**, 9, 1162.