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Research Article

Image-based disease detection and classification in Indian apple plant species by using deep learning

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ABSTRACT

Plant diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. Traditional farming methods are insufficient to address the impending global food crises. As a result, agricultural productivity growth is critical, and new techniques and methods are required for efficient and sustainable farming practices that balance the supply chain according to customer demand. Even though India is one of the most agriculturally dependent countries, it nevertheless suffers from various agricultural shortages. Plant diseases that go unnoticed and untreated are one such deprivation. Developing an intelligent automated technique for plant disease detection is explored in this research. Deep learning creates a smart system for image-based disease detection in Indian apple plant species. Specifically, this study uses a convolution neural network architecture, ResNet-34, to identify diseases in apple plants. Based on 70-30% and 80-20% dataset partition, the proposed model obtained an accuracy of 97.5% and 98.4%, respectively. The results obtained from this study illustrate the productive exploration and utility of the proposed model for future research by implementing various deep learning models and incorporating additional modules that provide cure and preventative measures for the detected diseases.

1. INTRODUCTION

A study notes that modern food processing technology has sufficient capabilities to provide for the food needs of 7 billion people worldwide [1]. The "Food and Agriculture Organization (FAO)" of the United Nations, a specialised body that directs international efforts to alleviate world hunger, believes that the global population will peak at 9.2 billion people in 2050. As predicted by many sources, global food consumption is expected to rise dramatically over the next few years, sparking an explosion in food shortages. Developing more sustainable and dependable agricultural practices is necessary to boost agricultural output, balance supply chains, and meet consumer demand in the face of a worldwide food crisis. Despite this, food security is still endangered by climate change, pollinator loss, plant disease, and more [2]. In addition to being a global problem, plant diseases can have devastating repercussions for smallholder farmers who rely on healthy harvests. Smallholder farmers generate more than 80% of agricultural production in developing countries, and estimates of yield loss of more than 50% due to pests and diseases are typical [3-5]. In addition, half of the world's hungry people live in smallholder farming households [6], making them particularly vulnerable to food supply interruptions caused by infectious diseases.

Similar to animals, plants also show symptoms of the diseases they are suffering from. These symptoms may be classified into many categories based on their apparent nature, such as microscopic or macroscopic, the location of the infection - local or systemic, and their severity - primary or secondary [7]. Macroscopic symptoms are visible to the unaided eye, and detection of the diseases is more accessible and inexpensive. Leaves are the parts of plants which show the most evident macroscopic symptoms of diseases such as apple scabs. Therefore, leaves are more often used to detect a disease evolving within a plant. With developments in computer vision technology, proper plant protection and computer vision applications in precision agriculture can be further expanded and improved. There are numerous methods for identifying plant diseases [8], including artificial neural networks [9] and support vector machines [10]. They are used with various image pre-processing techniques to improve feature extraction. Deep learning using visual input is being used to detect disease in apple plant species in this study. The most crucial thing in developing such a system is getting appropriate data in images.

Although much research has been conducted in this sphere, there is still a need for a generalised deep-learning model which can have promising performance when more disease classes are to be classified. Also, the accuracy of the present models tends to diminish due to issues such as overfitting, vanishing gradient, and many others; consequently, an automated model for plant disease detection is required to overcome these challenges and achieve a higher level of accuracy. Based on these issues, this paper aims to develop an automated deep-learning model for disease detection and classification among Indian apple plant species. The following is a breakdown of the paper's structure. The second section contains the literature survey. Section 3 presents the proposed methodology for developing an intelligent system using deep learning for image-based disease detection and classification in Indian apple plant species. The experimental data, results, and benchmarking are presented in Section 4. Finally, section 5 concludes the paper.

2. LITERATURE REVIEWS

As can be seen in Figure 1, implementing the appropriate management strategies for detecting crop diseases has been an intriguing issue among researchers over the past decade. There is an urgent need for a cost-effective, quick, and reliable health-monitoring model that aids in agricultural improvements, according to a review published by [11]. Researchers in [12] opted to apply the image processing technique for detecting plant diseases and other methods widely used for diagnosing plant diseases, such as microscopy, nucleic acid probes and double-stranded ribonucleic acid analysis. The use of computer vision for plant disease detection has resulted in various new methods. Disease diagnosis by extracting colour features, as demonstrated by [13] using the HSI, YcbCr, and CIELB colour models, is an example of such a technique.

Since leaves of plants show the most evident macroscopic symptoms of diseases, these are more often used to detect a disease evolving within a plant. Developing intelligent systems for smart agriculture machine learning algorithms, such as Support Vector Machine (SVM), Naïve Bayes, and k-nearest neighbours (KNN), have been used over the years. One such system was developed by [14] in which they used a two-step classification approach: first, the histogram representation of the pre-processed images was used to distinguish between uninfected and infected leaves, and in the second step, two machine learning algorithms were used to differentiate between infected leaves namely support vector machine and Bayes' theorem. According to [15], they developed a disease detection system using SVM; however, it was used to detect diseases affecting the fruit instead of leaves. While some research is carried out to classify healthy and infectious leaves, others focus on finding the extension of these diseases that evolved within plants. For instance, in [16], based on the damage caused by the yellow mosaic virus on the leaves classified-extremely damaged leaves were as Highly Susceptible (HS), moderately affected leaves as Moderately Susceptible (MS), and least damaged leaves were put under the Tolerable (T) category. The healthy leaves were classified as Resistive (R) using the Naïve Bayes classifier.

Artificial neural networks (ANNs) have also played a significant role in plant disease detection. In [17], they used ANN to classify four different diseases. Another popular disease detection approach is Convolutional

Neural Networks (CNN). CNN is a feed-forward deep learning neural network method which has got its inspiration from the organisation of an animal's visual cortex. CNNs provide both platform and support for analysing visual imagery and hence are more convenient for classifying images. A study notes that the CNN model is the most efficient compared to 5 different types of deep learning models, with an accuracy of 96% [18]. Pre-trained CNNs such as AlexNet and GoogleNet are also used for disease detection in plants. Some studies have been realised for disease detection, such as AlexNet [19] [20] and GoogleNet [21]. Their results show that the pre-trained model has better accuracy.

The feed-forward and backpropagation of neural networks with a single input, single output, and a hidden layer have been proposed by [22] to detect leaf pests or disease species. Particle Swarm Optimization (PSO) and a forward neural network are two different approaches presented by [23] that combine to improve the accuracy of their system and determine the damaged cotton leaf location with a final overall accuracy of 95%. Also, Support Vector Machine techniques can be used to detect and differentiate plant diseases. Sugar beet disease classification accuracy ranged between 65% to 90%, depending on the disease kind and stage, according to [24]. Further techniques combine feature extraction with Neural Network Ensemble for plant disease recognition. With ANNs and k-means as a clustering process, [25] presented another strategy based on images of leaves for automatically detecting and classifying plant illnesses. This method had a classification accuracy of 94.67% on average.

3. MATERIAL AND METHOD

This research primarily aims to identify and classify diseases in Indian plant species. However, only apple plants are considered for the experiment. As the Kashmir valley is one of the critical apple-producing regions of the country, the majority of apple diseases are common in this region. In general, a plant disease detection system based on image processing and machine learning follow the approach depicted in Figure 2. The input in the form of images is subjected to the pre-processing stage, in which various image-processing techniques are applied. After the images have been processed, they are segmented to extract the diseased portion of the leaf, if it exists. Feature extraction is utilised to learn the features from an image, which the CNN does in this study, ResNet-34. The model can be used to classify diseases after feature extraction and training. The outcomes of the classification are either healthy or infected. Apple scab, fire blight, apple mosaic virus, marssonina leaf blotch, Altern leaf spot, and powdery mildew are the six diseases considered for an infected leaf in this research.

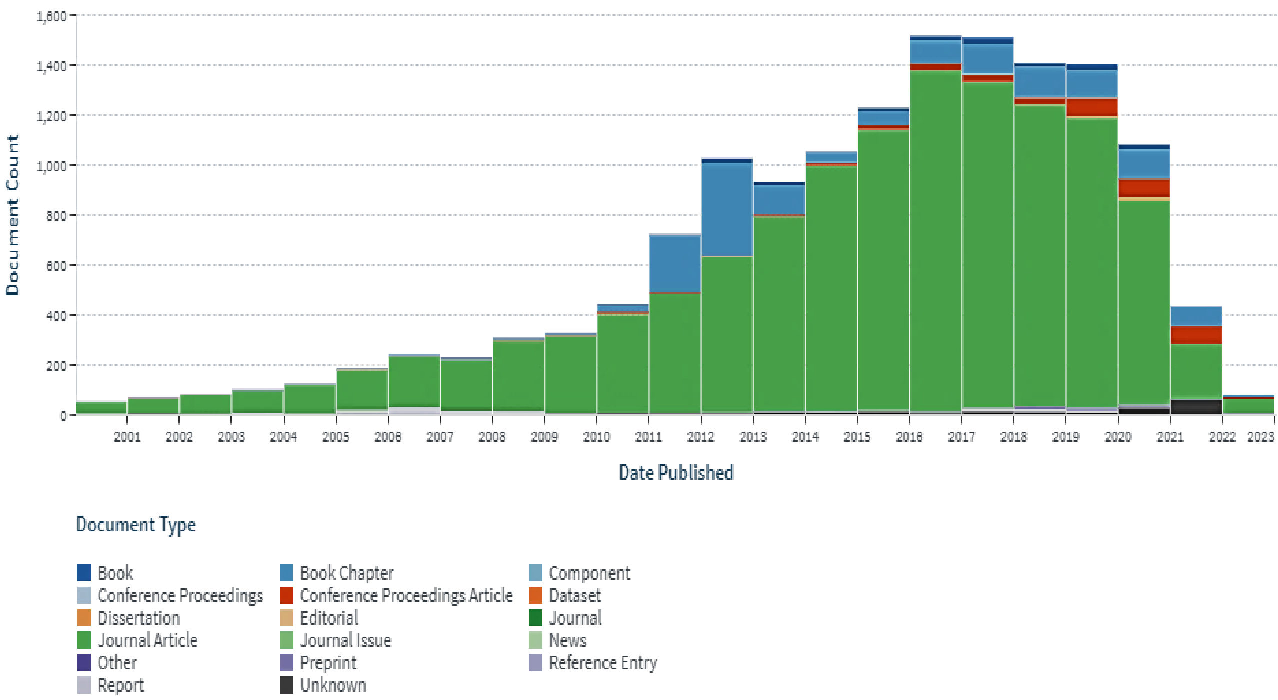

Figure 1. Scholarly works on plant disease detection from 2000-2020 (lens.org).

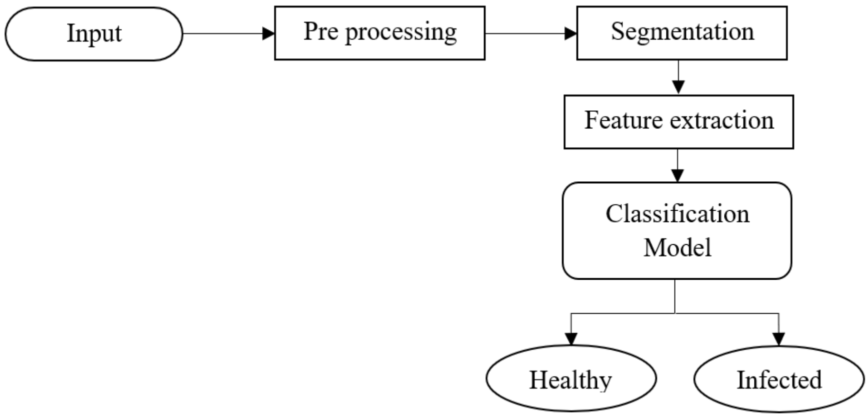

Figure 2. Flowchart of the proposed model.

3.1 Apple leaf diseases

In the Kashmir valley, apple trees are susceptible to many biotic diseases. This study focuses on the six diseases most usually responsible for stunting their development and productivity. These diseases were selected based on their evident impact on the leaves. In Table 1, introductory information regarding the diseases under consideration is provided. On the other hand, carbide percentages increased after the tempering process for all samples.

3.2 Data collection and preparation

Various plant image datasets have been examined, and the selected images are from two open-source datasets: PlantVillage and Plant Pathology Dataset. In addition, data has been collected from various areas of the valley. In order to increase the heterogeneity of the dataset, a total of 1990 images of healthy and infected plant leaves were captured. Ideally, data gathering was conducted throughout Kashmir's leaf-bearing season. The images were then carefully classified by domain experts into seven categories: Apple Scab, Fire Blight, Apple Mosaic Virus, Marssonina Leaf Blotch, Alternaria Leaf Spot, Powdery Mildew, and Healthy. The experiment utilised 7000 images of diseased and healthy apple tree leaf specimens. Table 2 provides an outline of the gathered leaf images for the dataset.

The images were pre-processed before being fed to the model. Each image has been downsized to the exact dimensions of 224 x 224 pixels. Figure 3 depicts the photos included in the dataset. Finally, the dataset is divided into training and testing sets for the model using two distinct ratios, namely 70-30% and 80-20%.

Table 1. Apple diseases, their causes, and their symptoms.

No.	Name of the disease	Cause	Symptoms on leaves
1	Apple Scab	Bacteria	Circular olive-green coloured spots which turn dark brown with age
2	Fire Blight	Bacteria	The brown or black hue of the entire leaf appears burned.
3	Apple Mosaic Virus	Virus	Pale or off-white coloured leaf spots and bumps.
4	Marssonina Leaf Blotch	Fungi	Standalone leaf blotch patches
5	Alternaria Leaf Spot	Fungi	Lesions of black or brown colour with yellowish borders
6	Powdery Mildew	Fungi	White-coloured fungal growth on the leaf surfaces

Table 2. Dataset outline.

Disease Name	Number of images collected from available online datasets	Number of pictures collected by us	Total number of images
Apple scab	760	340	1100
Fire blight	704	296	1000
Alternaria leaf spot	730	280	1010
Apple mosaic virus	801	172	973
Marssonina leaf blotch	732	320	1052
Powdery mildew	520	180	700
Healthy	763	402	1165
Total	5010	1990	7000

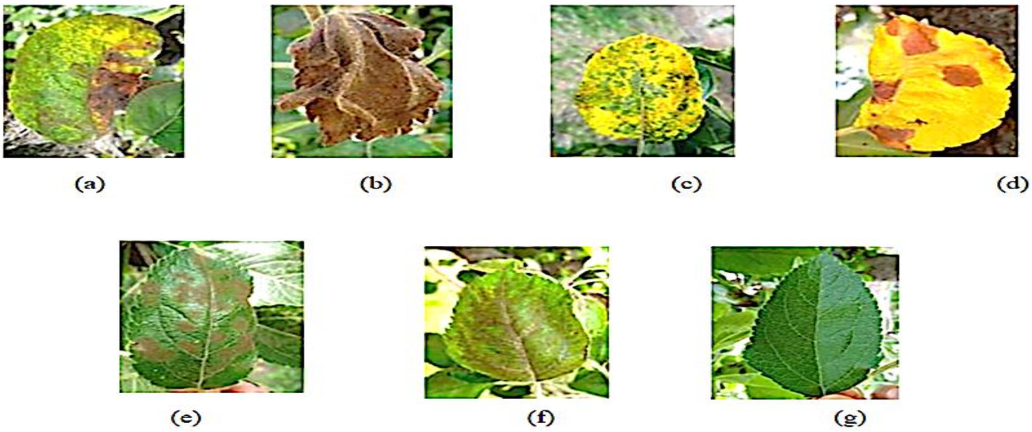

Figure 3. Images from the collected dataset (a) Apple cab, (b) Fire blight, (c) Apple mosaic virus, (d) Marssonina leaf blotch, (e) Alternaria leaf spot, (f) Powdery mildew and (g) Healthy.

3.3 Experimental setup

The experiment has been implemented in Keras, a high-level library built on TensorFlow. The latest version of Tensor Flow viz Tensor Flow 2 has been used. Residual networks are commonly called as ResNets. A ResNet is one of the convolutional neural network frameworks with an outclass efficiency and accuracy. It has various types, such as ResNet-34 and 50. ResNet has been considered for this research because networks of hundreds or even thousands of layers can be trained quickly with little or no increase in the training error rate. Using identity mapping, ResNets helps deal with the vanishing gradient problem.

ResNet-34 has been used for this research. This variant consists of 16 residual blocks; a residual block is also called an identity block and is typically formed when the activation is fast-forwarded into a layer more profound than the previous. Each of the residual blocks has a depth of two layers. The very first layer of ResNet, like other CNNs, is the convolutional layer. The convolutional layer extracts the features from the input images and maps them onto the feature maps. In our case, the convolutional layer of ResNet-34 takes the input images of 224 x 224 pixels and produces 64 feature maps of 112 x 112 sizes each. Before passing this convolved input data to the other layers of ResNet-34, the operations such as normalising features across the batch and max pooling are carried out. The ResNet-34 has four different layers; the first and the last layers are comprised of three residual blocks each, the next layer shall consist of four residual blocks, and the third layer includes six residual blocks. The output from the last ResNet layer is then passed on to the final pooling layer, which is a fully connected layer. For our modified system, we have a seven-way, fully connected layer, as we have only seven classes to represent; one class label is for healthy leaf images, and the remaining six are for infected leaf images.

For training, one of the most efficient algorithms, viz Stochastic Gradient Descent, has been used at a learning rate of 1/1000. The number of epochs chosen is 100, while the batch size of eighth has been considered. This combination of some epochs and the size of each batch has been selected to avoid overfitting the chosen learning rate. Also, it has been demonstrated from previous research that small batch training improves generalisation performance and permits a substantially smaller memory footprint, which is utilised to increase machine throughput. The modified architecture of the ResNet-34 used for this research is given in Figure 4.

4. RESULTS AND DISCUSSION

According to empirical studies, using 20-30% of the data for testing and the rest 70-80% for training yields the best outcomes. Therefore, for this research, both combinations are evaluated. The dataset is split into training and testing of the model with ratios 70-30% and 80-20%.

4.1 Results based on the 70-30% dataset division

Plant disease detection and classification results based on 70-30% dataset division of the proposed model are shown in as confusion matrix in Table 3. In simpler terms, the accuracy of each class is the number of correct predictions/ total number of forecasts calculated using Equation (1).

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

TP= True Positive, TN= True Negative, FP= False Positive and FN= False Negative. TP is the number of perfectly-identified images which were positive. TN is the number of ideally detected images which were negative. FP is the number of wrongly seen images as positive, which were negative. FN is the number of improperly detected images as unfavourable, which were positive.

In the apple scab class, the correctly predicted number of images is 323 among the total 330 photos; therefore, the accuracy = 323/ 330 = 0.978 or 97.8%. Similarly, the accuracy for other classes has been calculated as well. The accuracy shown is promising in most cases. However, the minimum accuracy is demonstrated by the prediction of the Apple virus mosaic class, which is 95.8%, and the Healthy leaf class shows the maximum with a tremendous accuracy of 99.1%. Figure 5 shows the graphical representation of the classification accuracy of the proposed model for different types of classes.

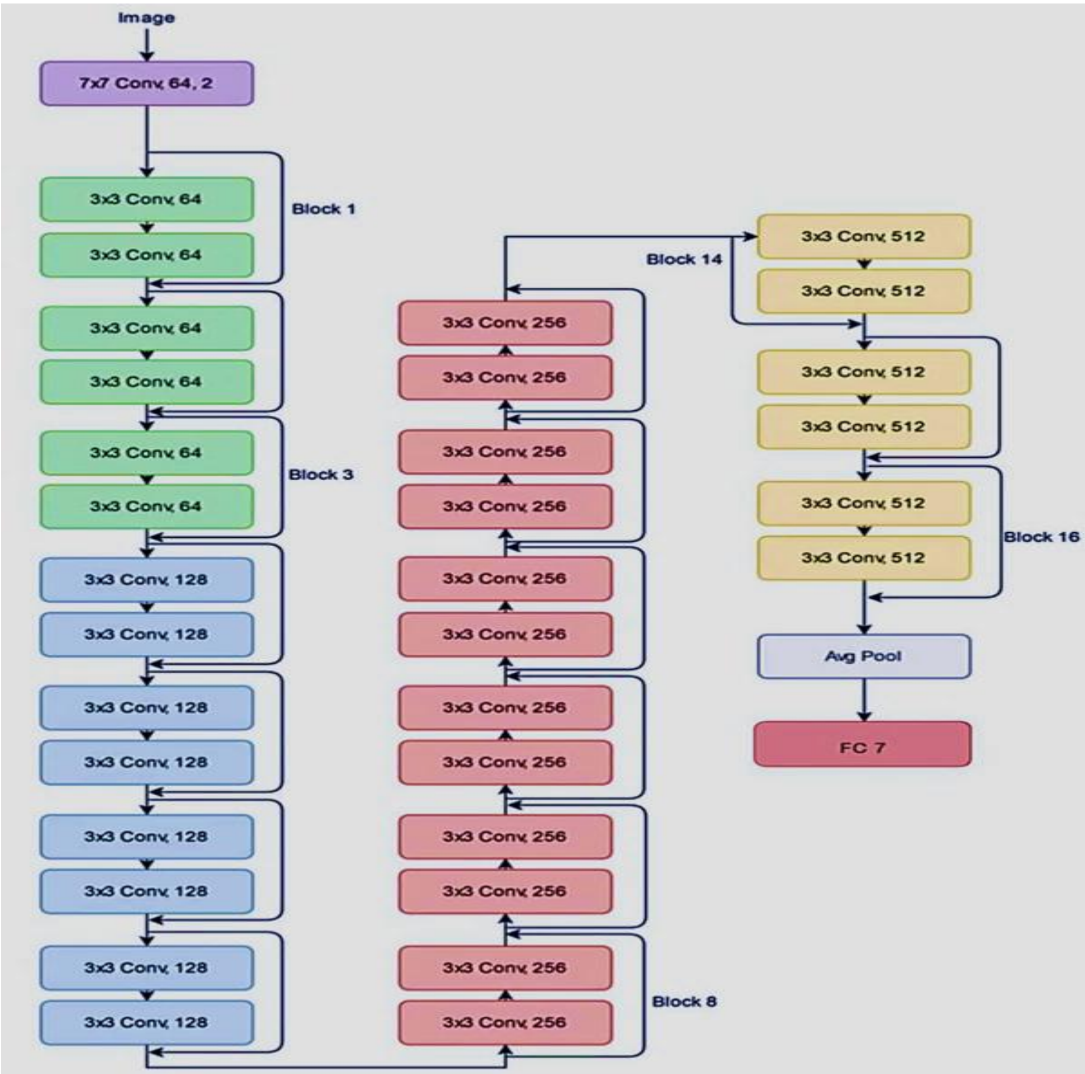

Figure 4. Architecture of ResNet-34.

For the dataset's 70-30% division, the model has achieved an average accuracy of 97.5%, as shown in training versus validation accuracy graph in Figure 6. Using the confusion matrix for each predicted class, it has also calculated other parameters like the precision, recall, specificity, and F1-score, by applying Equations (2), (3), (4) and (5), respectively.

$$Precision = \frac{True\ positives}{(True\ positives + False\ positives)} \tag{2}$$

$$Recall = \frac{True\ positives}{(True\ positives + False\ negatives)} \tag{3}$$

$$Specificity = True\ Negatives\ x\ (True\ Negative + False\ positives) \tag{4}$$

$$F1 - score = \frac{2\ x\ (Recall\ x\ Precision)}{(Recall + \ Precision)} \tag{5}$$

The calculated values of these parameters using Table 3 are presented in Table 4. The precision is highest for the Healthy class, with a percentage of 99.7%, followed by the accuracy of the AMV class, which is 98.9%, while the lowest precision is for the Scab class, with 94.7%.

4.2 Results based on the 80-20% dataset division

Plant disease detection and classification results based on 80-20% dataset division of the proposed model are shown in as confusion matrix in Table 5. Figure 7 shows the graphical representation of the classification accuracy of the proposed model for different types of classes based on 80-20% dataset division.

Compared to the dataset's 70-30% division, the model has achieved a better average accuracy of 98.4% using the 80-20% dataset division, as shown in the training versus validation accuracy graph in Figure 8. The Precision, Recall, Specificity and F1-Score based on the 80-20% dataset division is shown in Table 6.

Table 7 shows a comparative analysis of our research with similar projects. Our proposed model outperforms the benchmarked study because of the sequence of execution phases, including optimal algorithms and configurations, improved image processing approaches, and an optimal training environment.

Table 3. Confusion Matrix of the classified results 70-30% dataset division.

	Predicted Class							Accuracy
Disease	Scab	FB	AL	AMV	MLB	PM	Healthy	Average (%) 97.5
Scab	323	2	3	0	2	0	0	97.8
FB	3	291	1	0	3	2	0	97.0
AL	3	0	296	0	3	0	1	98.6
AMV	8	0	2	280	0	2	0	95.8
MLB	4	0	2	3	310	0	0	97.1
PM	0	2	0	0	5	202	0	96.1
Healthy	0	0	1	0	2	0	347	99.1

Table 4. Precision, Recall, Specificity and F1-Score based on the 70%-30% dataset division.

Parameters in %	**Classes**						
	Scab	FB	AL	AMV	MLB	PM	Healthy
Precision	94.7	98.6	97	98.9	95.3	98	99.7
Recall	97.8	97	98.6	95.8	97.1	96	99.1
Specificity	98.9	99.7	99.4	99.8	99	99.8	99.9
F1-Score	96.2	97.7	97.7	97.3	96.1	96.9	99.3

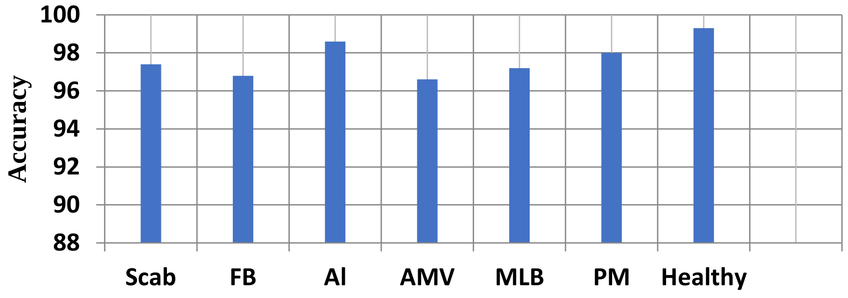

Figure 5. Accuracy graph for each class for 70-30% dataset division.

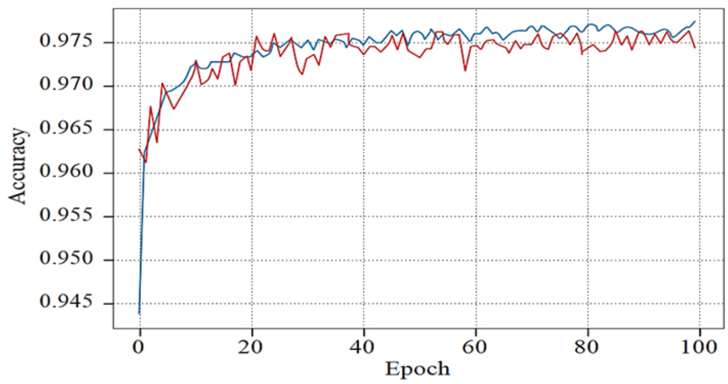

Figure 6. Training graph versus validation accuracy based on 70-30% dataset division.

Table 5. Confusion Matrix of the classified results 80-20% dataset division.

Disease	Predicted Class							Accuracy
	Scab	FB	AL	AMV	MLB	PM	Healthy	Average (%) 97.5
Scab	218	1	0	0	0	1	0	99%
FB	1	195	0	2	1	1	0	97.5%
AL	0	0	201	0	1	0	0	99.5%
AMV	1	0	3	189	0	2	0	96.9%
MLB	0	2	0	2	206	0	0	98%
PM	3	0	1	0	0	136	0	97.1%
Healthy	0	0	0	0	1	0	232	99.5%

Table 6. Precision, Recall, Specificity, F1- Score based on 80-20% dataset division.

Parameters in %	Classes						
	Scab	FB	AL	AMV	MLB	PM	Healthy
Precision	97.7	98.4	98	97.9	98.5	97.1	100
Recall	99	97.5	99.5	96	98	99.1	99.5
Specificity	99.5	99.7	99.6	99.6	99.7	99.7	100
F1-Score	98.3	97.9	98.7	96.9	98.2	97.1	99.7

Table 7. Comparison of apple disease detection models for accuracy in (%).

Paper	Deep learning models used	Diseases detected	Number of images for the dataset	Accuracy
Bi, C. et al. 2022 [26]	MobileNet, InceptionV3, ResNet152	Alternaria leaf spot, Apple Rust	2004	73.5%, 75.59%, 77.65% respectively
Yong Zhong et al. (2020) [27]	DenseNet-121	General Apple Scab, Serious Apple Scab, Apple Gray Spot, General Cedar Apple Rust, Serious Cedar Apple Rust	2456	93.7%

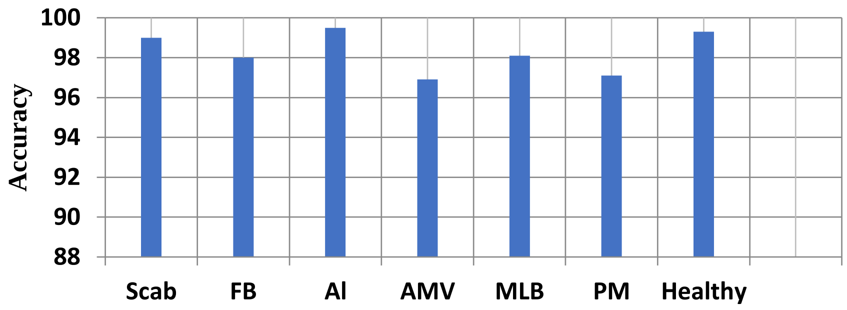

Figure 7. Accuracy graph for each class for 80-20% dataset division.

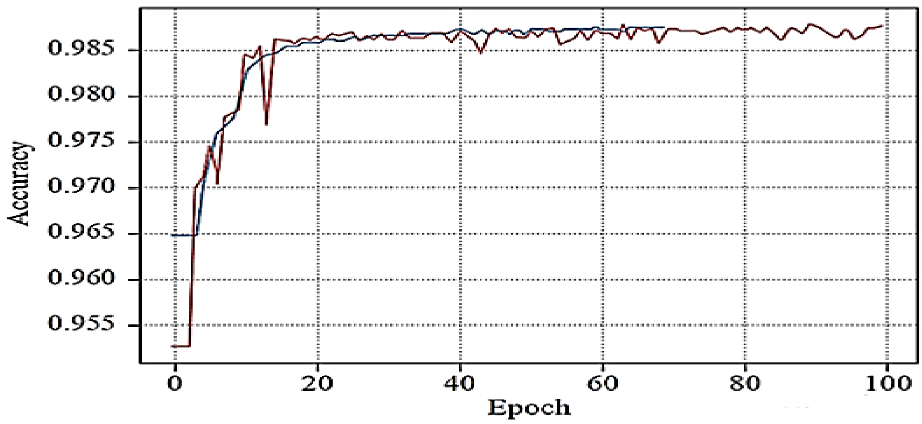

Figure 8. Training graph versus validation accuracy based on 80-20% dataset division.

5. CONCLUSION

This research is an assessment of disease detection in plants. The study was conducted for disease detection in Indian plant species. Six types of diseases commonly found in apple trees: Apple Scab, Fire blight Apple Scab, Fire Blight, Apple Mosaic Virus, Marssonina Leaf Blotch, Alternaria Leaf Spot and Powdery Mildew were considered. This research designed a dataset by combining the images from the two online datasets- Plant Village and Plant pathology- with our collected images. Together a total of 7000 images of healthy and infected apple tree leaf images were collected. The collected images were pre-processed before feeding them to the classifier. The focal point of this work was to identify and classify the diseases among the apple trees apparent on their leaves using a deep learning approach, i.e., Convolutional Neural Network (CNN). A modified version of ResNet-34 was used to decrease the training time and increase the accuracy parameter. The results were obtained from the proposed technique using two dataset division ratios, 70-30% and 80-20%. The system's accuracy based on 70-30% dataset division came out to be 97.5%, while that of 80-20% came out to be 98.4%. Thus, suggesting that the 80-20% dataset ratio works better with the model. Other parameters like precision, recall, specificity, and F1-score have also been calculated.

The research has tremendous potential in the present world towards digitisation. The proposed model finds its implementation in various innovative farming and agricultural approaches. The extension for future work upgrades is engaging for the research. Different types of deep learning models can be used to make a comparative decision for better accuracy and efficiency. Apart from just detecting plant diseases, the system can expand by including a new module that will provide the cure and preventive measures for the identified conditions. Additionally, multiple types of plant species can be considered in the forthcoming works.

CONFLICTS OF INTEREST

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

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