



Diseases Detection from Apple Leaf using Deep Transfer Learning Approach

Syed Al E Ali Naqi¹, Khurram Iqbal¹, Abdul Ayaz Khan¹, Rida Khan¹, Saba Jamil¹ and Uzair Ishtiaq^{2*}

¹Riphah College of Computing, Riphah International University, Faisalabad Campus, Pakistan.

²Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, Malaysia.

*Corresponding author: Uzair Ishtiaq (Email. uzair@um.edu.my)

<https://orcid.org/0009-0005-2407-0163>

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Abstract: Apples are one of the topmost eaten fruits around the globe and have a massive global production value. Although fertilizers and pesticides have improved the quality and quantity of apple production, certain diseases still need to be caught beforehand. This disease can cause devastation to fruit production. They also have chances to become life-threatening for the trees as well. Advances in imaging technologies are growing, and it is necessary to dedicate these state-of-the-art technologies into the agricultural division. This research presents the utilization of a deep learning algorithm for the detection of three major apple leaf diseases. The analysis utilizes image processing techniques such as K-mean clustering for segmentation. GoogleNet architecture has been used for the classification of the processed data set. A systematic performance of the proposed approach was also determined with the following accuracy of 98.54%, precision of 98.50%, recall of 98.50%, and F1-score of 98.50. This study will equip the farmers with a proper and effective method for early apple leaf disease detection to be able to act in good time to ensure the crops' safety, improvement in productivity, and sustainable agriculture.

Keywords: Deep Learning; Apple Leaf Disease; K-mean Clustering; GoogleNet; Agriculture

1. Introduction

Agriculture is the backbone of many economies around the globe and Pakistan is one of those countries. An agricultural country thrives off its agrarian good. This makes it very important for such countries to produce a gross amount of quality products that fulfill the import and export requirements. The agricultural industry has a worldwide demand and growing plants is an art. Certain natural phenomena can occur randomly and may cause massive losses to farmers and the industry. Diseases and pest infections are



illustrations of this phenomenon. As per the consensus report published by the United Nations Food and Agricultural Organization (FAO) in 2019, between 20% and 40% of world agriculture lost. Each year, plant diseases cost the world economy about \$220 billion, while invasive insects cost the global economy approximately US\$70 billion [1]. These numbers show that there is still a significant role in the agricultural industry that needs to be filled. Plant diseases are responsible for a \$220 million loss globally and are the primary issue that needs to be highlighted. Plant diseases have long been a significant source of anxiety in agriculture since they reduce crop quality and, as a result, output. Plant diseases can cause minor symptoms to severe damage to entire planted crops, resulting in high financial costs and having a significant impact on the agricultural industry [2], particularly in low-income countries like Pakistan, India, and Indonesia, etc. Farmers spend billions of dollars each year on plant disease management, sometimes without sufficient scientific assistance, resulting in poor disease control, contamination, and other negative consequences.

Furthermore, plant disease can potentially destroy natural ecosystems, exacerbating environmental issues such as habitat loss and bad land management. Crop losses are highest in tropical nations, where environmental conditions are ideal, incomes are poor, and few crop health management expertise and investment. As a result of disease losses, communities may become reliant on imported goods, frequently substituting processed foods for a balanced diet, leading to additional health issues.

Several agricultural goods can be discussed and covered. Still, this study majorly focused on one category of food known as one of the most commonly eaten categories: fruits. And one of the most common fruits out of the food category is apples. Apple trees are prone to leaf diseases and these diseases are very common in all the global apple production. There are several apple leaf diseases, but the major diseases are Apple Scab, Black Rot, and Cedar Apple Rust. Although these diseases are visible on the leaf, they greatly impact the yield of apples and may even cause tree death. Apple scab is one of the most frequent and dangerous diseases affecting apple plants. It typically emerges in early to mid-spring, and it is more common when it rains. The fungus *Venturia inaequalis* causes the illness, which overwinters in diseased leaves left on the ground [3]. A leaf with an apple scab is shown in Figure 1.



Figure 1: Leaf suffering from apple scab disease

Frog and black rot eye leaf spot refer to the same illness at various stages of its progression. *Botryosphaeria obtusa* causes the disease, which starts as brown patches on the fruit's ends. The dots grow larger and larger in concentric rings, ultimately becoming black and spoiling the fruit. Small brown patches or holes may appear on the leaves [3]. A leaf with black rot is shown in Figure 2.



Figure 2: Apple leaf suffering from Black Rot

Cedar-apple and crabapple rust is a dangerous disease. *Gymnosporangium junipers-Virginiana*, the fungus that causes the illness, is unique. It must spend part of its life cycle as a parasite on *Juniperus* species like red cedar and ornamental junipers. Apples may be severely affected by cedar-apple rust [4]. The distortion of an apple leaf caused by Cedar-apple rust is shown in Figure 3.



Figure 3: Apple leaf with Cedar-apple rust

Plant disease severity is traditionally determined by trained specialists visually inspecting plant tissues [5], which results in high costs and poor efficiency. Cultivation and management expert systems have been extensively utilized as digital cameras have become more widespread and information technology has advanced in agriculture, significantly increasing plant output capacity [6]. The "expert system," on the other hand, relies heavily on expert expertise to extract and convey pest and disease features, which may easily lead to a lack of uniformity and poor identification rates. With the rise in popularity of machine learning algorithms in computer vision, researchers have looked at automated plant disease detection using conventional machine learning methods like the random forest, k-nearest neighbor, and Support Vector Machine (SVM) [7,8]. These techniques improved identification accuracy but still low due to manual features selection. Recent advances in deep learning have changed the entire scenario by automatically selecting the most discriminative features for images categorization. Its advantages include the usage of shared weights to decrease the model's memory footprint and enhance speed and direct image input. This research focuses on establishing images acquired from a publicly accessible Kaggle data set of apple leaf disease photos using a new deep learning method based on GoogleNet and image processing techniques.

This study extends the methodology of past studies that combine RGB-to-LAB conversion of a color-space, K-means clustering, and flood fill segmentation and transfer learning-based techniques. Researching on detection of apple leaf disease, this research project is contrasted with the previously existing ones either working on unprocessed RGB pictures or using ready-made models to complete their segmentation. Rather, the proposed pipeline first detects and segments diseased leaf areas and then does classification, which stiffens the results. An impressive 98.54 % classification accuracy has been attained, which is a demonstration that the combination of classical apple-leaf-disease-detection techniques with deep transfer learning is useful. The framework that will result is computationally efficient and will be scalable and therefore will be useful in precision agriculture.

The rest of this paper is organized into a few sections: Section 2 describes previous works on leaf disease detection by other researchers. Section 3 represents the description of the proposed methodology. Finally, section 4 summarizes the results of the model, and Section 5 concludes the key findings.

2. Literature review

Plant diseases pose a significant danger to productivity and quality, and many researchers have made numerous attempts to manage them [9,10]. Traditional machine learning techniques have been extensively utilized to accomplish illness diagnosis during the past several years [11,12]. Early detection and correct identification of apple tree leaf diseases (ATLDs) may successfully limit infection spread, minimize losses, and guarantee the apple industry's continued health [13,14]. However, traditional techniques for identifying plant leaf diseases depend heavily on expert knowledge to manually extract color, texture, and shape characteristics from disease leaf images [15,16]. Due to the complexity and variety of the recorded backgrounds and disease patches artificially derived features employing image analysis techniques are often restricted to a single dataset. Consequently, their identification accuracy is not optimal when transferred to a new dataset [17,18]. Chao et al. [19] suggest using deep Convolutional Neural Networks (CNN) to solve the detection challenges associated with apple leaf diseases. The data set was gathered directly from labs and cultivation fields, and the deep convolutional neural network employed was a hybrid of DenseNet and Xception. The proposed convolutional neural network retrieved the characteristics ANN classified the apple leaf diseases using a support vector machine. The suggested technique and model produce a 97.82% accuracy rate.

Authors in [20], the Deep Convolution Neural Network is again used to detect apple leaf diseases. The study targets four-leaf diseases, namely, mosaic, rust, brown spots, and Alternaria leaf spots. Using the dataset of 13,689 images and the AlexNet model an overall accuracy of 97.62% was achieved [21]. Authors in [22], use DenseNet-121 deep convolution network and three regression methods multi-label classification and focus loss function was proposed to identify apple leaf diseases. The apple leaf image dataset used in this study comprised 2462 images of six apple leaf diseases. The proposed methods achieved 93.51%, 93.31%, and 93.71% accuracy on the test set respectively. The use of the LSA network in [23] for the detection of apple leaf disease was made and the authors achieved an accuracy of 89.4 %. The authors of [24] proposed a hybrid model of pre-trained DenseNet121, EfficientNetB7, EfficientNet, and NoisyStudent to classify leafs of apple trees images into one amongst the categories: healthy, apple scab, apple cedar rust, and multiple diseases. Numerous Image Augmentation techniques are enclosed during this analysis to extend the dataset size, and sub sequentially, the model's accuracy will increase. Our planned model achieves an accuracy of 96.25% on the validation dataset. The planned model will establish leafs with multiple diseases with 90% accuracy. Gandhi et al., [25] propose an image-based classification system to detect plant diseases in apple leafs. The research mainly argues that since current statistics are diffused over many countries and none are unique to Asian nations, there is a need to create a local dataset that would be useful to Indian farmers. It employs Generative Adversarial Networks (GANs) to bolster the limited number of available native images. The results are then classified by a Convolutional Neural Network (CNN) model deployed in an exceedingly sensible phone app. The research presented by Turkogluet al. [26] presents a novel methodology, especially Multimodel LSTM-based Pre-prepared Convolution Neural Networks (MLP-CNNs) as a group more significant part pick classifier for the identification of plant illnesses and vermin. The arranged approach toward the beginning utilized the changed CNN models for profound component extraction. Then, at that point, SVM and LSTM classifiers were being used to include grouping. Finally, the yields of the CNN models were utilized individually and

linked to gauge the profound models' presentation. The examination results show that the connected models made higher outcomes contrasted with the individual models. Also, the outcomes acquired with LSTM classifier were higher than the SVM classifier's accomplishments. The absolute best exactness score of 99.2% was acquired with MLP-CNNs and LSTM classifier.

Techniques other than the use of deep learning have also been utilized to detect plant diseases and apple leaf diseases. Authors of [27] have used AlexNet, VGGNet, ResNet, LeNet & Sequential model to detect diseases in potato leaves. Their designed model was able to achieve an accuracy of 97%. A study by Adedoja et al [28] proposes the methodology and technique for differentiating a healthy and a diseases plant leaf. A total of 5 different plant leaves were selected for the purpose. This was cultivated during this paper utilizing deep learning upheld NASNet plan. The model was calibrated utilizing procedures such as differential learning rates, cyclic learning rates and test-time expansion (TTA) to support model exactness. The prepared model accomplished a precision of 93.82% when preparing for nine epochs. Another unique approach for the detection of diseases in apple leafs is the use of the Internet of Things. In [29], the authors presented an Advanced Segmented Dimension Extraction (ASDE) with the Internet of Things (IoT) patch for repetitive and ongoing diseases detection for leaf images. This paper accomplished the HIoT examination on principally based illness for ongoing leaf sicknesses especially bacterium, growths, small organic entities, and infections. The trial outcomes pass on that the asked model recognizes an identification execution shutting of exactness (82.2%), Recall (95), and F-Measure (86%) and furthermore Accuracy (98.55%) with a high-location size connection. Table 1 shows the summary of literature review.

Table 1: Summary of relevant state of the art

Sr #	Year	Reference	Database	Methodology	Classes	Accuracy
1	2020	[18]	Local Dataset	DenseNet and Xception	6	97.82%
2	2018	[20]	-	AlexNet to detect apple leaf diseases	4	97.2%
4	2020	[22]	AI-Challenger-Plant-Disease-Recognition	DenseNet-121 convolution network,	deep 6	92.29%
5	2020	[23]	-	LSA Network	3	89.4%
6	2021	[24]	Plant Village	pre-trained DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent	4	96.25%
7	2020	[27]	Plant Village	AlexNet, VGGNet, ResNet, LeNet & Sequential model	2	97%
8	2019	[28]	Plant Village	NASNet architecture for the coevolutionary neural networks	5	93.82%

3. Proposed methodology

This study presents the use of deep learning algorithms to detect various categories of diseases existing in apple plant leaves. Figure 4 shows a process flow for the proposed framework of this study.

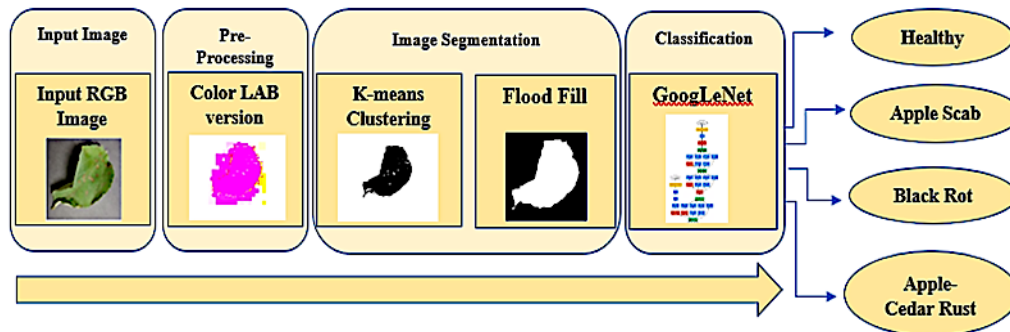


Figure 4: Process flow chart for the proposed framework.

The proposed methodology and techniques to serve the purpose of detective comprise three major steps: image pre-processing, image segmentation, and classification. The images in the available data set were in RGB, the first step was to convert these images into a process-able format using color LAB. The next was to create a mask to eliminate the background from the image, for that, k-means clustering and flood fill were performed and architecture and algorithm.

3.1. Database

This study uses the publicly available Kaggle dataset [30]. The data set consists of images from 14 plants, but this study focuses on the data set available for apple leaf diseases. For the apple data set, there are three diseases covered and images from healthy apple leaves. Therefore, this study utilizes all the available data for the apple-based plant. The entire dataset is split into an 80/20 training and validation set, with the directory structure preserved. Later on, a new directory containing 33 test images is generated for prediction. Figure 1, Figure 2, and Figure 3 represent all three categories of the diseases detected in this study.

3.2. RGB to LAB conversion

All of the images in the data are in RGB format. Because specific features of the image must be extracted, color LAB was utilized. Lab color space is three-dimensional with L representing brightness and a and b representing color dimensions. Working with the Lab, color space encompasses all colors in the spectrum and hues that are invisible to the human eye. The Lab color space is the most precise and device-agnostic method of expressing color. Due to its precision and mobility, it is ideal for various sectors, including printing, automotive, textiles, and plastics. While the Lab color space provides the most precise representation of color, it is not the most often utilized. The results of the RGB to LAB conversion are shown in Figure 5.



Figure 5: RGB to LAB conversion result.

3.3. Accuracies of models

Following image pre-processing, the next critical step is image segmentation. This step allows the system to extract out required sections of an image and reject all other sections. Several image segmentation is applicable but thus study opted for the use of K-means Clustering to serve the purpose. It is an unsupervised approach that is used to separate the region of interest from the surrounding area. It clusters or divides the input data based on the K-centroids into K clusters or portions. When there is unlabeled data, the algorithm is applied (i.e. data without defined categories or groups). The objective is to identify distinct groups based on the similarity between the data and the number of distinct groups indicated by K [31]. The following are the main stages in K-means clustering:

- Decide on the cluster count K.
- At random, determine the centroids of K points (not necessarily from your dataset).
- Assign each data point to the nearest centroid that results in the formation of K clusters.
- Calculate and reposition the cluster's new centroid.
- Reassign each data point to the new centroid that is closest to it. Proceed to step 4 if any reassignments occur; otherwise, the model is complete.

Figure 6 represents the results of K-means clustering implemented on the image obtained after RGB to LAB conversion.



Figure 6: Results obtained after K-means Clustering.

3.4. Flood fill

After K-means clustering, the next step in image segmentation is using the flood fill algorithm. The flood fill algorithm [32] will create the desired mask for the original RGB image. This operation helps remove the irrelevant objects in an image with the flood fill technique essentially does is that it finds a point or a seed inside the selected region. Finally, using four or eight linked methods, the desired color is filled. Numerous features of the flood fill algorithm are comparable to those of the boundary fill method. However, this technique is better suited to filling boundaries with various colors when a boundary is of many colors and the interior is to be filled with one color, this algorithm is used [33, 34]. Figure 7 exhibits the results of the flood fill algorithm.



Figure 7: Results of Flood Fill algorithm on the data set.

3.5. Mask refining

The last step for image segmentation is to extract out the section of the image that contains the required characteristics by implementing the mask on the complete original image. The mask obtained after the flood fill algorithm combined with the original RGB-based image gives a background-free image. As shown in figure 7, the image now only consists of the leaf and all the background containing unnecessary information has been eliminated. Keeping the background would have diverted the results thus, it was very crucial to extract out the leaf image only so that it becomes easier for the classifier to classify the data set based on the appearance of the leaf and distinguishing markers present on it. Figure 8 shows image obtained after mask refining image segmentation.



Figure 8: Final image obtained after mask refining and image segmentation.

3.6. Classification using GoogleNet

The last and most critical stage is classifying the data collection. The classification was accomplished using deep learning techniques. Existing deep learning models may attain high accuracy by increasing layers' numbers to boost ANN performance. These models often have a significant disadvantage in that the computational complexity rises exponentially as the layer depth increases. Google presented the inception structure, which is the best-performing model, during the 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC14). It is named GoogleNet[35]. The GoogleNet Architecture consists of 22 levels and 27 pooling layers. There are a total of nine inception modules stacked linearly. The inception modules' endpoints are linked to the layer of global average pooling [36]. Figure 9 exhibits GoogleNet Architecture.

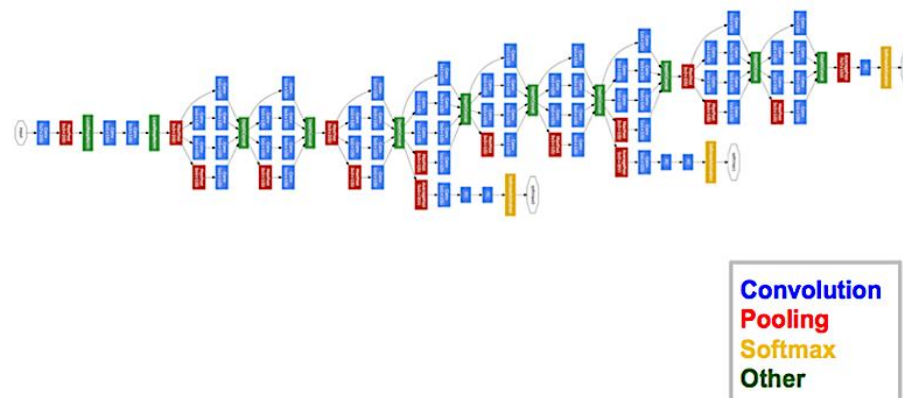


Figure 9: GoogleNet architecture

4. Results and discussion

In this research, a combination of RGB segmented images along with the GoogleNet network was used to classify the four classes of the apple that were used. The entire available data set can be divided into two sets (i) Training data (ii) Testing data. The purpose of this is to train the model with the available training data and then test it with another set of images different from the training data. For this purpose, 70% of data has been utilized as a training set and 30% as a testing set. Figure 10 represents the number of observations per class for the training data.

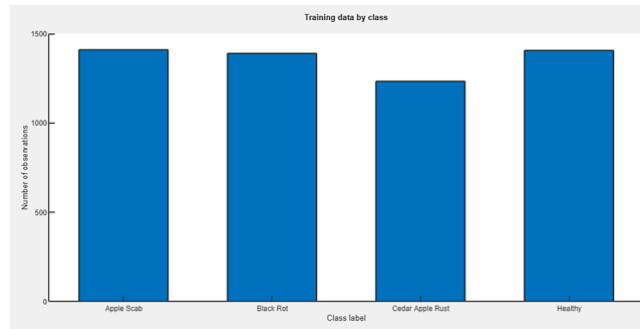


Figure 10: Data distribution for training data by class.

Firstly, the GoogleNet algorithm is trained for the training data of the leaf images using a learning rate of 0.001 for 12 epochs. The validation accuracy of 98.54% has been achieved with maximum of 336 iterations in 184 minutes 25 sec time. Figure 11 shows data distribution for validation data.

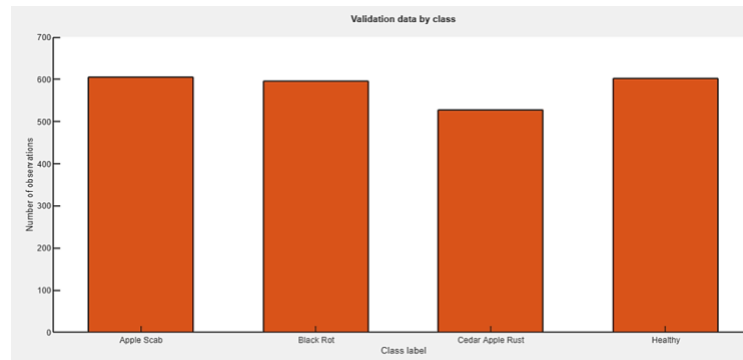


Figure 11: Data distribution for validation data by class.

Figure 12 shows the training of accuracy and error rate for the training data using GoogleNet. After that, the trained network is tested using test set of data and it classified the three classes with accuracy of 98.54%. Figure 13 shows the confusion matrix of validation data for four classes.

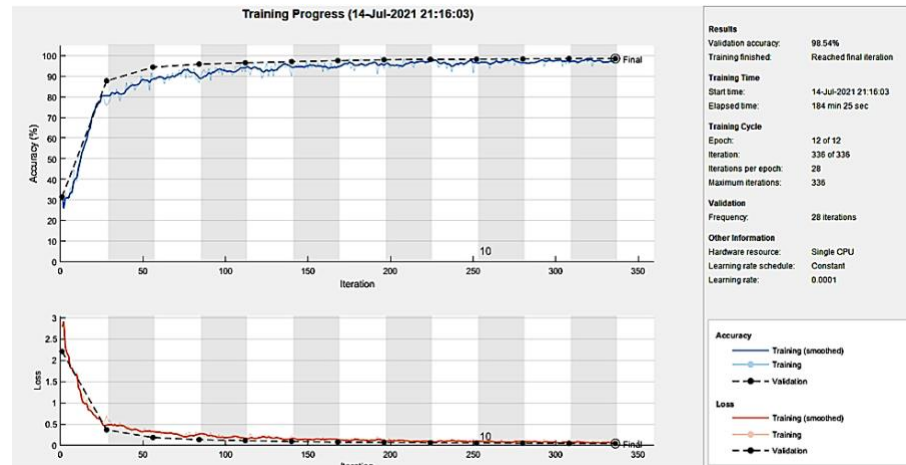


Figure 12. Image showing the Training progress for both categories of data

Confusion Matrix for GoogleNet								
True Class	Apple Scab	585	7	4	9	96.7%	3.3%	
	Black Rot	3	592	1		99.3%	0.7%	
	Cedar Apple Rust	3		524	1	99.2%	0.8%	
	Healthy	5	1		596	99.0%	1.0%	
						98.2%	98.7%	99.1%
					1.8%	1.3%	0.9%	1.7%
					Apple Scab	Black Rot	Cedar Apple Rust	Healthy
					Predicted Class			

Figure 13: Confusion matrix for the four classes after implementing GoogleNet classifier.

4.1. Evaluation parameters

In order to judge the credibility of any machine learning algorithm. In this study, the following evaluation parameters were used to evaluate the functional properties of the GoogleNet Algorithm:

1. Accuracy
2. Precision
3. Recall
4. F1-score

Before explaining these parameters separately, it is important to explain the following terminologies [37].

1. True positive (TP) —The number of samples expected to be disease-free.
2. False-positive (FP) —The number of samples with diseases expected to be negative for disease.
3. True negative (TN) —The number of samples in which disease is expected to be present is the number of samples in which illness is predicted to be present.
4. False negative (FN) —In fact, a small percentage of samples had the absence of illness predicted as the presence of disease.

Figure 14 represents the values obtained for evaluation parameters against every class.

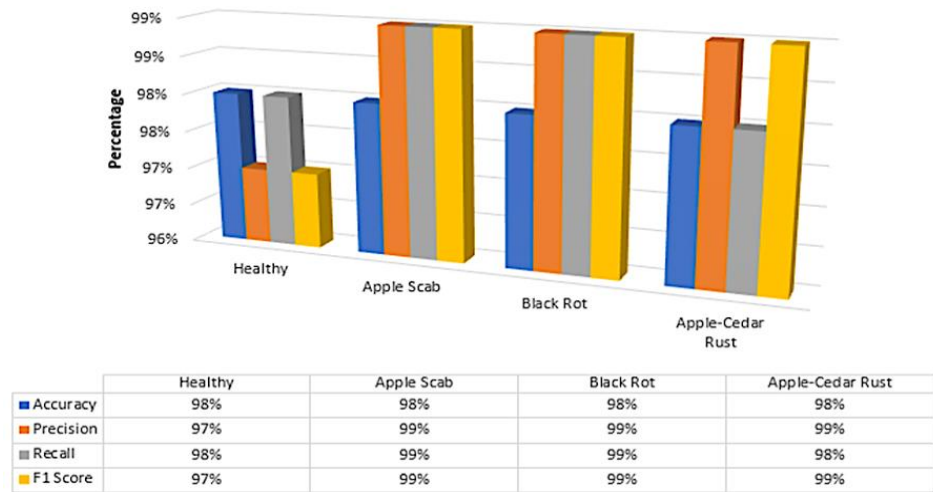


Figure 14: Evaluation parameters for the GoogleNet algorithm.

4.1.1. Accuracy

Accuracy is defined as the degree to which a value is approximated to its anticipated value. Thus, it refers to the outcome's quality and is not synonymous to precision [38].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

4.1.2. Precision

Precision is a qualitative concept that refers to the degree to which independent test findings acquired under specified circumstances coincide. Precision is independent of the actual value or recognized reference value and is determined solely by the distribution of random mistakes [38].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

4.1.3. Recall

Recall estimates the proportion of properly labeled positive cases, while precision quantifies the accuracy with which positive instances are predicted [39].

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

4.1.4. F1-score

The F1-score [40] is determined by both accuracy and recall. It is critical to grasp the distinction between precision and accuracy while doing statistical evaluations. F1 scores are useful when there is a requirement for balance between Precision and Recall, and they are most often employed when there is an uneven distribution of classes. Figure 14 depicts a graphical and tabular comparison of three classes' assessment parameters. Below is the formula for calculating the f1-score.

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.2. Comparison of proposed method

The results thus obtained are comparable to closest relevant researches reported in the literature. This study presents robust framework with the highest accuracy-based results. In addition, the techniques used in this study are relatively less complex, low computational cost and overall enhanced system efficiency. Table 2 presents comparison with the reported techniques in the literature.

Table 2: Comparison of proposed method in state of the art

Author	Year	Database	Methodology	Accuracy
Proposed Method	2025	Plant village 896 images	RGB Image, segmentation and GoogleNet	98.54%
XiaoFei Chao [18]	2020	Laboratories and Cultivation Fields	DenseNet and Xception for feature extraction and SVM for Classification	97.82%
Bin Liu [20]	2018	-	AlexNet to detect apple leaf diseases	97.62%
Muqadas Bin Tahir [21]	2021	Plant village	Inception V3 deep architecture via transfer learning	97%

5. Conclusion

For many years, in agriculture, plant diseases have posed a significant problem. Precision agriculture enables disease detection at an early stage and loss reduction by making the best choices possible based on DL findings. Recent advancements in deep learning have resulted in very accurate solutions, and the available technology allows for quick processing. This study suggests using GoogleNet architecture to identify four different apple leaf plant diseases using publicly accessible data. The RGB data set was processed and segmented to provide the image's necessary attributes for categorization. The categorization yielded a 98.54 percent accuracy, 98.50 percent precision, 98.50 percent recall, and 98.50 percent F1-score. New technologies in the form of Artificial Intelligence (AI) approaches give a reliable system on predicting the apples tree leaf diseases. Practitioners can also detect many pathogens at the same time with a very good precision and recall rate by using machine learning algorithms and deep neural networks., which may assist solve the asymmetry of professional apple tree leaf disease identification requirements against the shortage of expert resources in future. In addition, IoT-based real-time image acquisition and deep learning for on-field disease detection will be integrated in future work.

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Authors contributions. Conceptualization: SAN, KA, UI; methodology: SAN, KA, AAK, RK, SJ, UI, validation: RK, SJ, UI; writing—original draft preparation, SAN, KA, AAK; writing—review and editing: SAN, KA, SJ, UI; visualization: SAN, KA, AAK, RK, SJ, UI; supervision: SAN, KA, AAK; project administration: SJ, UI; funding: HA; The author had approved the final version.

AI usage declaration: AI Grammarly toll used solely for proofreading and improving linguistic quality

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