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Leaf Disease Identification through Transfer Learning: Unveiling the Potential of a Deep Neural Network Model

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Abstract: Grapes are one of the world's most crucial and widely consumed crops. The yield of grapes varies depending on the method of fertilization. There are so many factors that impact crop production and quality. One of the major elements affecting crop quality output is leaf disease. Therefore, it is necessary to diagnose and classify diseases at an early stage. This paper aims to assist farmers in accurately analyzing grape leaf disease and informing them about in early stages. Using image preprocessing, argumentation, and semantic segmentation, an image was partitioned into many tiles and then used in the subsequent stage of the proposed method. Histogram Equalization was used to improve the contrast of the images by spreading out the most frequent intensity values. Convolutional processing is carried out to extract meaningful data from the input. A 3x3 convolution filter is used to extract features from images in the dataset. Max pooling layers mitigate the exponential increase in network parameters caused by many convolution layers. The detection and classification operations of leaf diseases are completed by the fully connected layer. A dataset of 3297 images of grape leaves affected by four distinct diseases and healthy leaves is used to conduct the entire experiment. The proposed model yields 99.3% correct classification accuracy.

Keywords: Deep Neural Network, Transfer Learning Leaf Diseases, Classification, VGG, SquezeNet

1. INTRODUCTION

Wine, brandy, non-fermented beverages, and fresh or dried raisins are all made from grapes, which are among the most widely cultivated fruits in the world. Approximately 81.22% of India's total grape production comes from Maharashtra, which also happens to be a significant exporter of fresh grapes [1][2]. The grapes are processed into juice and dried to produce raisins[3]. Also, wine and brandy are prominent spirits made from fermented grapes [4]. However, the grape industry has suffered significant losses due to diseases in grape leaves. Black rot, a disease transmitted by pathogens, is one of many disorders that damage grapes. Hence, leaf disease is a primarily focused pest control and disease detection area in orchards [5]. Unfortunately, a human was only responsible for detecting leaf disease, which led to a decade of time, money, and productivity loss.

As a result, new diseases emerged in unknown places where the native ability to combat them was inadequate. Therefore, an automated disease detection system is necessary for earlier disease detection. Furthermore, earlier disease detection will save money and improve product quality [6][7][8][9]. Plant diseases, including black rot, Esca, and Leaf Blight, and insect pests like beetles, thrips, and wasps, can cause significant damage to grapevines [10][11]. Problems can be eliminated with the use of sprays[12]. Early detection and treatment of infections are essential to produce a healthy crop of grapes. Deep learning techniques and methods are the best ways to detect infectious objects.

When two tasks are similar enough, machine learning experts may use what they have learned in one to tackle the other. This technique is called transfer learning. Transfer learning can improve a model's performance in detecting objects. The application of deep learning aids in developing solutions to various problems. Responses to the problem based on technology have been implemented. However, the same issue is addressed in this study with a more effective method. The following points are considered in the proposed techniques.

Shift in light and spectrum reflectance are two concerns that the suggested technique aims to accomplish. It must address insufficient image contrast in the supplied image.Image contrast, grayscale conversion, and image scaling are all examples of pre-processing operations [13][14][15].

The next stage is to break an image down into its

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constituent parts. Using these items, researchers can identify contaminated areas in the image. The segmentation method has some drawbacks:

Color segmentation fails when lighting conditions change from those of the original images. Seed selection plays a role in regional segmentation. All the many types of texture take too long to manage.

The use of CNNs in disease detection on grape leaves is discussed in this research. This strategy addresses two significant issues: CNN models need training data for starters. While each disease emerges at a different time of year, there is limited time to collect images. A sample's classification begins with deciding which category it falls within. This process also polls this method's input variables. A specific input type is recognized a few times a year. The most challenging task is to increase classification accuracy. This data is then used to develop and verify new datasets that are different from the training set. Therefore, creating the best CNN structure to detect grape leaf diseases is problematic. Grape leaf disease detection using a better CNN algorithm is the paper's essential contribution and innovation, and it is summarized below:

A grape leaves disease data set must be constructed to generalize the model. The model's sturdiness is enhanced by acquiring images of damaged grape leaves with complex and consistent backgrounds. In addition, data augmentation techniques are used to build additional training images from the initial diseased grape leaf shots, which reduces the model's tendency to overfit. Using digital image processing technologies, it is also possible to mimic images of grape leaf diseases in various conditions. This method improves the generalization performance significantly [11]. Using a more advanced CNN model, diseases affecting grape leaves may be identified.

Furthermore, the deep convolution neural network model is proposed to investigate the features of sick grape leaf images. One benefit of deep separable convolution is that it helps keep the model's first two convolutional layers from being overfitted by reducing the number of parameters. Afterward, the Inception structure improves the extraction performance for multiscale illness areas. These four cascade Inception structures are then given a dense connection method to alleviate the disappearing gradient problem, promote feature propagation, and reuse.

This research focuses on the features of different transfer learning techniques for better disease classification. In the proposed algorithm, we have used semantic segmentation of images to enhance disease prediction. The suggested algorithm is contrasted with both contemporary and conventional methods. Experiments have shown that the proposed model has a greater accuracy rate (99.3%) than any classic model.

A. Contributions

- Partition images into multiple tiles using semantic segmentation to focus on relevant sections of the leaf.
- Enhance detection accuracy by targeting unhealthy portions of the images, improving disease segment extraction.
- Use pre-trained models (e.g., SqueezeNet, VGG16) for transfer learning by adding new layers (convolutional, fully connected, and softmax).
- Employ different configurations of dropout percentages, learning rates, and batch sizes to optimize model performance.
- Improve feature extraction and disease classification through consistent preprocessing and segmentation techniques.
- Leverage semantic segmentation for better feature extraction and localization of disease-affected areas.
- Retain high accuracy in classifying grape leaf diseases by retraining existing neural networks with enhanced image datasets.
- Demonstrate the effectiveness of preprocessing, segmentation, and transfer learning in accurately classifying grape leaf diseases.
- Provide a scalable and efficient approach to agricultural disease detection using advanced image processing and deep learning techniques.

The paper is organized as follows: Section 2 highlights similar work done in the same field. Section 3 describes the methodology used in the research. The analysis and discussion of the findings are explained in section 4. Section 5 concludes the paper.

2. RELATED WORK

Artificial intelligence has made significant strides in recent years because of developments in Deep Learning. This is very helpful for image-based classification and recognition. Applications include the detection and classification of plant leaf disease and object recognition. The advantages and power of deep learning techniques are foreshadowed in earlier research. For example, in recent years, the researchers used many deep-learning algorithms to recognize plant leaves. As a result, deep learning techniques in image-based problems and agricultural applications are becoming increasingly common [12], as given below:

Principal Component Analysis (PCA) and back-propagation networks are used to develop a method for detecting and classifying diseases of grape leaves. The leaf disease samples included in the study are grape downy mildew and grape powdery mildew, respectively. It can recognize diseases with 94.2% accuracy using this method.

Classification of grape leaf diseases has never been easier than it is, thanks to the technique used by the author in the thresholding technique. First, the image is pre-processed, and then the K-mean algorithm is used to segment the diseased area. By utilizing the hue features, this strategy produced better results in terms of accuracy [16][17].

Crop types and diseases were identified using deep-learning models by researchers in [13]. Various training models, datasets, and training-testing sets are used to obtain a 99.35% accuracy rate. A mobile application was created to assist farmers in identifying wheat leaf disease. Many different CNN models are employed in [14] to diagnose weed disease accurately; however, the highest score is reached using VGG Net. The authors use an open library of 87,848 images of plant leaves to identify leaf disease using five alternative CNN architectures [15]. When applied to the ImageNet database, SIFT encoding and pre-trained deep learning model achieves a 91% accuracy rate [18].

A novel neural network model is proposed in [19] based on VGG Net and inception to detect apple leaf disease that achieves 78.8 % accuracy. The authors used deep convolution neural networks to create a Refinement Filter Bank architecture to diagnose illnesses and pests of grape plants to avoid false positives and class imbalance. Primary diagnosis, secondary diagnosis, and integration made up the system's map, 13% higher than Faster R-CNN. Plant leaf disease can be diagnosed more quickly and accurately using an innovative deep-learning approach with CNNs. According to this research, plant disease detection has been dramatically improved using CNNs. Furthermore, grape leaf diseases can be detected in real-time, although there are no adequate CNN models for this purpose. Therefore, this work proposes a real-time grape leaf disease detector based on Faster R-CNN [20].

Various authors developed methods for detecting diseases on the leaves of orchid plants. Digital cameras capture images of orchid plant leaflets. The programmer employs a variety of tactics, including boundary segmentation, morphological processing, and a filtering strategy, to classify images into two disease categories: black leaf spot and solar burn [1]. Authors in [2], are primarily concerned with detecting disease in cotton and estimating its stage. The leaf can find most diseases and their symptoms. The authors in [3] provide an overview of the characterization and detection of diseases of cotton leaves. It is tough to pinpoint the exact type of plant leaf disease afflicting a leaf. Accurately identifying cotton leaf diseases can benefit from image processing and artificial intelligence (AI). This research was based on information from a computerized camera.

The Rainbow Connection and Google Net Inception's structure using CNNs seems powerful for finding apple leaf disease. A dataset of 26,377 images of damaged apple leaves may be used to identify these five most common ailments, according to the INAR-SSD model proposed in [21]. The Authors in [22] developed an SVM classifier with an identification rate of 90% for grape downy mildew disease and a recognition rate of 93.33% for grape powdery mildew disease. Many plant diseases are detected via image analysis because of advances in image processing technology.

In [23], authors employed a neural network to identify whether a potato leaf was healthy or sick. Results show that the proposed approach accurately identifies 92% of the disease. By recognizing pathological signs with extremely high visual variance, significant intraclass dissimilarity, and low interclass similarity deep CNNs have significantly done advanced plant disease classification[8]. On a dataset of 44 species, the CNN leaf image recognition accuracy was 99.7%. A limited number of large datasets were accessible. Using Google, the authors discovered cherry leaf powdery mildew disease 99.6% of the time. Transfer learning could help a deep learning algorithm recognize plant illnesses[24][25]. To identify fourteen distinct crop species and twenty-six distinct disease types, the authors used ImageNet-trained deep-learning models. Gathered 54,306 images of healthy and wounded plant leaves to verify the models' accuracy. In a hold-out test, they got 99.35% of the answers right[13].

CNN frameworks are widely used to classify agricultural illnesses. Many of these experiments have yet to improve classification accuracy, though. There will be no room for error if only one model is used. Therefore, teams generally combine multiple models to win a significant machine learning competition rather than relying solely on a single model as the Inception-ResNet-v2 [26] constructed by merging two huge deep CNNs, as its name implies. Integration is the most exact and practical solution for significantly different models [16]. As a result of our investigation, we've developed the United Model. With GoogLeNet and ResNet, the United Model combines two of the most prominent deep learning architectures. As a result, use transfer learning for better accuracy and reduced training time.

Deep learning has produced significant advances in computer vision since the advent of artificial intelligence. This method is one of the most common ways to diagnose and classify plant diseases. For example, grape disease can be identified using principal component analysis and a backpropagation network[16]. The prediction accuracy was as high as 94.29% for downy mildew and powdery mildew grape diseases in the dataset. It was possible to distinguish two different grape diseases using the method described by [27]. The technique acquired good training accuracy using anisotropic diffusion and K-means clustering with characteristic hue thresholding. The authors used two deep-learning models to detect 14 crop species and 26 illnesses (AlexNet and GoogLeNet). The study showed that 99.35% of the training-testing sets were accurate after looking at two other training processes and three distinct dataset types [13]. To help farmers diagnose disease, the Authors created a smartphone application. After applying two other frameworks for the task, the mean recognition accuracy on WDD 2017 was 97% and 95%, respectively. The prior accuracy of 93.27% and 73.000% of the conventional CNN framework has been improved by this model. Weed detection in Bermudagrass lawns using deep CNN models has been previously reported. This study indicated that the VGG Net model outperformed the Detect Net model when detecting three of the most common turfgrass diseases. Considering these findings, a DCNN-based weed management system was presented. The authors reached the best results by applying five fundamental CNN architectures to 87,848 images spanning 25 plant species from 58 different classes, with an accuracy of 99.53% (2018a). Real-time disease detection during plant growth is more important than a deep CNN classification for preventing diseases from spreading [15].

Deep learning algorithms could be used to detect plant leaf disease reliably, which an increasing number of researchers are examining. The authors used signs of grape leaf Esca in the summer to identify and detect the disease. An image classification accuracy of 91% was achieved on ImageNet using the MobileNet network, trained on the ImageNet dataset. It uses Classification and detection networks to reach the best Esca AP score (RetinaNet) [18]. The authors created the INAR-SSD network architecture using VGG Net and Inception building to identify apple leaf disease and achieved a 78.8% mAP success rate. It used Refinement filter banks to cope with false positives, class imbalance in disease and pest detection in grape plants, and a deep convolution neural network. With Faster R-CNN—which includes a main diagnostic unit, a secondary diagnostic unit, and an integration unit—the mAP is 13% more than the best result. A new deep learning approach based on CNNs has been developed to identify plant leaf disease accurately. Many studies have found that CNNs have helped detect and identify plant diseases [28]. Various methodologies and models are offered; however, more people produce adequate results. Therefore, a Faster R-CNN-based detector for grape leaf illnesses has been proposed as a real-time outcome of this study.

Various techniques and methods are proposed in the state of the art [29][30], but this paper is concerned with a high-performance deep learning model to detect grapes leaf disease. Prior work in grape leaf disease classification has leveraged traditional image processing techniques. While these methods are straightforward and computationally efficient, they often struggle with accurately segmenting and classifying diseases due to limited feature extraction capabilities and sensitivity to noise and variations in image quality. Our approach addresses these limitations by incorporating advanced image preprocessing techniques, such as histogram equalization and Gaussian blur, to enhance image quality and feature visibility. We also utilize semantic segmentation to focus on relevant image regions, improving disease detection accuracy. By retraining pre-trained neural networks with standardized and enhanced images, our method benefits from deep learning's superior feature extraction capabilities. This approach not only mitigates the weaknesses of prior work but also demonstrates improved accuracy and robustness in classifying grape leaf diseases. The performance of these neural network typologies was evaluated using a range of measures, including F1-score, recall and precision, and the model's inference time. This paper discusses various evaluation measures and unique deep neural network models.

3. MATERIAL AND METHODS

This section provides results using modern methodologies, models, and datasets.

A. Dataset

In the dataset, diseases are separated into groups. Fig. 1 shows sample images from the dataset discovering several pathogens on grape leaves. The complete dataset is split 80:20 between training, and testing data.

1) Dataset Description

The dataset consists of 3297 images split into four groups representing different diseases and their symptoms. Table I provides a comprehensive explanation of the dataset.

B. Image Processing and Argumentation

Using image preprocessing, argumentation, and semantic segmentation, an image was partitioned into many tiles and then used in the subsequent stage of the proposed method. After segmentation, images are used to retrain already trained models, like SqueezeNet, VGG16, etc. The many convolution layers in each pre-trained neural network are followed by several ReLu layers. The same output is subsequently fed into the deep neural network's upgraded, fully connected layer to initiate treatment. The proposed building's layout is shown in Fig. 2.

The images were preprocessed to increase the quality of the dataset used to train a deep learning network. As a first step, we have standardized image size by scaling each image to 256×256 pixels using the Python Imaging Library and a Python script. Pixel values were normalized to a range of [0, 1] by dividing by 255. This step helps in accelerating the convergence of the neural network by standardizing the input values. Histogram Equalization was used to improve the contrast of the images by spreading out the most frequent intensity values. It enhances the visibility of features in low-contrast areas of the images. Gaussian blur was applied to reduce noise and detail in the images. Pixel values were clipped to a specific range to handle outliers and ensure that the input data remained within the desired range for the model. The next step classifies the grapes leaves images into groups and then specifies them for each disease.

Utilizing semantic segmentation enhanced the detection accuracy in this instance. The first algorithm describes

Figure 1. Sample of diseased or pathogenic leaves

TABLE I. Dataset Description

Grapes Leaf Disease type	Count of images
"Grape___Black_rot"	843
"Grape___Esca_(Black_Measles)"	852
"Grape___Leaf_blight_(Isariopsis_Leaf_Spot)"	762
"Grape___healthy"	840
Total Images	3297

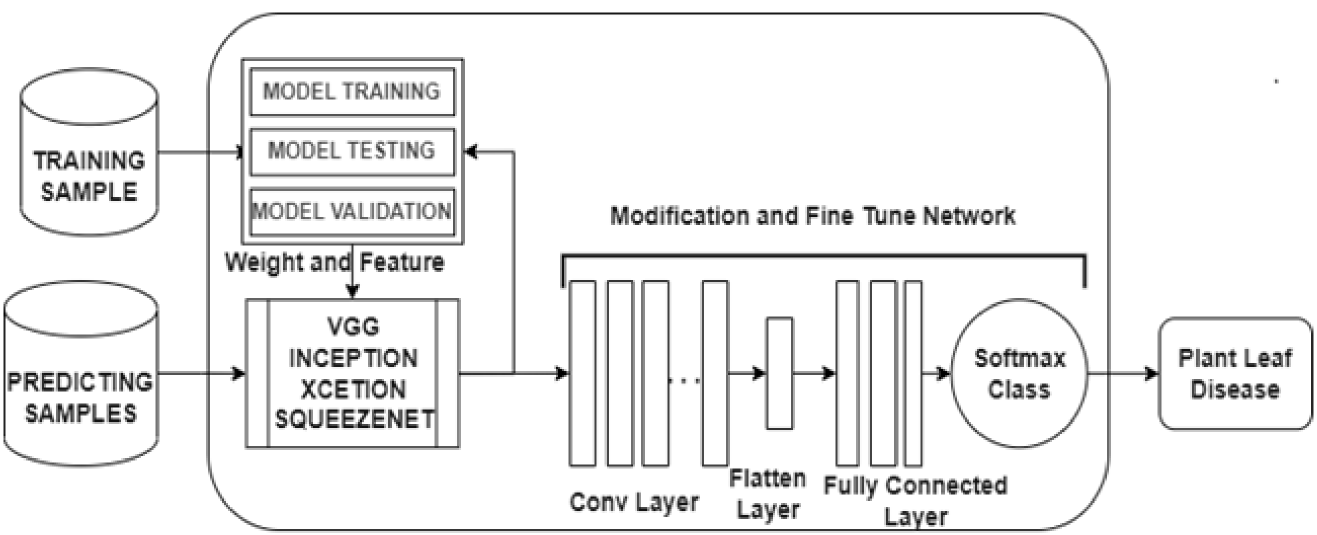


Figure 2. Transfer Learning with DNN

segmentation as splitting the entire image into a predetermined number of tiles. The segmented tiles' assistance effectively extracted the leaf image's necessary portion. In both instances, feature extraction was performed using the same model training and evaluation data set. This technique was also intended to focus on the desired location inside an image, thereby reducing the unhealthy portion of the image and increasing the detection rate. The images were then fed into a neural network that had already been trained.

The following is an algorithm for the detection of disease that has been proposed:

Algorithm 1 Semantic Masking

Input: Grapes Images Dataset
Output: Masking Grapes Image
Generate the masked image ($Mask_V$) from Input Image (In_p)
With In_p and $Mask_V$ to get $Mask_f$
Segment image $Mask_f$ into $Image_t$ (square tiles)
for $Image_t$ in $Mask_f$ **do**
    Categorize $Image_t$ into $Mask_f$ Grape diseases
    if $Image_t$ is a disease **then**
        Identify the Disease
    end if
end for

With the help of previously unexplored datasets, the validity of a machine learning model can be tested by cross-validation (also known as k-fold). After a small sample of data was analyzed, the model's performance was evaluated on all available data. Because of the new information, they could make predictions about data that had not been included in the training procedure [15]. Our study used four pre-trained Convolutional Neural Networks on the ImageNet dataset.

C. Training Phase

This process involved numerous iterations in rationalizing the model's internal weights. The information was used to train a model that could then classify leaf diseases.

To train a model, one can either start from scratch or use transfer learning. Pre-trained on a large set of images (such as ImageNet's 1.2 million images in 1,000 classifications), a network was then used and tweaked for a new purpose. Multiple transfer learning procedures are available to deal with such problems.

A deep learning technique known as transfer learning involves retraining a network on a different dataset. The transfer learning process, seen in Fig. 3, entails adding new layers to the top of a prior-trained network (InceptioNet, SqueezeNet, VGGNet,). These layers are convolutional, fully connected, and multi-class softmax classification layers. Each model was tested using a range of dropout percentages, learning rates, and batch sizes. Sections to follow will go into greater depth on the instructional and structural approaches.

TABLE II. Deep Neural Network Description.

Hyper Parameter	Description
No. of Con. Layer	15
No. of Max Pooling Layer	15
Dropout rate	0.25, 0.5
Network Weight Assigned	Uniform
Activation Function	Relu
Learning rates	0.001, 0.01,0.1
Epoch	50,100
Batch Sizes	32, 50, 60, 100

This cutting-edge method was created by adapting transfer learning models for agriculture, yielding useful insights. Transfer learning can be advantageous when training a model without access to previous weights. A new model was supposed to be trained with features derived from a huge dataset, as shown in Fig. 3, and then fine-tuned with specific data.

Essential things that must be considered while applying transfer learning methodologies are domains and tasks. Our objective is to classify leaf diseases; the relevant domain is image classification. As mentioned before, re-training would require several adjustments, extra data, and more time. Once these are known, training a Deep Neural Network (DNN) that is well-suited to the job is a breeze. This is the goal of transfer learning, and it is successfully achieved. The entire process flow is depicted in Fig. 4, while Table II outlines the enhanced architectural qualities utilized in the design.

The following is a description of the deep neural networks utilized by TL:

1) Convolutional Layer

The convolutional layer is a vital part of any deep neural network, as it extracts both low-level and high-level features from the input image. Convolutional processing is carried out by this layer to extract meaningful data from the input. The network's early layers learn to categorize data concretely based on the input, while the later layers learn to classify the data abstractedly based on the output. In this study, we use a 3x3 convolution filter to extract features from images in the dataset. The first convolution layer consists of 33 filters with a kernel size of 5x5 and a ReLU activation function. As a result of this capability, more intricate traits can be learned from data. Therefore, the problem of vanishing gradients no longer exists. Convolution operation * between two real-valued functions (say, Z

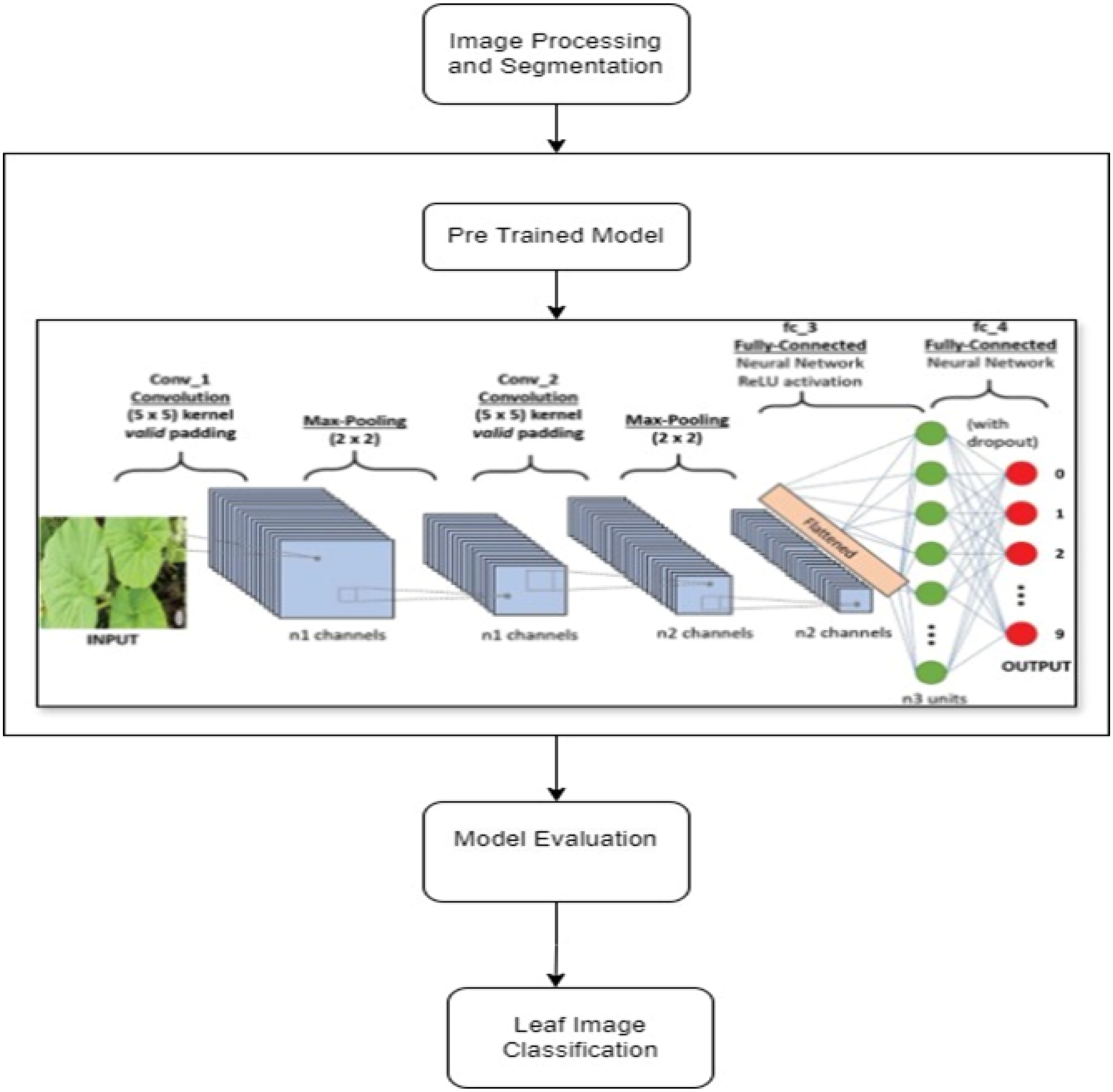


Figure 3. Proposed Model

and Y) always produces the same outcome, as shown by the equation 1. An abundance of input attributes is associated with each map feature. For instance, the input x of the ith convolution layer can be described by the following equations:

$$h_{i_c} = F(Z_i * Y) \tag{1}$$

This formula is composed of three parts: the activation function F, the convolution Y, and the convolution kernel Z. For a kernel with a single layer of convolutions, we have $Z = \{Z_{i_1}, Z_{i_2}, \ldots, Z_{i_k}\}$.

Here k is the number of convolutions.

A*A*B is the is the weight matrix of kernel Z_{ik}.

Where:

A represents the window, while B represents the number

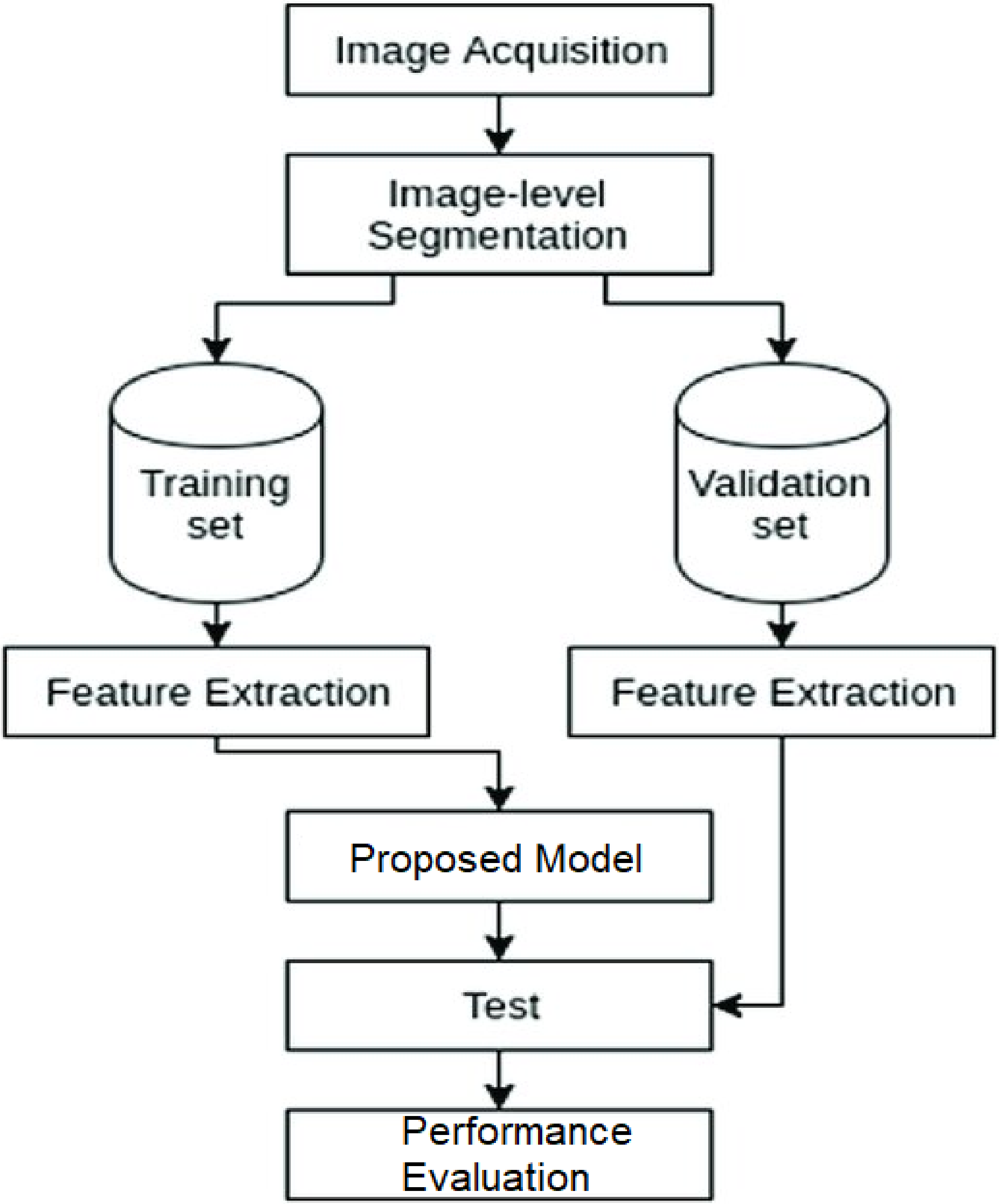


Figure 4. Methodology Flow Graph

of channels.

2) Pooling Layer

Using max pooling layers can mitigate the exponential increase in network parameters caused by many convolution layers. We can use pooling layers to decrease the massive feature map produced by the convolution layer. The layer's job is to find promising features in the feature map and pull them out. We use the feature map's absolute maximum when calculating this layer's value. As a bonus, the pooling layer can help make translations more robust. To begin, the maximum pooling in Region R is equivalent to the average pooling in other regions.

$$M_p = \max_{i \in R_j}(x_i) \tag{2}$$

$$A_p : \left\{ \frac{x_i}{\sum_{i \in R_j} x_i} \right\} \tag{3}$$

Two-stage kernel sizes and pooling are necessary. The highest values are depicted on the map in the upper left corner, while the middle represents the average value obtained by adding all four values together.

Prior-trained models generate a fixed feature vector by running image segments through a convolution and pooling layer. Color, texture, and form are the usual characteristics mined by computers. After processing an image using previously trained models, a feature vector will be generated. This technique is applied to the diagnosis of plant diseases. To maximize characteristics for disease identification in leaves, a fully linked layer uses the feature vector.

3) Fully Connected Layer

The detection and classification operations are completed by the FC layer, which follows the max pooling layer. The second-to-last layer is masked using probability dropout to prevent overfitting. The final classification is depicted as follows:

$$\hat{t} = \mu \left(x_I \left(h_s \otimes I \right) + w_I \right) \tag{4}$$

Hence, DNN Qc, which can mean bacterial blight, leaf blast, or brown spot, is the categorized result.

The primary focus of the model is to unearth hidden information. Overfitting is a serious problem in neural networks. However, the overfitting problem can be mitigated by utilizing regularization techniques to overcome insufficient data or a larger dataset than the network can handle.

D. Evaluation Phase

Evaluation of proposed models is done using the following metrics:

1) Training Loss

The training loss is a measure of how well the model is performing on the training data. It is typically calculated as the average of the loss function values across all training samples.

$$\text{Training Loss} = \frac{1}{N} \sum L(y_{\text{true}}, y_{\text{pred}}) \tag{5}$$

where $L(y_{\text{true}}, y_{\text{pred}})$ is the loss function (e.g., cross-entropy loss, mean squared error) evaluated for the true target y_{true} and the model's prediction y_{pred} for each training sample.

2) Validation Loss

The validation loss is a measure of how well the model is performing on a separate validation dataset, which is not used for training. This provides an estimate of the model's performance on unseen data.

$$\text{Validation Loss} = \frac{1}{M} \sum L(y_{\text{true}}, y_{\text{pred}}) \tag{6}$$

where M is the number of validation samples.

3) Training Accuracy

The training accuracy is a measure of how well the model is classifying the training samples correctly. It is typically calculated as the percentage of correctly classified samples out of the total number of training samples.

$$\text{Training Accuracy} = \frac{\text{Number of correctly classified training samples}}{\text{Total number of training samples}} \tag{7}$$

$$\text{Validation Accuracy} = \frac{\text{Number of correctly classified validation samples}}{\text{Total number of validation samples}} \tag{8}$$

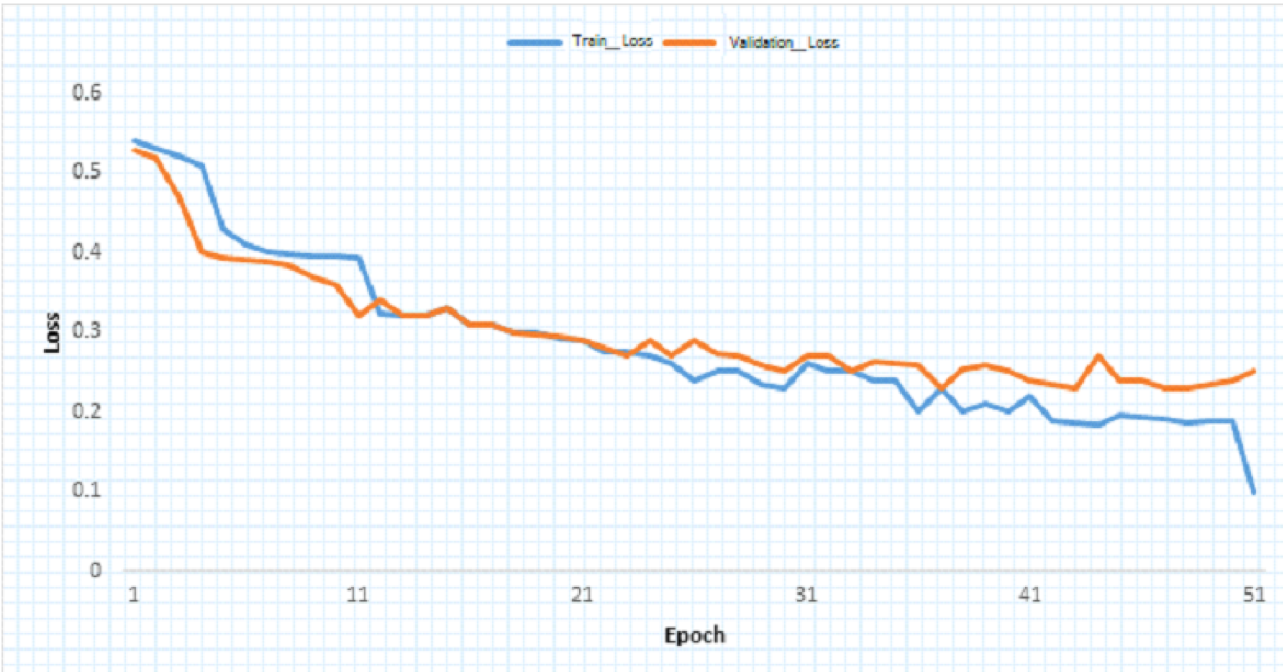
4. RESULT ANALYSIS AND DISCUSSION

1) Determine the Number of Epochs

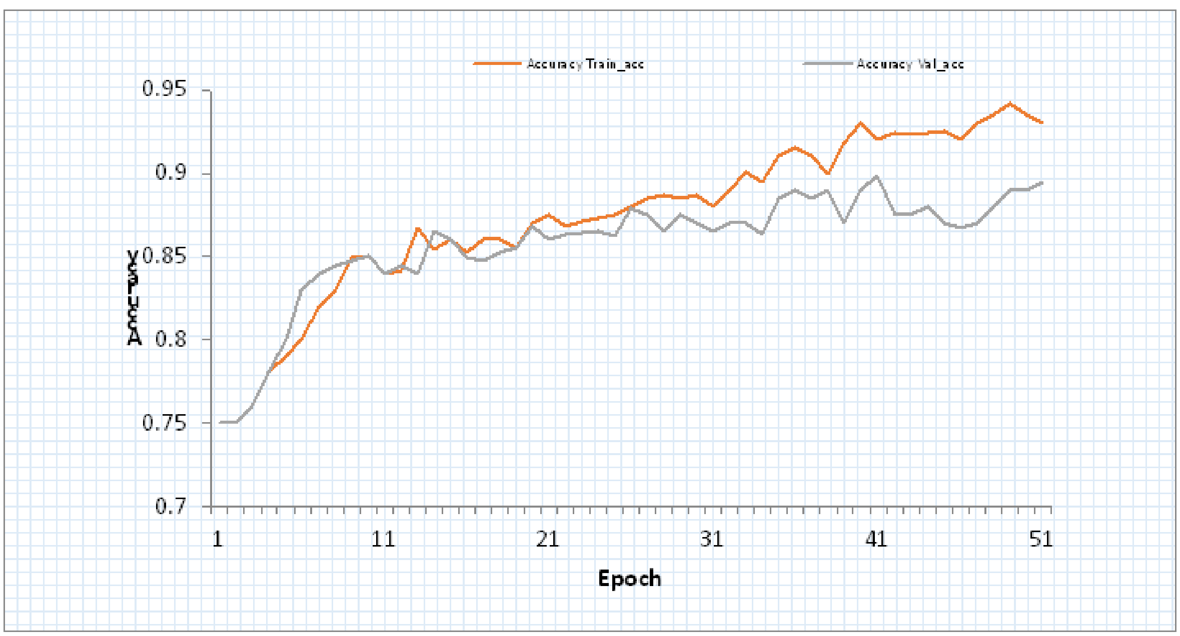
Quantity epochs' potential impact on system performance is the focus of current testing efforts. The tests use epoch 50 and 100 for comparison and rates of leanings are 0.0001. In Fig. 5, the test is shown.

With 50 epochs of training and a learning rate of 0.0001, as shown in Fig. 5, the accuracy rate is 98.2%.

According to Fig. 6, a precision rate of 98.32% is attained with the training stage 100 epoch and a learning rate of 0.0001. Based on the testing method, it may be extrapolated that more epochs are more dependable. However, the higher the epoch frequency, the longer it takes to finish the training.

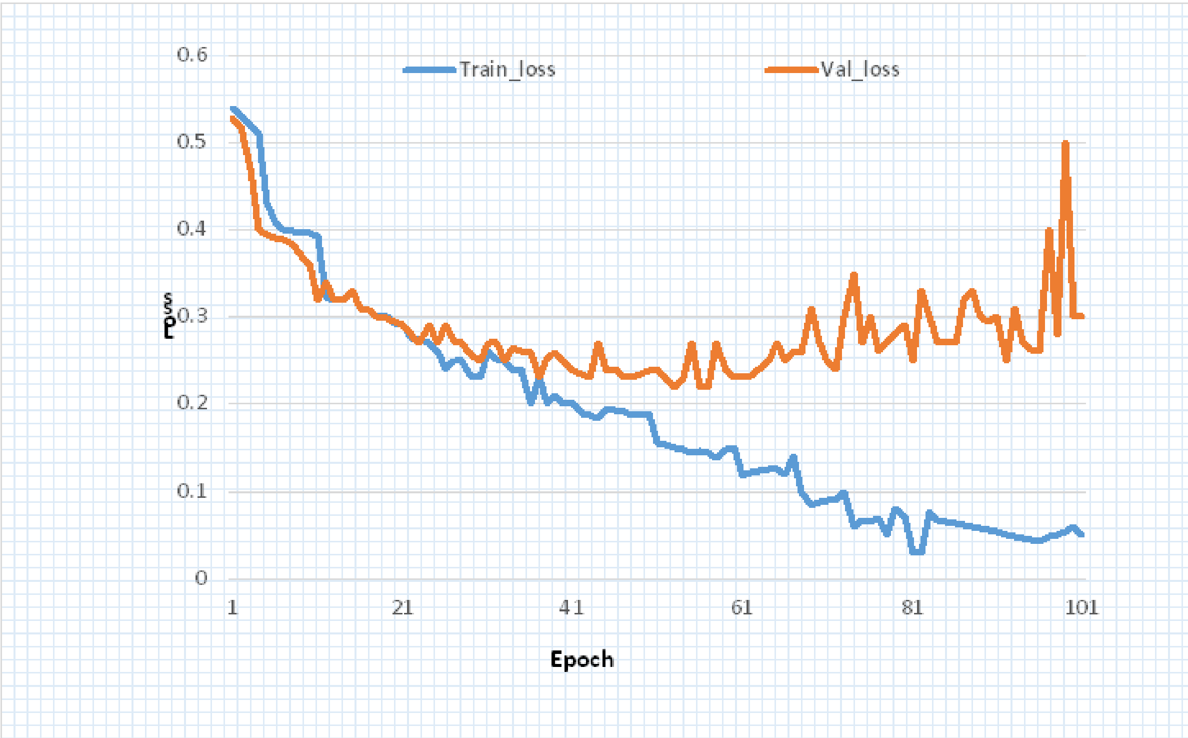


(a) Epoch wise loss

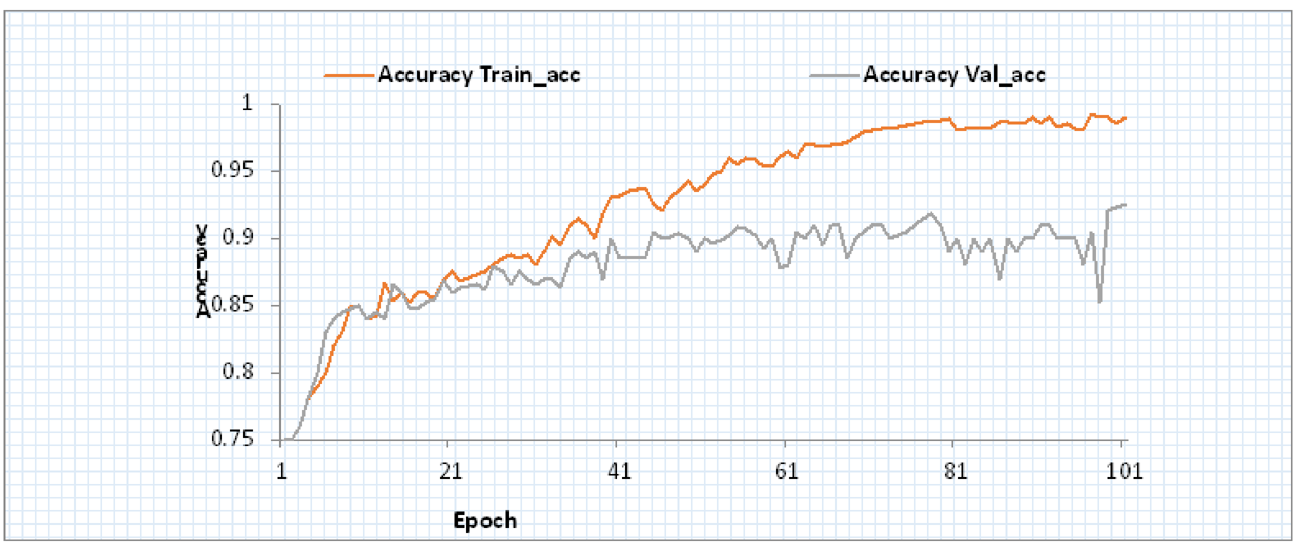


(b) Epoch wise accuracy

Figure 5. Training accuracy and loss rate at 0.0001 with epoch 50



(a) Epoch wise loss



(a) Epoch wise accuracy

Figure 6. Learning rate of 0.0001 with training accuracy and loss at epoch 100

2) Determine the Rate of Learning

An evaluation was done on how much learning affects machine efficiency. One of the training parameters is the learning rate for estimating the weight correction value. In this test, 50 and 100 epochs are employed instead of 0.001 and 0.01. Fig. 7 shows the outcomes of the tests.

Based on Fig. 7, the test shows a precision rate of 98.37% in epoch 50 and a learning rate of 0.001.

Based on Fig. 8, the test shows a precision rate of 98.61% in epoch 100 and a learning rate of 0.001.

Based on Fig. 9, the test shows a precision rate of 99.1% in epoch 50 and a rate of learning of 0.01.

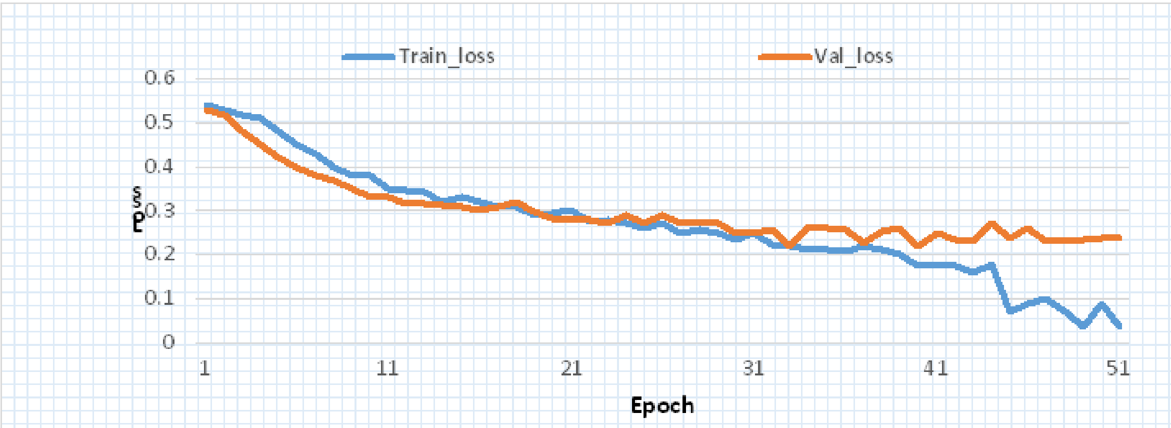
In the 100-epoch training stage, a precision rate of 99.31% and a learning rate of 0.01 are achieved (see Fig. 10). A higher pace of learning yielded a higher percentage of accurate data, as seen in the testing phase.

The result demonstrates that the ranking of accuracy is based on the metrics of learning rate and epoch. A better outcome can be expected from using a more trustworthy epoch value. Cross-validation is a metric to assess the quality of a model's predictions. The models' efficacy was the target of this investigation. Each subset of the data is tested many times after being separated into k groups. The kth subset is used for training in each cycle, whereas the k-1st subset is evaluated afterwards. Five to twenty number of cross-validation is used for model testing. The term "folds" refers to the process of partitioning the available data into multiple subsets for the purpose of training and evaluating a model. Table III displays the results of model testing with 5, 10, and 20 cross validation. The five models vary in accuracy by around 5% throughout all iterations. Fig. 11 shows that the proposed model consistently outperforms the alternatives across many iterations, with an overall accuracy of 99.3%. Mobile Net's 96.8% accuracy is the lowest of the five models.

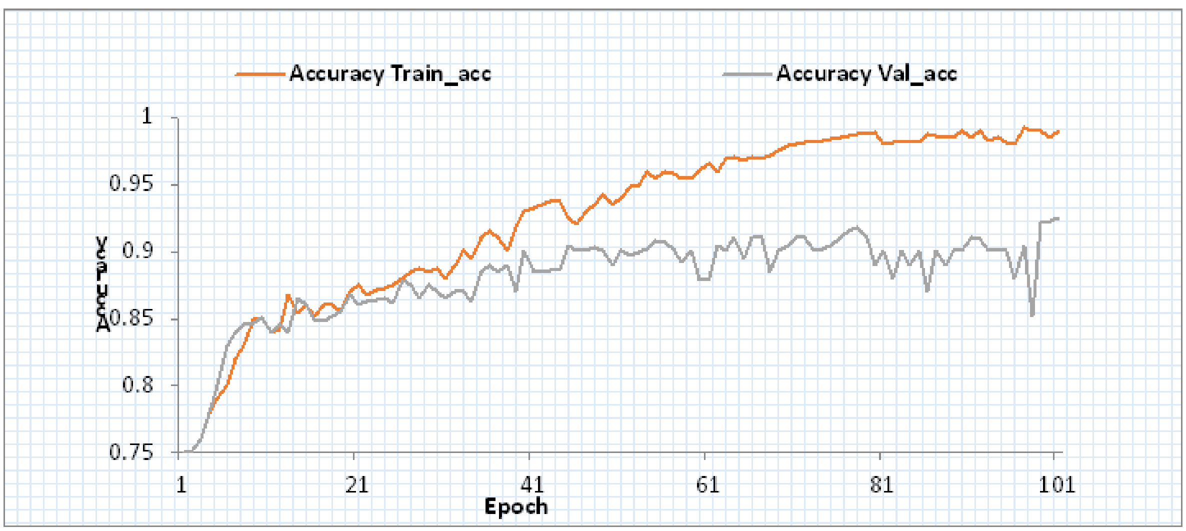
Diseases were discovered and predicted using a collection of 3,297 grape leaf images. We created and used five unique deep-learning models as classifiers from the outset. Predictions and evaluations were made using the models of deep learning programmes. Table III summarises the results of a 20-fold cross-validation test for recall, accuracy, and precision for all deep learning application models. A precise AUC (Area under the Curve) of 1 would indicate that a predictive or classifying test is 100% accurate. The outcomes indicate that AUC optimization yielded a value of 0.9997%. Thus, CNN's research plan can diagnose and categorize grape leaf diseases. Sample collection took time and labour, making using lab data to predict future diseases hard. Nonetheless, Inception V3 had the highest recall, f1-score, and accuracy for predicting leaves (all 99.3%). Considering Inception V3's suitability for a high-level image processing function, this is expected. In artificial intelligence, the k-fold cross-validation approach is frequently utilized for disease classification and identification studies, even with very small and medium data sets. Neural Network had the highest AUC (99.97%), accuracy (99.30%), f1-score (99.3%), precision (99.3%), and recall (99.3%) when predicting leaves using 20-fold cross-validation. There was a train-test split evaluation of each deep learning model. The linear distribution of the suggested model and the confusion matrix are displayed in Table IV (Number of instances).

The percentage breakdown of Table IV's confusion matrix is shown in Fig.11. Grape black rot had a TP rate of 98.6%, Grape esca black measles at 98.9%, Grape leaf blight at 100%, and 99.8% overall (Grape healthy). A confusion matrix evaluates many metrics, including accuracy, precision, sensitivity, error rate, and specificity. The results are expressed as a percentage: Fig. 12 shows the suggested model's ROC (receiver operating characteristic curve).

The suggested model outperforms the other machine learning models in terms of F1 score, Recall, and, Precision as shown in Fig. 13.

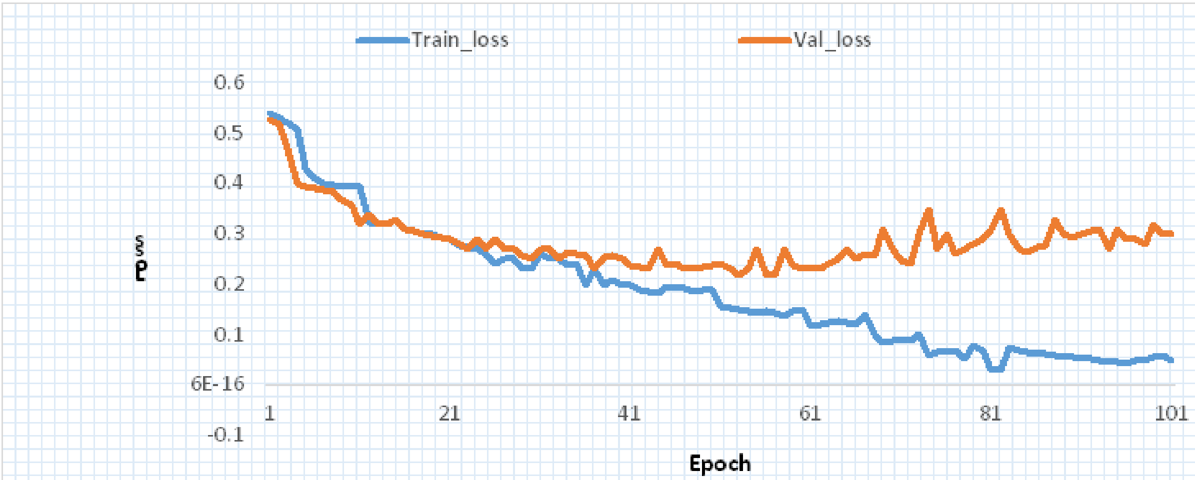


(a) Epoch wise loss

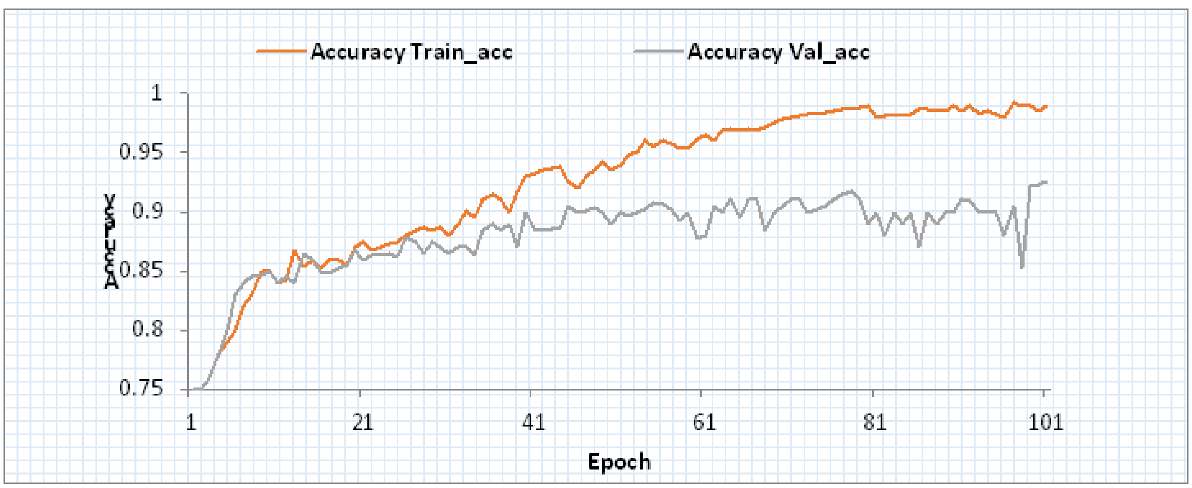


(b) Epoch wise accuracy

Figure 7. Accuracy of training at epoch 50 and learning rate 0.001

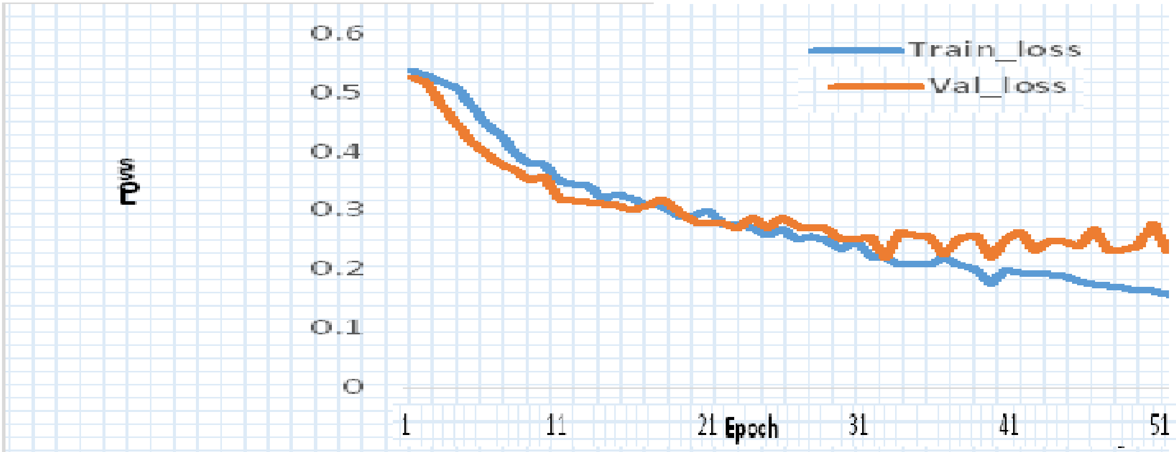


(a) Epoch wise loss

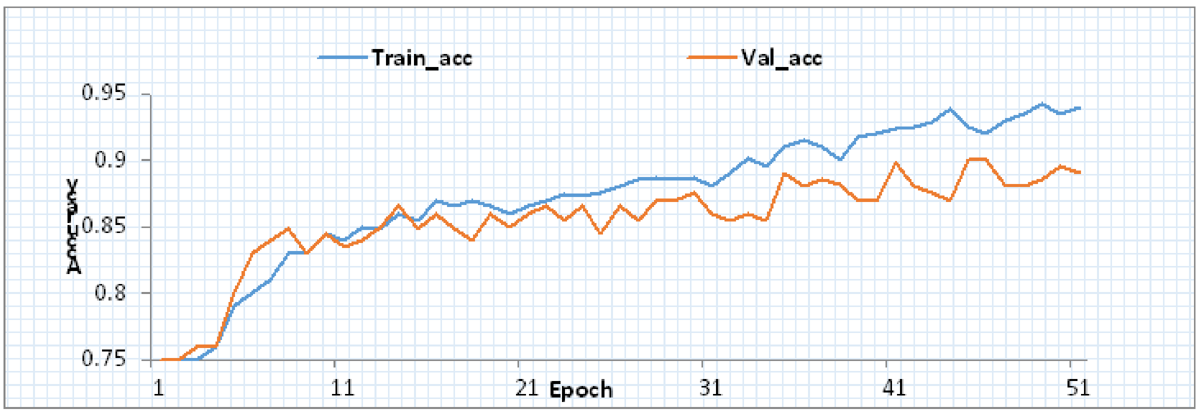


(b) Epoch wise accuracy

Figure 8. Learning rate of 0.001 with training accuracy and loss at epoch 100



(a) Epoch wise loss



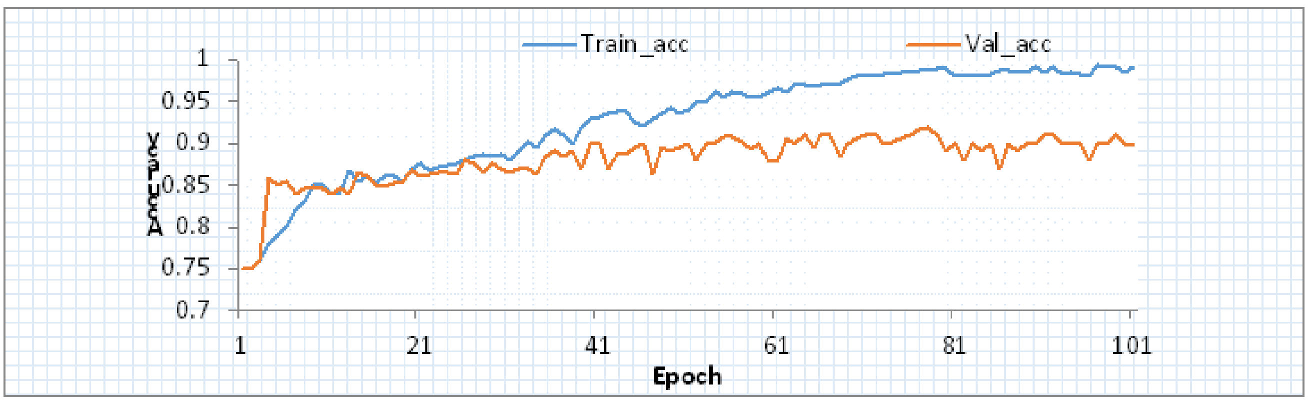
(b) Epoch wise accuracy

Figure 9. Learning rate of 0.01 with training accuracy and loss at epoch 50

TABLE III. Comparison of different models

Dataset used	Model	Number of folds	Accuracy	F1 score	Precision	Recall
	Proposed Model		0.988	0.958	0.981	0.979
	VGG19		0.981	0.981	0.981	0.981
	VGG16	5	0.982	0.980	0.979	0.968
	SqueezeNet		0.986	0.971	0.965	0.958
	MobileNet		0.9574	0.9578	0.9588	0.950
	Proposed Model		0.991	0.908	0.981	0.962
	VGG19		0.887	0.883	0.859	0.862
Grapes Leaves	VGG16	10	0.983	0.981	0.978	0.974
	SqueezeNet		0.987	0.980	0.968	0.979
	MobileNet		0.951	0.955	0.958	0.943
	Proposed Model		0.993	0.992	0.989	0.993
	VGG19		0.983	0.979	0.958	0.984
	VGG16	20	0.984	0.977	0.984	0.980
	SqueezeNet		0.987	0.947	0.967	0.977
	MobileNet		0.968	0.968	0.9687	0.968

(a) Epoch wise loss



(b) Epoch wise accuracy

Figure 10. Learning rate of 0.01 with training accuracy and loss at epoch 100

TABLE IV. Matrix of confusion for the suggested model

	Grape Black rot	**Grape Esca (Black Measles)**	**Grape Leaf blight (Isariopsis Leaf Spot)**	**Grape healthy**	∑
Grape Black rot	98.6 %	0.9 %	0.0 %	0.1 %	843
Grape Esca (Black Measles)	1.3 %	98.9 %	0.0 %	0.0 %	852
Grape Leaf blight (Isariopsis Leaf Spot)	0.0 %	0.0 %	100.0 %	0.1 %	762
Grape healthy	0.1 %	0.1 %	0.0 %	99.8 %	840
∑	846	850	761	840	3297

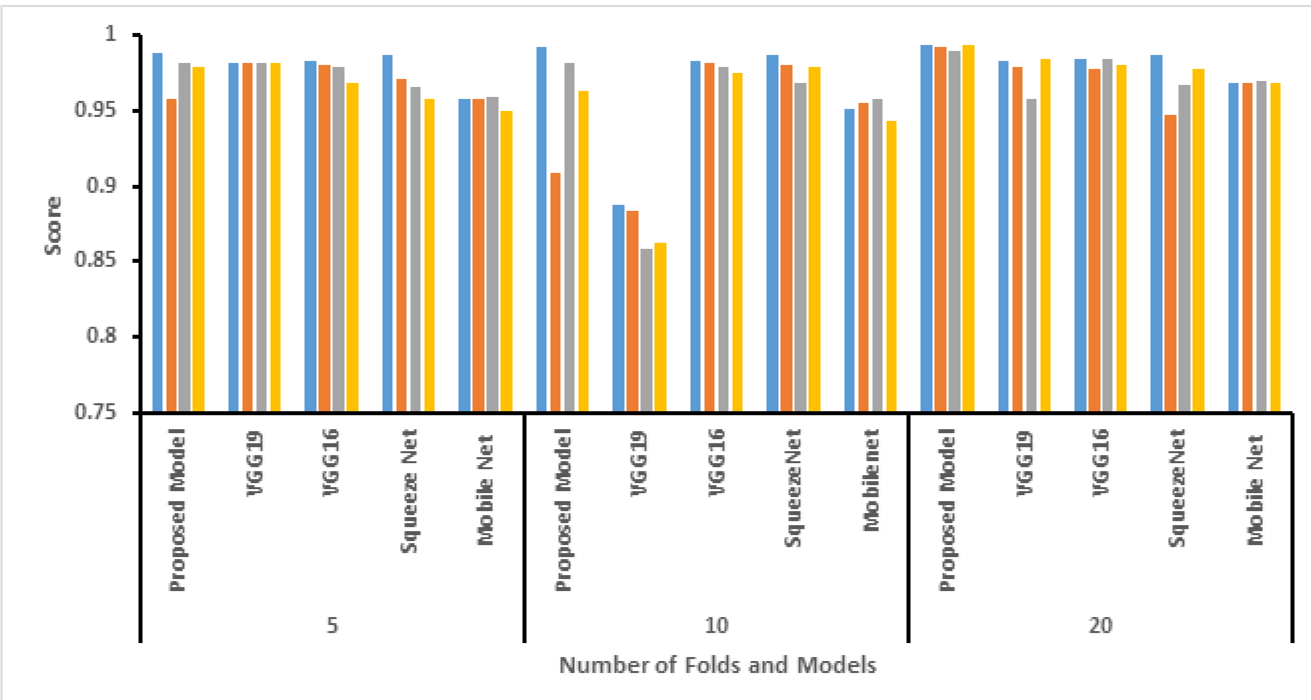


Figure 11. Performance Comparison of different deep learning models with the proposed model

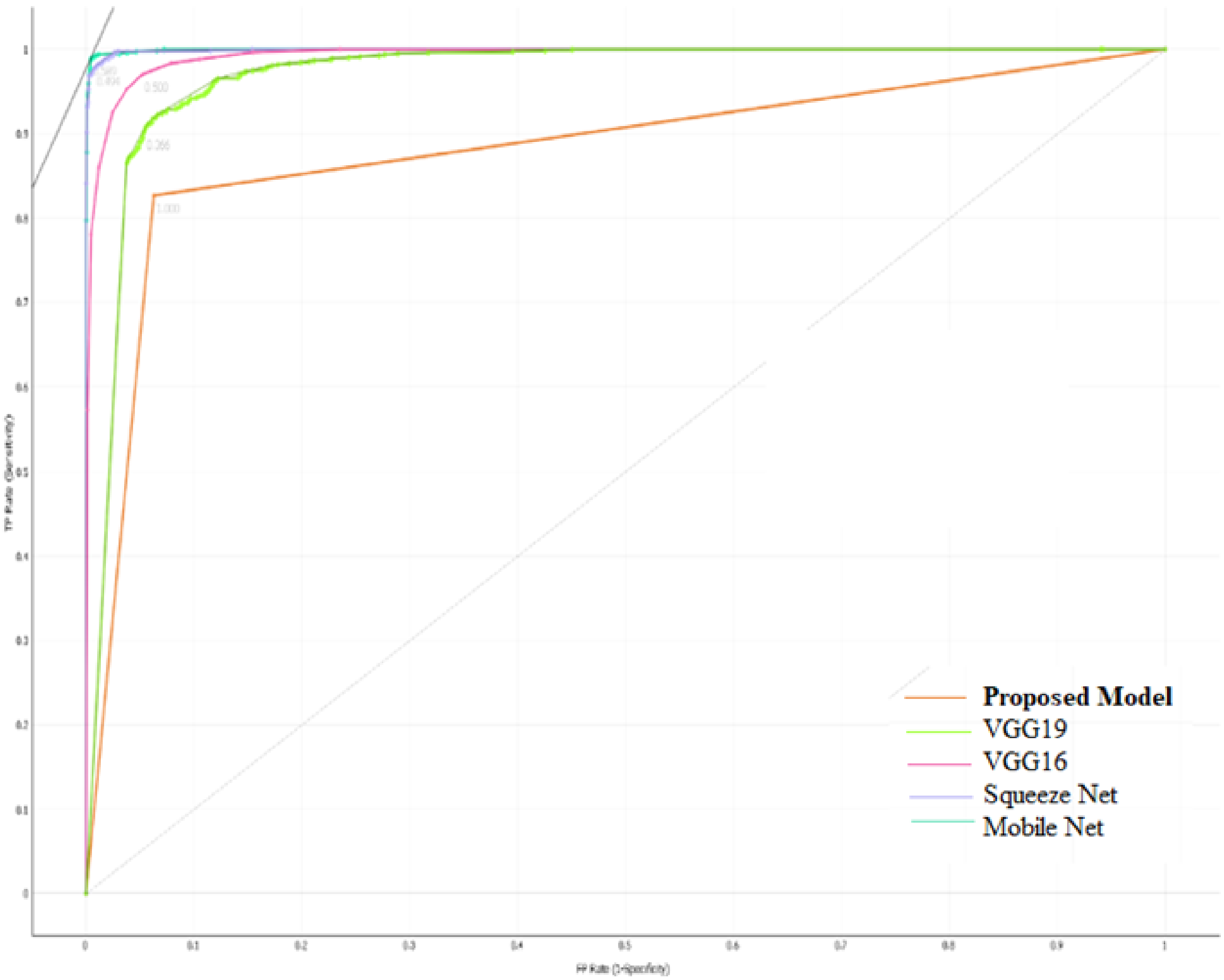


Figure 12. ROC curve for Proposed model with k fold 20

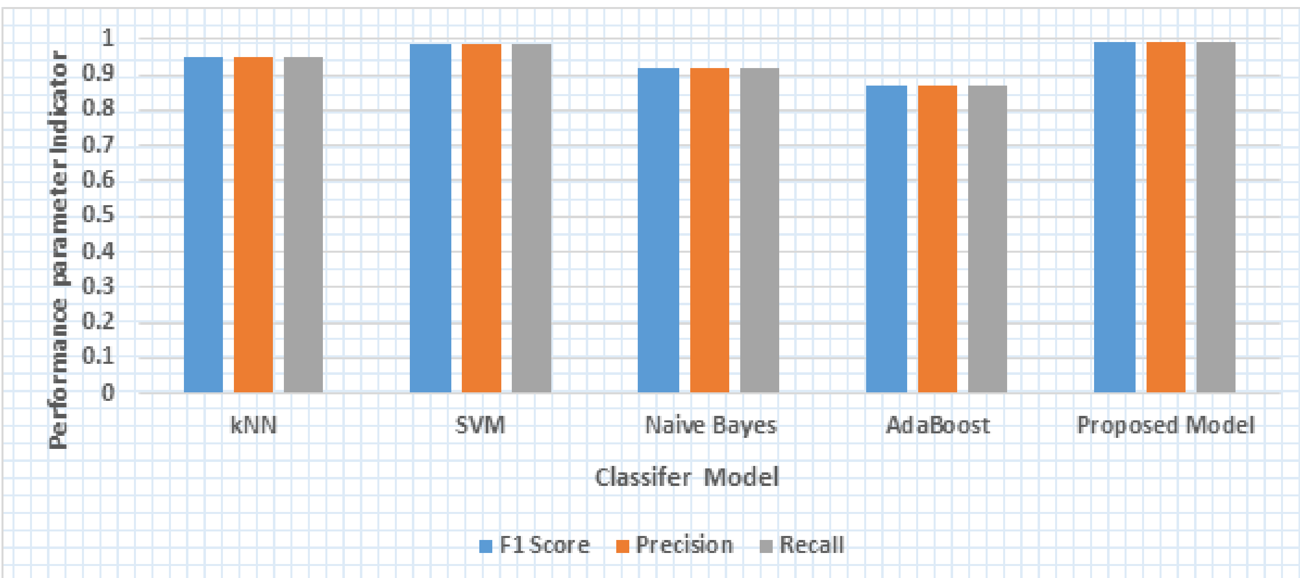


Figure 13. Comparison against other classifiers

5. CONCLUSION AND FUTURE WORK

Academic interest in artificial neural networks (ANNs) has been revitalized by the tremendous progress in image processing and image applications using CNN. This research proposes a novel method to classify grape leaf diseases which yields prediction accuracy 99.3%. This method exploits the concept of semantic masking. When the performance of proposed model is compared with other transfer learning approaches, the proposed model emerges as a much superior model. The limitation of this work is that semantic segmentation relies on manual tuning and expert knowledge for optimal performance. In future, the model can be expanded to recognize the impact of multiple pathogens on a plant leaf or a combination of pathogens. Also, the role of abiotic causes, such as nutritional levels, in the development of leaf diseases can be explored in the future.

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