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Identification of plant leaf diseases using a nine-layer deep convolutional neural network[☆]

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ABSTRACT

In this paper, we proposed a novel plant leaf disease identification model based on a deep convolutional neural network (Deep CNN). The Deep CNN model is trained using an open dataset with 39 different classes of plant leaves and background images. Six types of data augmentation methods were used: image flipping, gamma correction, noise injection, principal component analysis (PCA) colour augmentation, rotation, and scaling. We observed that using data augmentation can increase the performance of the model. The proposed model was trained using different training epochs, batch sizes and dropouts. Compared with popular transfer learning approaches, the proposed model achieves better performance when using the validation data. After an extensive simulation, the proposed model achieves 96.46% classification accuracy. This accuracy of the proposed work is greater than the accuracy of traditional machine learning approaches. The proposed model is also tested with respect to its consistency and reliability.

1. Introduction

Identifying diseases from images of plant leaves is one of the most important research areas in precision agriculture [1]. Advances in artificial intelligence, image processing and graphical processing units (GPUs) can expand and improve the practice of precise plant protection and growth. Most of the plant diseases generate various symptoms in the visible spectrum, and thus learning models should possess good observation skills so that one can identify the characteristic symptoms of any diseases [2].

Several artificial intelligence approaches are currently used for detecting and classifying plant diseases. The most common approaches are the K-nearest neighbours (K-NN), logistic regression, decision tree, support vector machine (SVM) [3] and deep convolutional neural network (Deep CNN). These approaches are combined with various image pre-processing methods in order to enhance feature extraction. The K-NN is a simple memory-based classification algorithm that classifies the data based on a similarity measure. It was used to classify unlabelled objects using neighbouring labelled objects. The Decision tree is a supervised learning algorithm, the nodes represents the decision attributes, the branches represent the possible

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outcomes from the nodes, and the leaves represent the classes. Additionally, overlapping nodes and data overfitting are major disadvantages of decision trees. Moreover, the logistic regression is a special case of the linear regression technique when the output value is categorical using probability distributions [4]. As a popular supervised machine learning technique, the SVM is defined using a separating hyper-plane, which can be used for classification and regression applications based on statistical learning concepts. SVMs have been extensively used in several fields such as image and text classification in the last decade [5].

This work intends to use a Deep CNN based model to solve the plant leaf disease identification problems. The Deep CNN is a class of deep learning algorithm. The deep learning extends traditional machine learning by adding more complexity and hierarchical data representations into the model. The Deep CNNs have wide applications in image classification, object detection, speech recognition, recommender systems and natural language processing [6]. Transfer learning is a knowledge-sharing method that reduces the size of the training data, the time and the computational costs when building deep learning models [7]. Transfer learning helps to transfer the learning of a pre-trained model to a new model. Transfer learning has been used in various applications, such as plant classification, software defect prediction, activity recognition and sentiment classification. In this research, the performance of the proposed Deep CNN model has been compared with popular transfer learning approaches, such as AlexNet, VGG16, Inception-v3 and ResNet.

The Deep CNN requires a large volume of training data in order to achieve better outcomes. In order to construct the best Deep CNN Model using insufficient training data, image augmentation is typically required in order to enhance the performance of the model. The Image augmentation artificially produces training images using several processing methods or a combination of various processing methods, such as image flipping, gamma correction, noise injection, principal component analysis (PCA) colour augmentation, rotation, and Scaling [8]. Gradient descent is an optimization algorithm that often applied for updating the model parameters of neural networks, which decreases the error of the model when using the training dataset. Mini-batch gradient descent is one gradient descent algorithm that splits the training dataset into small batches that are used to compute the model's error and update the model's parameters. The mini batched updates offer a computationally more efficient process than the stochastic gradient descent algorithm. The mini batch is the most common implementation of the gradient descent algorithm that is used in the field of deep learning [9]. The proposed Deep CNN model can be trained using different mini-batch sizes varying from 64 to 160 with the augmented dataset. Overfitting happens when the model learns the features and noises in the training data and it negatively impacts the performance of the Deep CNN model when using new data. Dropout was proposed in order to overcome the overfitting problem in machine learning algorithms. Dropout randomly fixes some neurons to zero in every forward pass [10]. The proposed model used dropout in the fully connected layer and increased the fraction of dropout from 0.0 to 0.8 with a step size of 0.2. Our evaluations show that the proposed Deep CNN model can achieve excellent results with the dataset compared with the state-of-art algorithms.

The rest of the paper is organized as follows. Section 2 presents the related works. Section 3 discusses the materials and methodology of plant disease identification. The results and related discussions are given in Section 4. Finally, Section 5 presents the conclusions and future research direction.

2. Related works

The purpose of this review is to show the capability of some commonly used machine learning approaches that can efficiently handle these different but closely related objectives. It also conducts a comparative study of various artificial intelligence techniques that are applied to the same task of plant leaf disease detection and diagnosis systems. Some technical aspects of the learning techniques that are used in the reviewed studies are discussed. Machine learning provides a flexible and powerful framework for decision making and the incorporation of expert knowledge into the system. These are some of the few advantages of machine learning algorithms that make them be extensively used in many fields, and they are greatly applicable in agriculture mechanization. In [4], the authors proposed a model for classifying hyper spectral images for agricultural decision making using decision trees and logistic regressions, and the former proved to be more accurate. Artificial neural networks (ANNs) are mathematical models for processing complex input data that were inspired by the biological neural networks that constitute animal brains. In [11], the authors proposed and developed the feed forward neural network with back propagation model for recognizing various pests and diseases in leaves. The back propagation method helps to calculate the gradient descent values for artificial neural networks that are needed in order to minimize the error function. The authors in [12] presented a review of the most distinguished conventional methods of plant disease detection techniques. These techniques include spectroscopic-based, imaging-based, and volatile profiling-based plant disease detection methods. The paper compares the benefits and restrictions of these approaches.

Another technique that was proposed by the authors in [13,14] incorporates the features that are extracted by the SVM with respect to the Huanglongbing (HLB) or citrus greening disease of lemon trees. The technique improves the accuracy of the system with a final overall accuracy of 85% using multi-band imaging sensor inputs [13] and 92.8% using the fluorescence imaging technique [14]. The authors of [15,16] used SVM classification methods and hyper spectral imagery for the Automatic early detection of plant diseases. In [17], the author proposed hyperspectral image classification using the K-NN algorithm with the guided filter technique. The authors in [18] proposed a model for identifying infected tomato leaves with yellow leaf curl disease. The SVM with different kernels and 200 images of infected and healthy tomato leaves were used to construct the classification model. The average classification accuracy of the model was 90%.

Likewise, the Identification of plant genome associations with bacteria can be achieved using support vector machines. This technique was implemented for various species and presented in [19]. Another approach based on SVMs for the identification of leaf diseases in vine plants was proposed by the author in [20]. The author in [1] reviewed the machine learning approaches for solving the plant disease identification and diagnosis tasks in different research areas such as plant gene detection and plant leaf disease classification. Furthermore, the author in [21] presented a model for plant disease diagnosis using image processing with the Naive-Bayes classification model.

Deep learning based applications are mostly proposed using medical image analysis for automated disease diagnosis [22]. However, in the literature, plant leaf disease identification using deep learning have not been handled so much. Therefore, novel approaches in this area are required. The authors in [23,24] presented deep CNNs for solving disease identification tasks using different datasets and different number of layers for various plant leaf diseases. In [25,26], the authors developed a similar deep CNN approach for different plant identification tasks using plant leaf images and different amounts of data. Additionally, the identification of plant diseases and pests can be achieved using deep CNNs. This technique was implemented for tomato plant diseases and pest detection [27]. The authors in [28] studied 40 different research works that were based on deep learning approaches and were applied to several agricultural challenges. There are some approaches that apply the 14-Layer Convolutional Neural Network with Batch Normalization, Dropout, and Stochastic Pooling in order to identify Multiple Sclerosis in human brains, such as the model that was proposed by the authors in [10]. On average, the classification accuracy using this approach was 98.77%.

Most recently, a 13-layer convolutional neural network was developed in [8] for learning some high-level features in order to classify fruit images using data augmentation methods and stochastic gradient descent with momentum, and it reached a classification accuracy of 94.94% in the final experiment. Additionally, the classification of multi-temporal crops can be achieved using convolutional neural networks. This technique was implemented for economic crops and presented in [29]. The maximum classification accuracy using this approach was 85.54%. In our study, the K-NN Classifier, Decision Tree, SVM, and Deep CNN were trained and evaluated in order to design a plant disease identification model based on a plant leaf image dataset. The succeeding section presents the fundamentals of the implemented models and the training and testing datasets.

3. Materials and methods

The complete processes of designing, training and validating the model for plant disease identification using the Deep CNN are described further in detail. The entire method is separated into a number of stages in the following subsections, starting with collecting the images for the classification process.

3.1. Data acquisition and pre-processing

The diseased and healthy plant leaf images were downloaded from the plantvillage dataset. The dataset containing 54,305 images of 13 different plant leaves was used for training and testing the proposed Deep CNN model. The database includes 38 different classes, and each class is defined as a healthy or infected plant using disease labels. As mentioned earlier, one more class is also present and has 1143 background images. The sample images of the random classes are presented in Fig. 1.

Image transformations are used in order to increase the number of images in the dataset and reduce the overfitting by adding a few distorted images to the training data. Image flipping, Gamma correction, noise injection, PCA colour augmentation, rotation, and Scaling transformations are used to create the augmented images for the training data. Fig. 2 shows the transformations that were applied in the augmentation process of the sample images in the training data.

At last, the dataset containing 55,636 images for training has been created using data augmentation. Furthermore, the size of the augmented dataset is 61,486 images. Table 1 shows all the classes with the numbers of original and augmented images for each class that were used by the disease identification model. The models were trained using an image augmented image dataset and a non- augmented image dataset.

3.2. Experimental setup

The training and testing processes of this Deep CNN model and all other start-of-art models were implemented using the scikit-learn, Keras, pillow and opencv libraries, which use the python programming language. The training and testing of the models were executed using an NVIDIA DGX-1 V100 with 8X Tesla V100 GPUs with the performance of one petaFLOP.

3.3. Training the Deep CNN network

The Deep CNN constitutes a class of deep learning as a feed forward artificial neural network, and it is applied in several of the agricultural image classification works [28]. One of the key benefits of using Deep CNN in image classification is reducing the necessity of the feature engineering process. Training the Deep CNN for the plant leaf disease image classification task using the datasets that are described in Section 3.1 was proposed. The model was separately trained with the augmented and non-augmented image datasets. Fig. 3 illustrates the architecture of the proposed Deep CNN model.

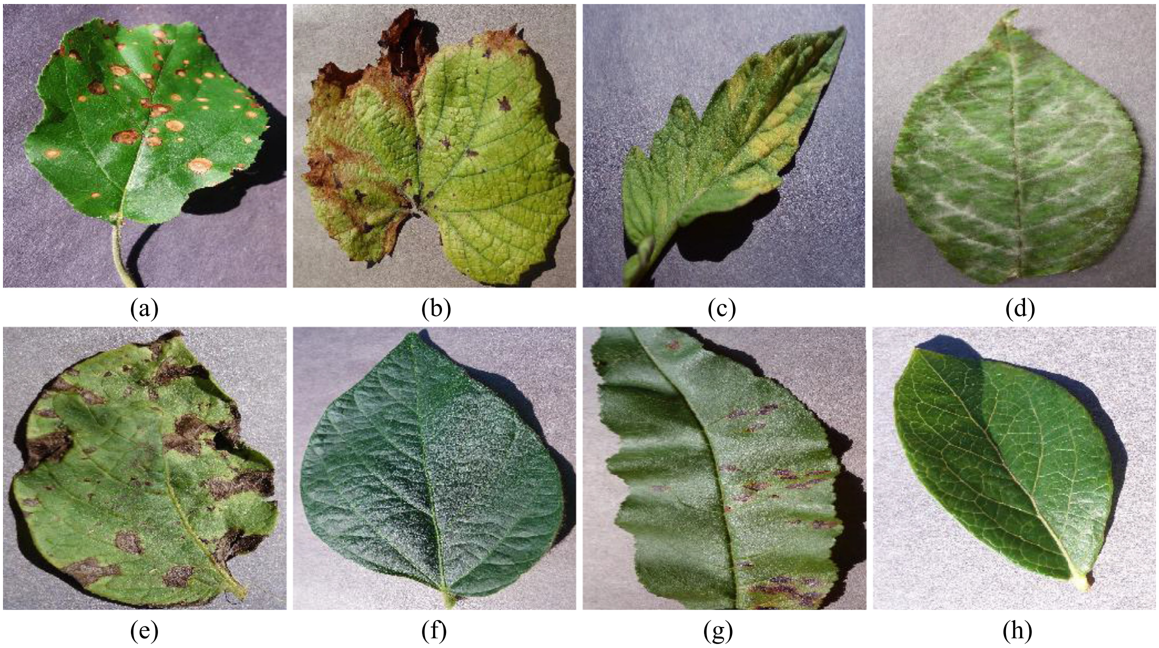

Fig. 1. (a) Apple with black rot, (b) grape with leaf blight, (c) tomato with leaf mold, (d) cherry with powdery mildew, (e) potato with early blight, (f) healthy soybean, (g) peach with bacterial spots and (h) healthy blueberry.

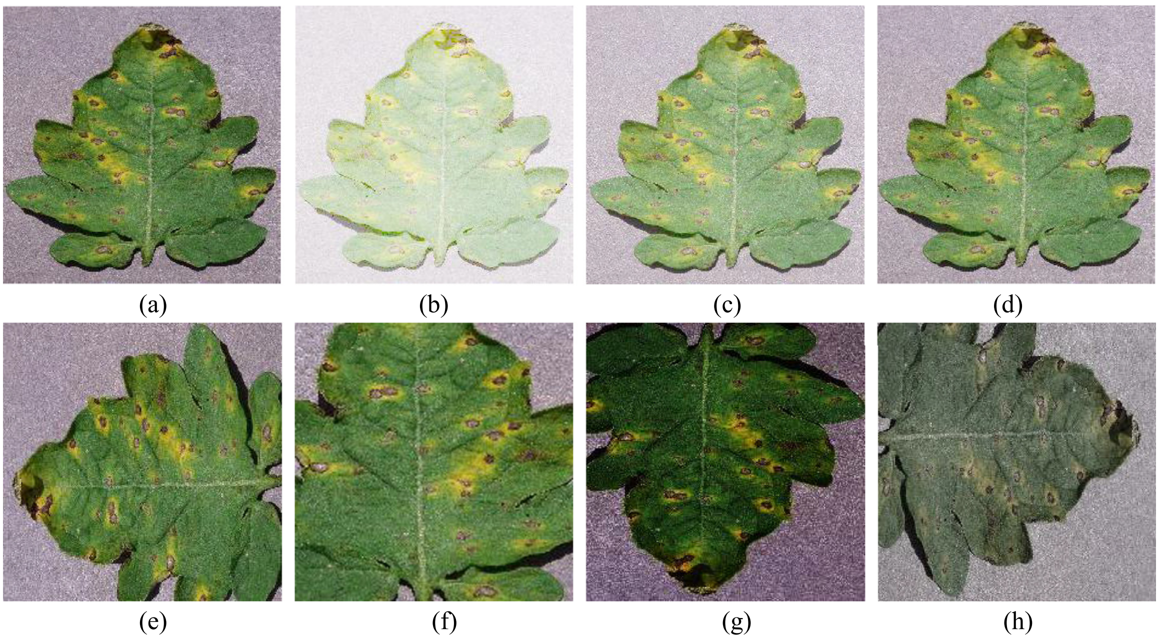

Fig. 2. (a) Original image, and (b)–(h) are augmented images.

There are different convolutions that are performed in several layers of the Deep CNN. They generate various representations of the training data, starting from more common ones in the first larger layers and becoming more detailed in the deeper layers. Initially, the convolutional layers perform like feature extractors from the training data whose dimensionality is then minimized using the pooling layers [28]. The convolutional layers extract various lower level features into additional discriminative features. Additionally, the convolutional layers are the fundamental building blocks of the Deep CNN [30].

Table 1
Classes of leaf disease dataset.

Class name	Number of images	
	Without using data augmentation	Using data augmentation
Apple with scab	630	1000
Apple with black rot	621	1000
Apple with cedar apple rust	275	1000
Healthy apple	1645	1645
Blueberry with healthy	1502	1502
Cherry with powdery mildew	1052	1052
Cherry with healthy	854	1000
Corn with grey leaf spot	513	1000
Corn with common rust	1192	1192
Corn with northern leaf blight	985	1000
Healthy corn	1162	1162
Grape with black rot	1180	1180
Grape with black measles	1383	1383
Grape with leaf blight	1076	1076
Healthy grape	423	1000
Orange with Huanglongbing	5507	5507
Peach with bacterial spot	2297	2297
Healthy peach	360	1000
Pepper with bacterial spot	997	1000
Healthy pepper	1478	1478
Potato with early blight	1000	1000
Healthy potato	152	1000
Potato with late blight	1000	1000
Healthy raspberry	371	1000
Healthy soybean	5090	5090
Squash with powdery mildew	1835	1835
Healthy strawberry	456	1000
Strawberry with leaf scorch	1109	1109
Tomato with bacterial spot	2127	2127
Tomato with early blight	1000	1000
Healthy tomato	1591	1591
Tomato with late blight	1909	1909
Tomato with leaf mold	952	1000
Tomato with septoria leaf spot	1771	1771
Tomato with two spotted spider mite	1676	1676
Tomato with target spot	1404	1404
Tomato with mosaic virus	373	1000
Tomato with yellow leaf curl virus	5357	5357
Background without leaf	1143	1143
Total number of images	55,448	61,486

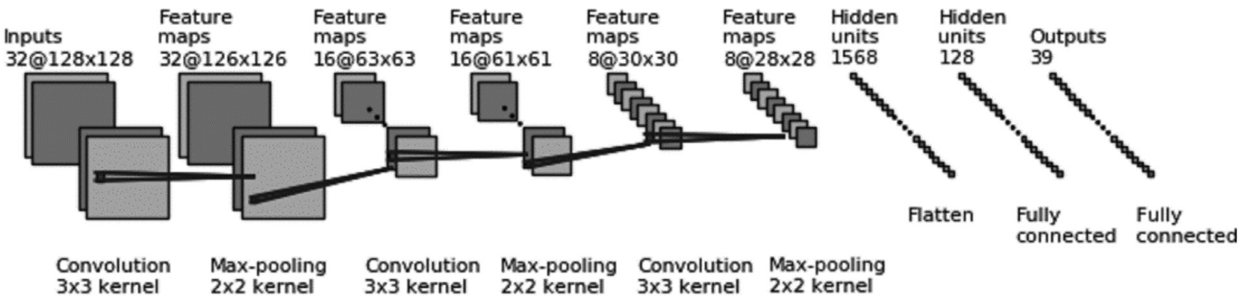

Fig. 3. Layered architecture of the proposed Deep CNN model.

Feature engineering is a very distinctive part of Deep Learning and a major step ahead for traditional Machine Learning. Fig. 4 shows the visual representation of the different layers' outputs of the proposed model.

The pooling layer conducts the down-sampling operation along the spatial dimensions. It supports reducing the number of parameters. The max pooling process was used in the pooling layer of the proposed model. Max pooling achieves better performance than average pooling in the proposed Deep CNN model. Another important layer is dropout, which refers to removing entities from the network. It is a regularization technique for reducing overfitting. The proposed model was trained and compared using different dropout values varying from 0.2 to 0.8. As shown in Fig. 5, the highest validation accuracy was achieved when using the dropout probability of 0.2.

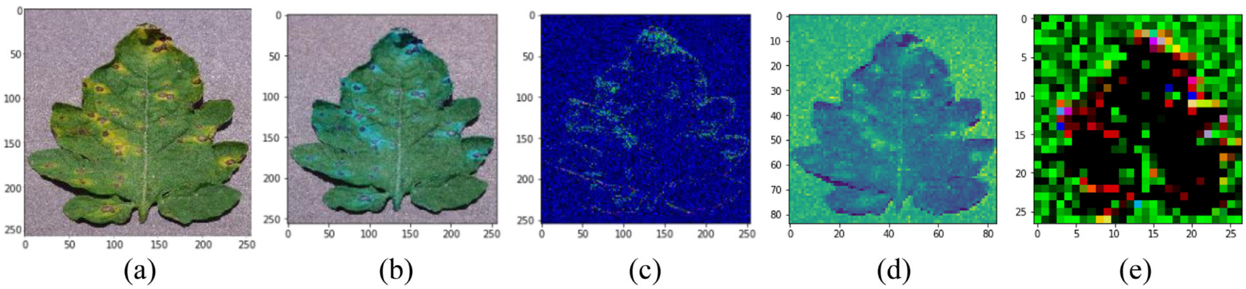

Fig. 4. (a) Input image, (b) convolutional layer – 1, (c) convolutional layer – 2, (d) convolutional layer - 3 and (e) flattening layer.

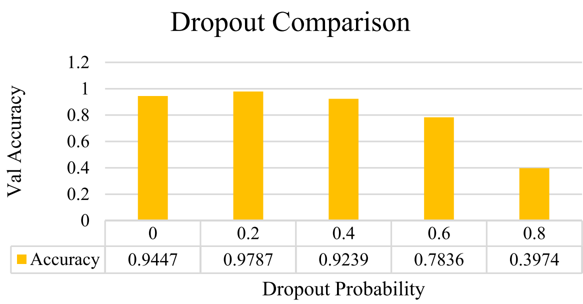

Fig. 5. Validation accuracy of the different dropout rates.

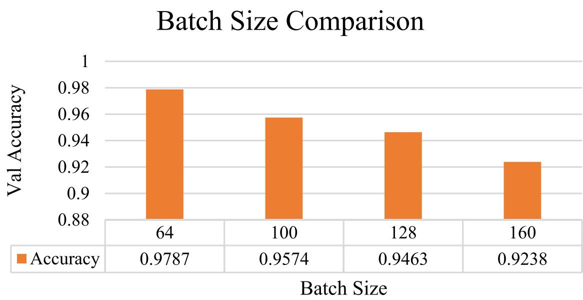

Fig. 6. Validation accuracy of the different batch sizes.

Finally, the dense layer performs the classification using the output of the convolutional and pooling layers. The Deep CNN is an extremely iterative process and it should train numerous models in order to discover the best one. Gradient descent is a simple optimization method that conducts the gradient steps using all training data on each step, and it is also known as batch gradient descent. The implementation of gradient descent with a large training set is difficult [8]. On the other hand, mini-batch can be used to calculate the gradient of the loss function and update the weights of the network. It is a subset of the training dataset. It reduces the computational costs and improves the efficiency of the model. Fig. 6 compares the validation performance of the different batch sizes of the proposed model.

An epoch is a hyper parameter that defines a single pass through the complete training set when training a deep learning model. As shown in Fig. 7, the highest validation accuracy of 97.87% was achieved by the proposed Deep CNN model with 3000 epochs using the augmented dataset.

The model was individually trained using the augmented and non-augmented datasets with optimized hyper parameters. Fig. 8 shows that the validation accuracy of the proposed Deep CNN model was improved by using the augmented image dataset.

The model that was trained using the augmented dataset with the optimized hyper parameters performed well in the training and validation process. Table 2 presents the optimized hyper parameters of the proposed Deep CNN model. Fig. 9 shows the training and validation results of the proposed Deep CNN model using the optimized hyper parameters.

Transfer learning consists of training a precise neural network and reclaiming this knowledge in similar tasks. The performance of the proposed Deep CNN model was compared with popular transfer learning approaches, such as AlexNet, VGG16, Inception-v3 and ResNet. Fig. 10 presents the performances of the proposed model and the standard transfer learning

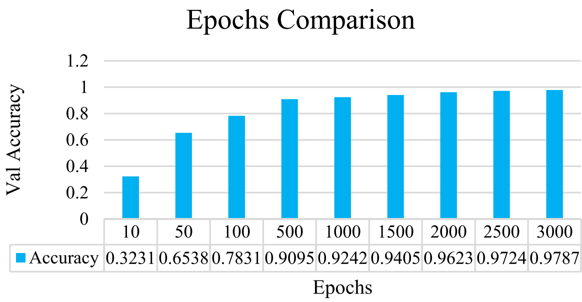

Fig. 7. Validation accuracy of the different training epochs.

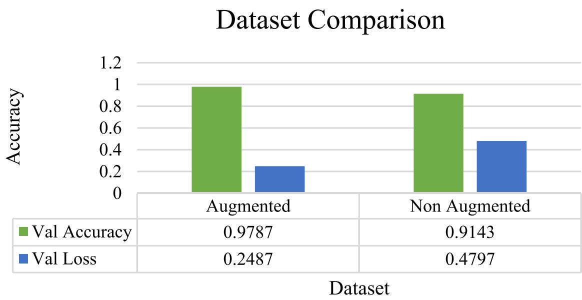

Fig. 8. Validation accuracy of the augmented and non- augmented datasets.

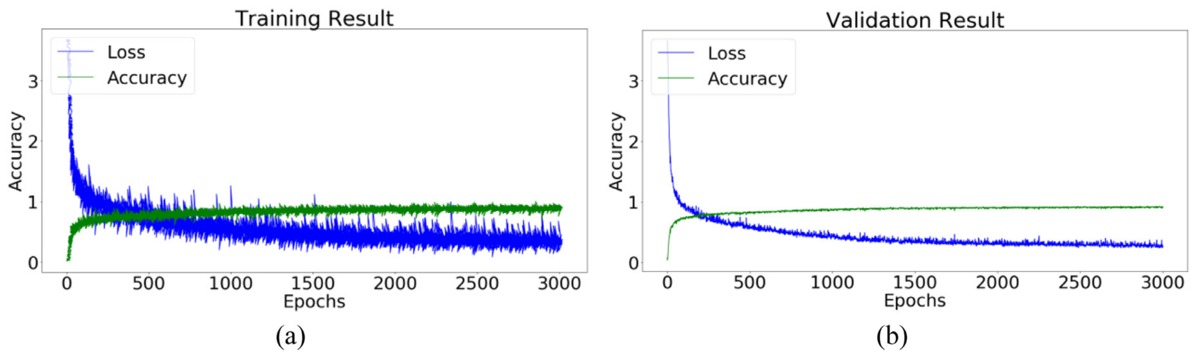

Fig. 9. (a) Training accuracy and (b) validation accuracy of the proposed model.

Table 2
Hyper parameters of the proposed Deep CNN model.

Parameters	Value
Training epochs	3000
Mini batch sizes	64
Validation steps	100
Dropout value	0.2
Learning rate	0.01–0.0001
Training set size	55,636
Validation set size	3900
Test set size	1950

techniques using the validation dataset. The proposed Deep CNN model achieves the highest validation accuracy and is followed by AlexNet, VGG16, Inception-v3 and ResNet.

After the completion of the training and validation processes, the proposed Deep CNN model was selected for the testing process. In addition, the trained models were tested with new inputs and the results were compared with the start-of-art machine learning algorithms in the following section, which were quite indicative.

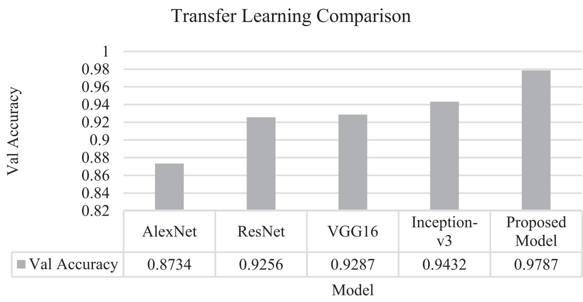

Fig. 10. Validation accuracy of the popular transfer learning approaches.

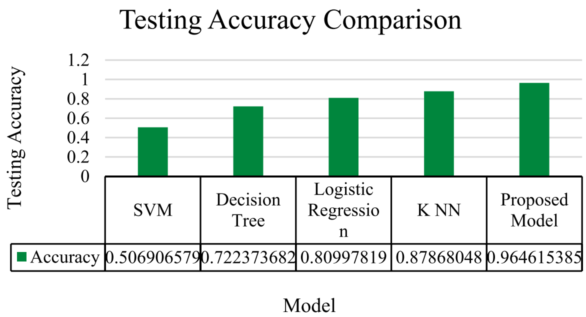

Fig. 11. Average testing accuracy of the different models.

4. Results and discussions

The proposed deep CNN model was trained and tested using the plant leaf disease dataset. The dataset was split into training, validation and testing sets with 55,636, 3900 and 1950 images, respectively, and were labelled with 39 different classes of diseased and healthy plant leaves and background images. The proposed model was compared with the SVM, logistic regression, decision tree and K-NN. Moreover, the following testing procedures are compared with respect to the performances of the models. Finally, the results show that the proposed model is superior to all of the abovementioned models. The succeeding subsection will assess the average testing accuracy. Fig. 11 presents the testing accuracy during the testing of the various models.

The accuracy is the number of right predictions that is made by the model with respect to the total number of predictions that were made. The proposed Deep CNN model achieves better prediction accuracy at 96.46% compared with other models that range from 50% to 87%. The results that are presented in Table 3 show that all classes of the proposed Deep CNN model achieve better testing accuracy between 92% and 100% when using the leaf image test dataset. In addition, the confusion matrix of the proposed Deep CNN model is given in Appendix A. It describes the performance of the proposed Deep CNN model.

Furthermore, the Area Under the Receiver Operating Characteristic (AUC – ROC) curve is also one of the popular metrics that is used to evaluate the performance of learning algorithms. The ROC curve plots the difference between the False Positive Rate (FPR) and True Positive Rate (TPR). Table 4 compares the False positive (FP), True Negative (TN), False Negative (FN) and True Positive (TP) values of all the models.

The TPR represents the amount of positive data that is correctly predicted as positive with respect to all positive data. The FPR represents the amount of negative data points that are wrongly predicted as positive with respect to all negative data. The range of the FPR and TPR is between 0 and 1, and is calculated using the following equations:

$$TPR = \frac{TP}{TP + FN} \tag{1}$$

$$FPR = \frac{FP}{FP + TN} \tag{2}$$

Fig. 12 shows the AUC – ROC curves of the four randomly selected classes from the testing dataset. The results that are presented in Fig. 12 indicate that the proposed Deep CNN model performs better than all other machine learning techniques. Additionally, the AUC – ROC curves of all the classes for the proposed model are given in Appendix B.

In addition, the Precision is defined as number of true positive results (TP) divided by the number of positive results (TP + FP) that are predicted by the model. The range of the precision is between 0 and 1, and is calculated using the

Table 3
Testing accuracy of the proposed model for each respective class.

S. No.	Class name	Testing accuracy
1	Apple with scab	0.96
2	Apple with black rot	0.98
3	Apple with cedar apple rust	0.98
4	Healthy apple	0.96
5	Blueberry with healthy	1
6	Cherry with powdery mildew	0.98
7	Cherry with healthy	1
8	Corn with grey leaf spot	0.96
9	Corn with common rust	1
10	Corn with northern leaf blight	0.94
11	Healthy corn	1
12	Grape with black rot	0.9
13	Grape with black measles	0.98
14	Grape with leaf blight	0.96
15	Healthy grape	1
16	Orange with Huanglongbing	1
17	Peach with bacterial spot	0.96
18	Healthy peach	0.98
19	Pepper with bacterial spot	0.92
20	Healthy pepper	0.94
21	Potato with early blight	0.98
22	Healthy potato	1
23	Potato with late blight	0.92
24	Healthy raspberry	1
25	Healthy soybean	0.94
26	Squash with powdery mildew	0.92
27	Healthy strawberry	1
28	Strawberry with leaf scorch	1
29	Tomato with bacterial spot	0.9
30	Tomato with early blight	0.94
31	Healthy tomato	0.98
32	Tomato with late blight	0.94
33	Tomato with leaf mold	0.96
34	Tomato with septoria leaf spot	0.96
35	Tomato with two spotted spider mite	0.92
36	Tomato with target spot	0.94
37	Tomato with mosaic virus	1
38	Tomato with yellow leaf curl virus	0.96
39	Background without leaf	0.96
	Average accuracy	0.964615

Table 4
TP, TN, FP and FN values of different models.

Algorithms	TP	FP	TN	FN
SVM	5493	5368	85	58
Decision tree	7823	3038	126	17
Logistic regression	8785	2076	128	15
K-NN	9565	1296	104	39
Proposed model	1833	67	48	2

following equation:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

The Precision is used to find the proportion of positive identifications that is true. Fig. 13 shows that the proposed Deep CNN model achieved much better Precision than all other machine learning techniques.

Additionally, the recall is the number of true positives (TP) divided by the number of all relevant sample data (TP + FN). The following equation is used to calculate the recall:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

The recalls are used to determine the proportion of actual positives that was correctly identified. Fig. 14 presents the precision value on the testing dataset for different models.

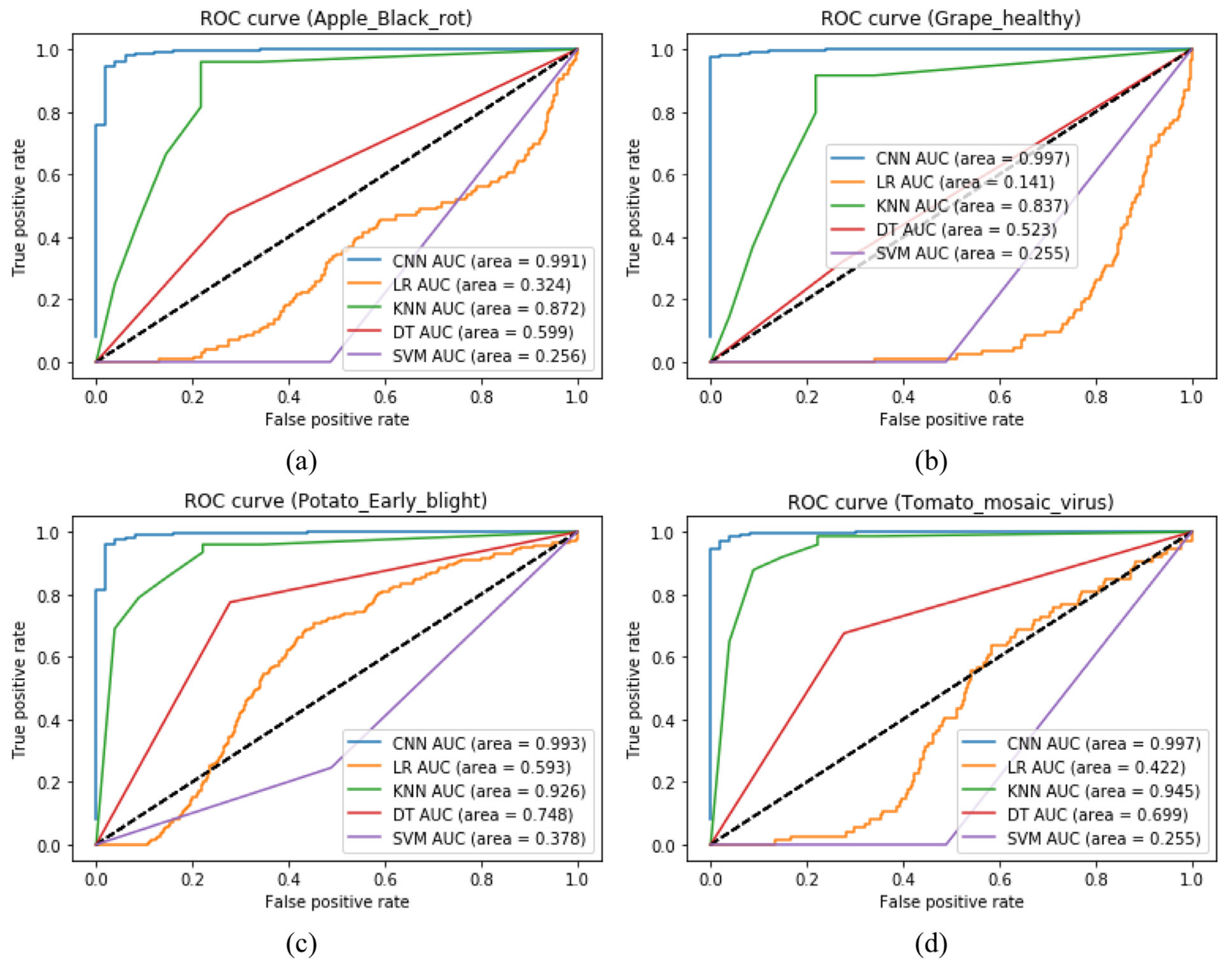

Fig. 12. The AUC – ROC curves for (a) apple with black rot, (b) healthy grape, (c) potato with early blight and (d) tomato with mosaic virus images of the different models.

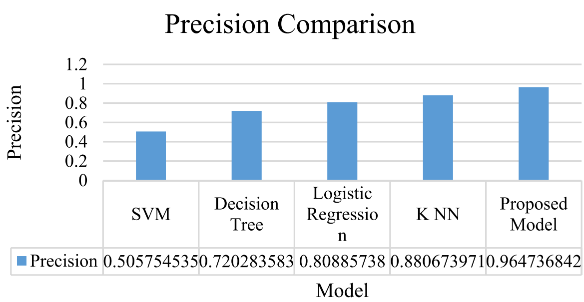

Fig. 13. Precision values of the different models.

Moreover, the F1 Score is one of the widely used metrics for the performance evaluation of machine learning algorithms. The F1 Score is defined as the harmonic mean between the precision and recall. The range of the F1 Score is between 0 and 1, and is calculated using equation:

$$\text{F1 Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{5}$$

The F1 scores reflect the number of instances that are correctly classified by the learning models. Fig. 15 shows that the F1 Score of the proposed Deep CNN model is much higher than those the other algorithms.

Finally, comparing our outcomes with other machine learning methods for identifying plant diseases using leaf images, it can be said that our proposed Deep CNN model presents better results than those of traditional machine learning algorithms.

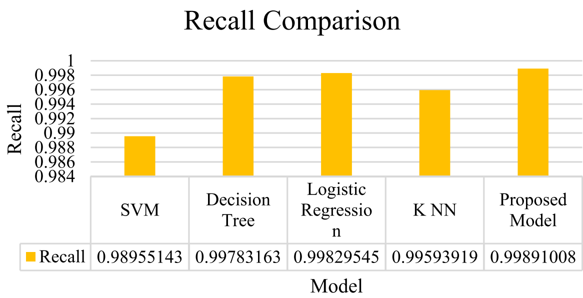

Fig. 14. Recall values of the different models.

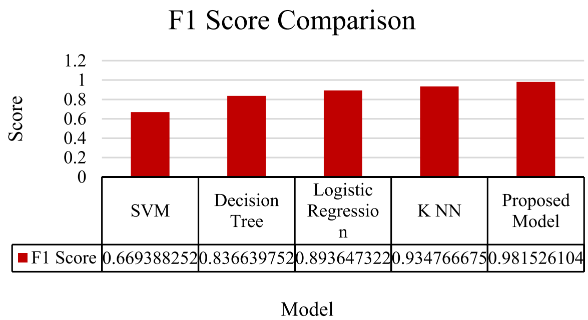

Fig. 15. F1 Scores of the different models.

5. Conclusions

Deep learning is a recent research technique for image processing and pattern recognition, and it can effectively solve the problems in the identification of plant leaf diseases. The proposed Deep CNN model can effectively classify 38 distinct classes of healthy and diseased plants using leaf images. In addition, the data augmentation increases the amount of training data from 49,598 to 55,636. The most successful Deep CNN model was trained and tested with using an augmented dataset with 61,486 images and 3000 training epochs. The proposed model achieves an average accuracy of 96.46% in the classification of the testing set plant leaf images, and between 92% and 100% for the individual class. The number of training epochs, batch size and dropout had greater influences on the respective results. The max pooling method performs much better than average pooling. Compared with other machine learning models, the proposed Deep CNN model has a superior predictive ability and performance. Moreover, the consistency and reliability of the proposed model is measured in terms of the AUC – ROC curves, Precisions, recalls and F1 Scores. An extension of this research will be collecting new images from several sources of different plant species, geographic areas, leaf growths, cultivation conditions, image qualities and modes in order to increase the number of database classes and the database's size. The enhanced dataset will improve the performance and accuracy of the model using some fine-tuning techniques. The most important goal of the feature work will be to extend our plant disease identification objective from plant leaves to other parts of the plants, such as flowers, fruits and stems. Additionally, we can extend this model for plant leaf disease diagnosis. Moreover, we plan to conduct a deeper investigation of the training process without labelled images.

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Conflict of interest

None.

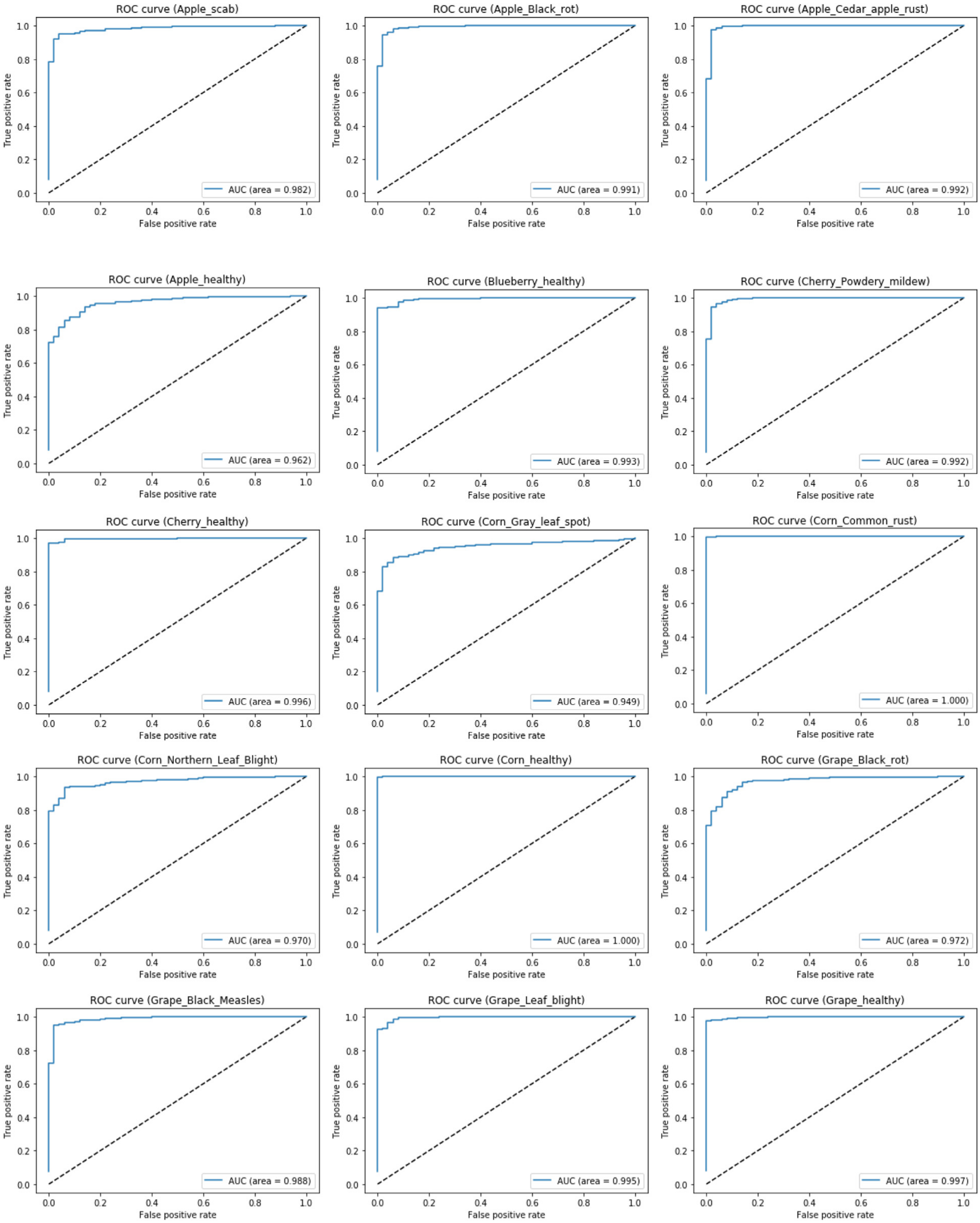
Appendix A. Confusion matrix of the proposed Deep model

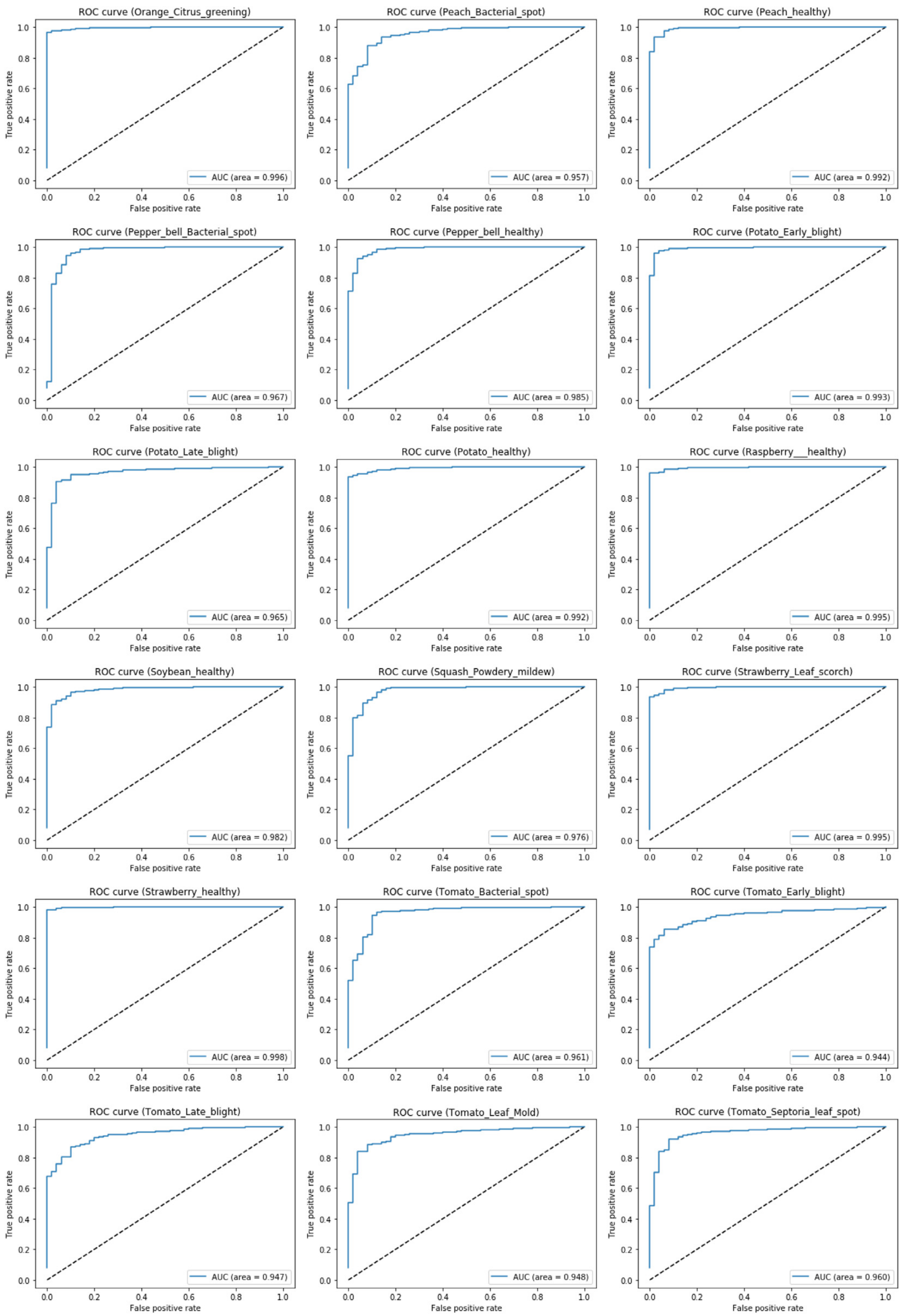
Output

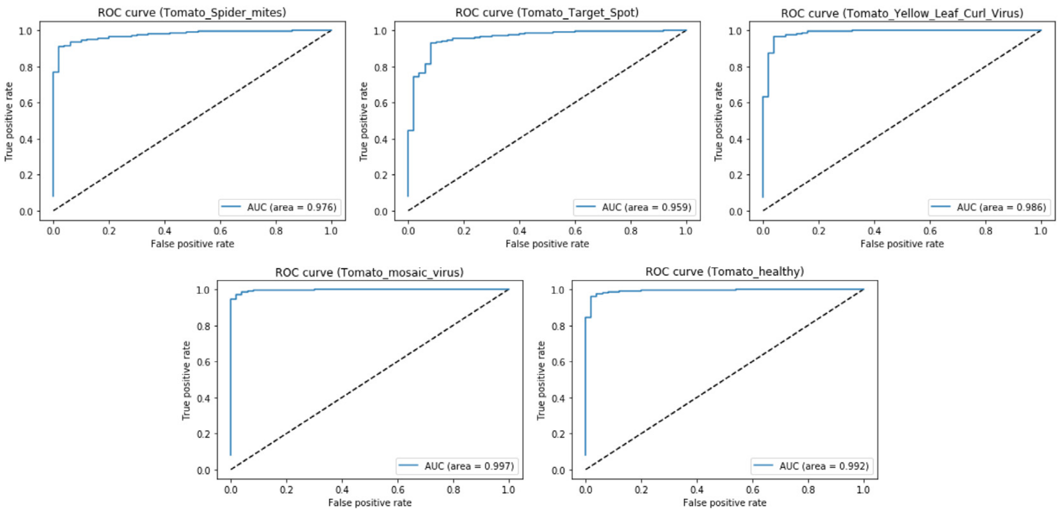
Target

Classes	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
0	48															1																	1						
1		49			1																																		
2			49																																	1			
3				48	2																																		
4					50																																		
5						49																																	1
6							50																																
7								48		2																													
8									50																														
9								3		47																													
10											50																												
11												45	2	1													1		1										
12												1	49																										
13												2		48																									
14															50																								
15																50																							
16												1					48										1												
17																	1	49																					
18		1																	46	1				1						1									
19		1																		47			1								1								
20	1																				49																		
21	1																		1		1	46										1							
22																							50																
23																								50															
24				1			1													1					47														
25											1														1	46		1								1			
26																											50												
27																												50											
28				1				1									1												45	1						1			
29																					1								2	47									
30																														3	47								
31																															2	48							
32																														2			48						
33																																		46	2	1	1		
34																																	1	3	45			1	
35																																		2		48			
36																																					50		
37																																	1					49	
38														1							1																		48

Appendix B. The AUC – ROC curves of the proposed model




ROC curve (Orange_Citrus_greening)
AUC (area = 0.996)
ROC curve (Peach_Bacterial_spot)
AUC (area = 0.957)
ROC curve (Peach_healthy)
AUC (area = 0.992)
ROC curve (Pepper_bell_Bacterial_spot)
AUC (area = 0.967)
ROC curve (Pepper_bell_healthy)
AUC (area = 0.985)
ROC curve (Potato_Early_blight)
AUC (area = 0.993)
ROC curve (Potato_Late_blight)
AUC (area = 0.965)
ROC curve (Potato_healthy)
AUC (area = 0.992)
ROC curve (Raspberry___healthy)
AUC (area = 0.995)
ROC curve (Soybean_healthy)
AUC (area = 0.982)
ROC curve (Squash_Powdery_mildew)
AUC (area = 0.976)
ROC curve (Strawberry_Leaf_scorch)
AUC (area = 0.995)
ROC curve (Strawberry_healthy)
AUC (area = 0.998)
ROC curve (Tomato_Bacterial_spot)
AUC (area = 0.961)
ROC curve (Tomato_Early_blight)
AUC (area = 0.944)
ROC curve (Tomato_Late_blight)
AUC (area = 0.947)
ROC curve (Tomato_Leaf_Mold)
AUC (area = 0.948)
ROC curve (Tomato_Septoria_leaf_spot)
AUC (area = 0.960)
True positive rate
False positive rate



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