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AHMET ALKAN

MUHAMMED USAME ABDULLAH

HANADİ OMAİSH ABDULLAH

MUHAMMED ASSAF

HUIYU ZHOU

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A smart agricultural application: automated detection of diseases in vine leaves using hybrid deep learning

Ahmet ALKAN[1,*], **Muhammed Üsame ABDULLAH**[1], **Hanadi Omaish ABDULLAH**[2], **Muhammed ASSAF**[3], **Huiyu ZHOU**[4]

[1]Department of Electrical and Electronics Engineering, Kahramanmaraş Sütçü İmam University, Kahramanmaraş, Turkey
[2]Department of Civil Engineering, Gaziantep University, Gaziantep, Turkey
[3]Faculty of Agriculture, Kahramanmaraş Sütçü İmam University, Kahramanmaraş,. Turkey
[4]School of informatics, Leicester University, Leicester, United Kingdom

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Abstract: This paper reports a study which utilizes deep learning for automated detection of the symptoms of diseases on vine leaves. Vine fruits or grapes are very important and have existed in Syria and surrounding areas (e.g., Turkey) for many years. Quality of vine fruits is also very important in grape production as it is consumed in these areas every day. The aim of this study is to improve disease-detection accuracy in vine leaves and to develop a system to help Syrian and Turkish farmers and agricultural engineers to maintain the quality of grape production. In this study, over 1000 images of vine leaves have been collected from vine yards in Syria and the internet. These images are processed using MATLAB 2018B, Deep Learning Toolbox including convolutional neural networks (CNNs) with AlexNet, GoogleNet and ResNet-18. A standard transfer learning (TL) algorithm is also used with CNNs, whereas a multiclass support vector machine (SVM) is used with AlexNet, whilst GPU and CUDA are used for accelerating the process of the disease detection for vine leaves. A software system has been created that enables the automatic and efficient detection of nine types of leaf diseases and the identification of healthy leaves. Experimental studies showed that the total detection accuracy of this system reaches 92.5%, 87.4% and 85.0%, 85.1% when AlexNet+TL, ResNet-18+TL, GoogleNet+TL and AlexNet+SVM are used respectively. This smart agricultural application can provide early identification of the symptoms of grape diseases on leaves and thus help maintain the quality of vine fruits.

Key words: Convolutional neural network, deep learning, transfer learning, vine leaf diseases, automated detection, image processing, support vector machine

1. Introduction

Grape production is an important agricultural sector globally, and in particular in Syria and Turkey. There are many common diseases affect the quality and production of grapes such as powdery mildew (Atak et al., 2017; İçli and Tahmas, 2020). Early detection of these diseases is crucial for minimizing the losses of fruits. Syria ranks 28th globally produce grapes with 0.4% of global yield (Idris and Arabi, 2014) over an area of 70,000 hectares, equivalent 540,000 tons of vine fruits per year. In 1920 in Syria, the grapevines were infected with phylloxera, which spread rapidly and affected a large area (Contaldo et al., 2011). This disease is characterized by its devastation on grape production and spreads quickly. Currently, the symptoms of vine shrub diseases on leaves can be detected by experts who then request the pesticides to be used. However, this method relies on a number of resources. First, it requires the availability of human resources. Second, farmers may notice the occurrence of diseases on leaves but fail to report the case and hence delay the handling of the disease at a suitable time. Our study is focused on early, accurate and accessible detection of vine leaf diseases. This paper reports a method of using deep learning for rapid detection of diseases and then determines the best way to handle the circumstance. Deep learning has extended classical machine learning by adding more 'depth' (complexity) into the model as well as transforming the data using various functions that allow data representation in a hierarchical way through several levels of abstraction (Kamilaris and Prenafeta, 2018). Smart agriculture uses artificial intelligence (AI) technology for quality control and disease detection (Tongke, 2013). Many models of artificial networks have been used to diagnose plants diseases such as CNN (Ferentinos, 2018; Pradhan and Patil, 2020), deep Siamese networks (DSN) (Goncharov et al., 2020), deep convolution neural network (D-CNN) (Howlder et al., 2019), feed forward neural network (FFNN), learning vector quantization (LVQ)

* Correspondence: aalkan@ksu.edu.tr

(Muthukannan et al., 2015), K-NN, SVM and random forest (Islam et al., 2017; Sanjeev et al., 2013). In the natural environment of vines, a method of image processing has been used (Reis et al., 2012), where they recognized white and red grapes both in daylight and at night to inform the harvesting robot. They tried to introduce precision agriculture (PA) and precision viticulture (PV) into the farmers' daily routine. In other studies, deep learning has been used to classify diseases on plants (Muthukannan et al., 2015; Sharath Kumar and Suhas, 2017). Mohanty et al. (2016) obtained an automated detection accuracy of 99.35% using D-CNN on 14 plant species with 26 diseases, which were classified using a public accessible dataset consisting of 54.306 images from PlantVillage dataset. Classification of diseased/healthy leaf images (e.g., bean and bitter gourd leaves) was carried out using FFNN which is one kind of the standard artificial neural network algorithms. In the meantime, LVQ, a supervised version of vector quantization, was used with labeled input data. In the study conducted at Anna University in India, images of various plant leaves collected from agricultural fields and 118 diseased leaf data (Bean leaf-63, Bitter gourd-55) were used (Muthukannan et al., 2015). Deep learning with an unmanned automated vehicle (UAV) system and RGB cameras was used to detect a vine leaf disease. Images were obtained at an altitude of 25 meters, and the major limitation of the study was that it detected just one disease (Kerkech et al., 2018). Kamilaris and Prenafeta-Boldu (2018) surveyed 40 papers related to the field of smart agriculture and found that deep learning is the best way for object detection (Kamilaris and Prenafeta-Boldú, 2018). Classical machine learning approaches also can be used in various studies on leaves. For example, (Pukkela and Borra, 2017) evaluated several techniques for the detection of diseases in a variety of plants (apple, potato, tomato and rice), including radial basis function (RBF) kernel-based support vector machine (SVM) learning algorithm, and SVM with k-means clustering algorithm. Thermal imaging technology can also be employed to detect diseased regions in a nondestructive way (Raza et al., 2015). For this aim, they developed a SVM based system to examine the diseases on the thermal profile of a plant remotely. Other studies show that the automated segmentation model of diseased leaf with active gradient and local information can be used to examine seven diseases over leaf images of cotton under natural conditions. The Jian's model has good segmentation accuracy with less running time when being used to process seven diseases over leaf images of cotton under different conditions (e.g., uneven lighting, leaf disease spot blur, adhesive diseased leaf, shadow, unclear diseased leaf edges, complex background, and staggered condition). Compared with geodesic active contour (GAC) (Kass et al., 1988), Chan-Vese (CV) (Chan and Vese, 2001), and local binary fitting (LBF) algorithms (Li et al., 2007) the Jian's model has the best detection accuracy (Jian-hua et al., 2018). Transfer learning and deep learning have been used with classifiers such as SVM and LDA for plant classification. Flavia, PlantVillage, and Swedish leaf datasets were used as an input to pretrain AlexNet and VGG16 (Kaya et al., 2019). They demonstrated that transfer learning with deep learning models can provide better performance compared to the other combinations. Their dataset is widely available on the internet, including the shapes of the leaves for classification. Pulse-coupled neural network (PCNN) has been used for segmentation of tomato plant images captured at night (Xiang, 2018). The existing solutions shown above have demonstrated promising outcomes in the detection of vine leaf diseases. As can be seen from the studies above, transfer learning based deep learning has shown successful cases in leaf disease detection and we wish to continue to work along this direction. Our study will contribute to vine leaf disease detection by presenting a new technique based on deep learning to improve the accuracy of disease detection in vine leaves with satisfactory efficiency.

2. Materials and methods

In this paper, based on the leaves image input it is aimed to identify normal (healthy) ones and nine different diseases such as anthracnose, black rot, downy mildew, powdery mildew, Fe deficiency, K deficiency, Mg deficiency, mite infections and phylloxera infection. The nine diseases selected are the most common diseases affecting vine leaves in Syria and the surrounding regions.

2.1. Materials

2.1.1. Data set

A total of 1000 digital color images of vine leaves were used, comprising 100 images of leaves showing signs of disease for each of the nine diseases selected, and 100 images of normal leaves. The images were supplied by experienced viticulturists and some were collected from horticultural websites[1] and verified by horticultural experts. A sample of the dataset is shown in Figure 1. The images were applied as an input into the experimental hybrid deep learning classification system. We train the deep neural networks with ImageNet, and then train the parameterized neural networks using our dataset again (in this case, 1000 images) through the transfer learning scheme (See Figure 2).

2.1.2. Computational set-up

We employed MATLAB 2018B with Deep Learning Toolbox. Transfer learning algorithm is illustrated in Figure 3.

[1] https://www.agric.wa.gov.au

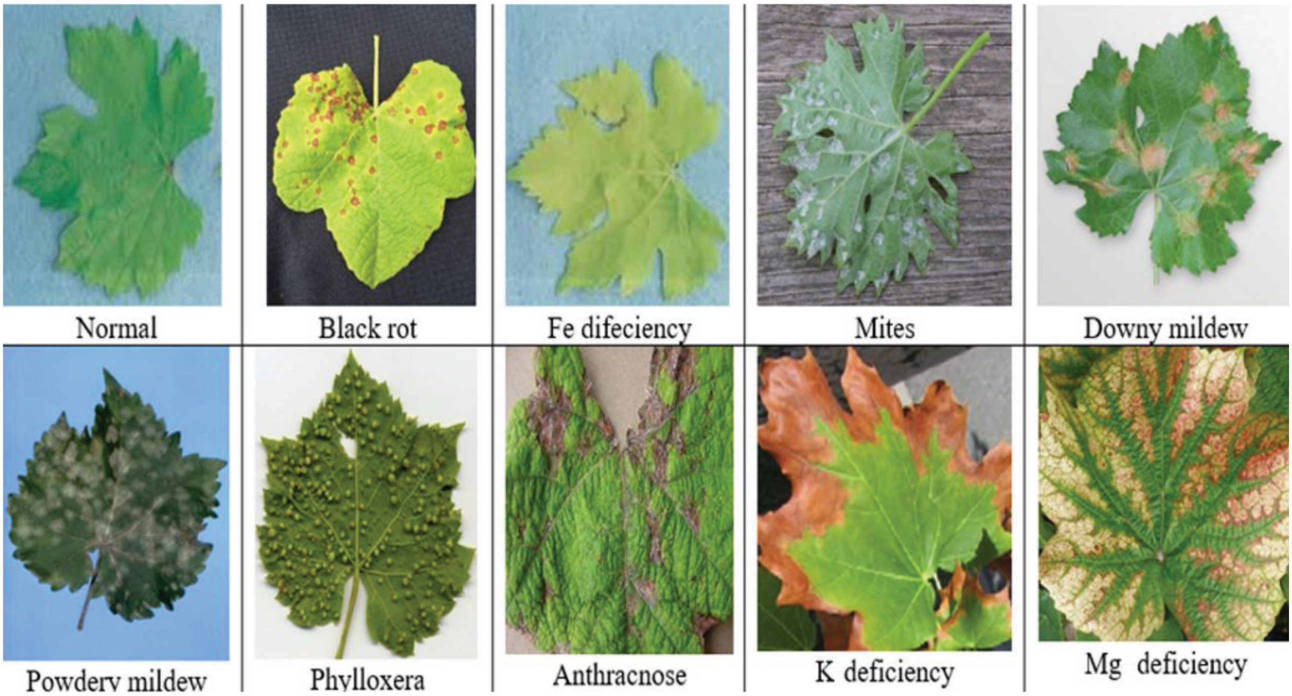

Figure 1. A sample of dataset for each class.

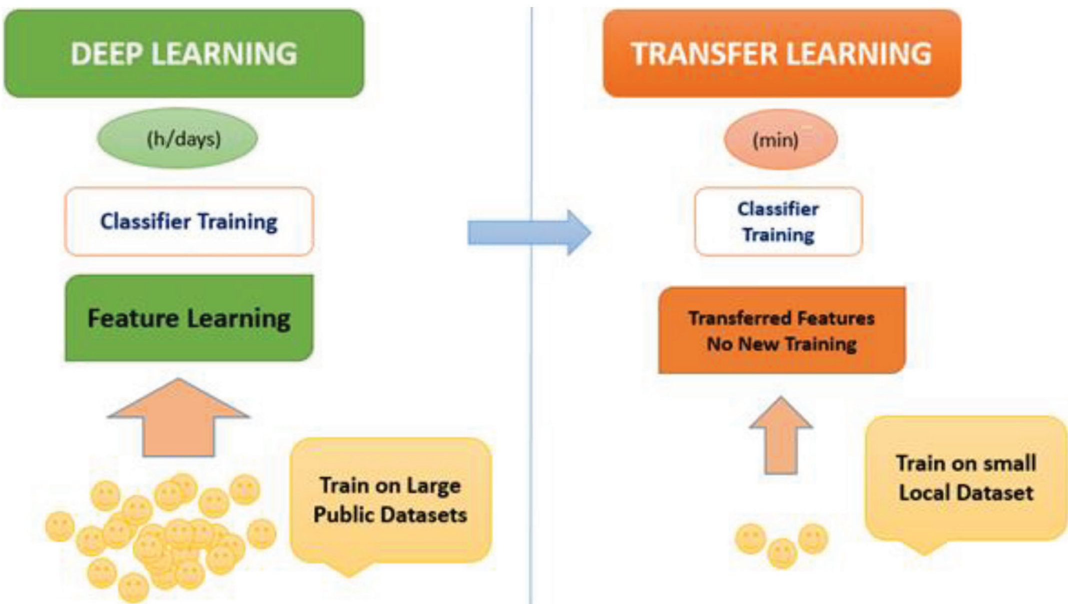

Figure 2. Comparison of building a network from scratch (left) and by transfer learning (right).

We used AlexNet+TL, GoogleNet+TL, ResNet-18+TL, and AlexNet+SVM which are pretrained networks where AlexNet contains 25 layers. The first five layers are convolutional layers and the final three layers are fully connected layers as shown in Table 1.

The first layer, namely the image input layer, requires input images of 227 × 227 × 3 pixels. In this study, we have used a computer with CPU i7/7th, 16GB RAM, and GTX 1050 4GB. These features enable the use of the GPU/CUDA to accelerate the processing in the training and the testing stages. The NVIDIA CUDA Deep Neural Network library (cuDNN) is a GPU-accelerated library of primitives for deep neural networks. cuDNN provides highly tuned implementations for standard routines such as forward

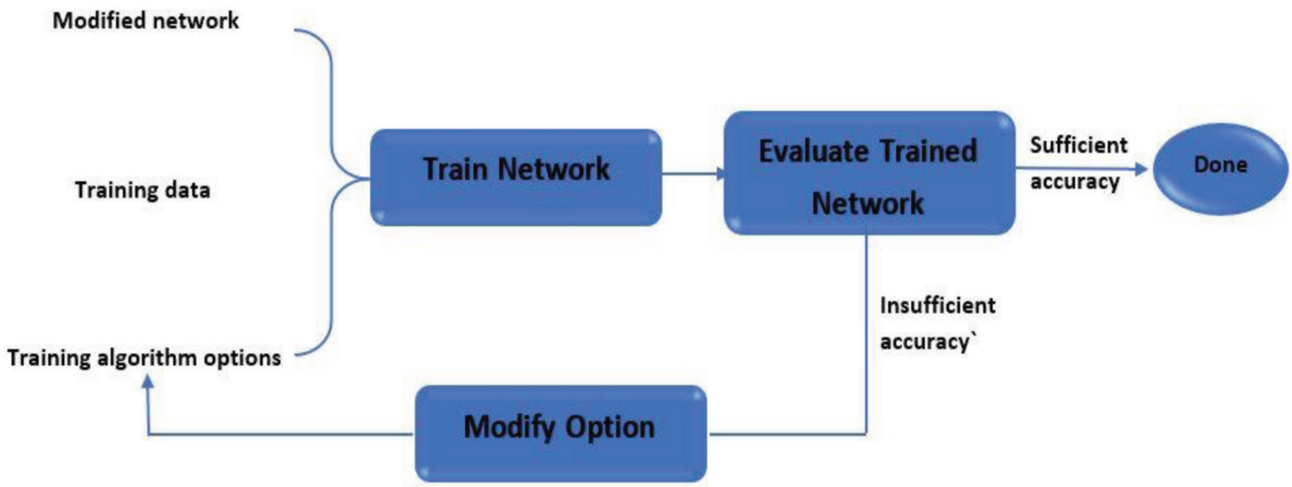

Figure 3. Workflow of transfer learning.

and backward convolution, pooling, normalization, and activation layers[2]. Table 1 illustrates the overall layers of the AlexNet architecture.

2.2. Methods

In this study, three pretrained networks (AlexNet+TL, GoogleNet+TL, ResNet-18+TL and AlexNet+SVM) were used to compare the accuracy of four model networks. ROC-AUC curves of three pretrained networks+TL and AlexNet+SVM (Alkan, 2011) will be given in the experiments.

2.2.1. AlexNet

The images were manually cropped to remove irrelevant background and the resolution of each image was reduced to 227 × 227 × 3 pixels, where 3 is the number of the color channels. Since color changes are an important sign of diseases in vine leaves, it was essential that the proposed system have the ability to distinguish colors.

For the purpose of this study, we decided to use transfer learning because it is an efficient and powerful solution for many classification problems. Training requires enough data and computer time, but much less than training from scratch (see Figure 2 for a comparison with pretrained networks and training from scratch) (Bengio, 2012), and the result is a network specifically tailored to our objectives. It is beneficial that we use the pretrained AlexNet architecture to build the network[3] where Figure 4 shows the AlexNet architecture.

2.2.2. ResNet-18

This pretrained network is a convolutional neural network that is trained on more than a million images.[4] It contains 18 layers and can classify images into 1000 object categories, where the input layer includes the images of a size of 224 × 224 × 3 pixels (see Table 2) for the ResNet-18 architecture (Napoletano et al., 2018).

2.2.3. GoogleNet

This pretrained network is also a convolutional neural network that is trained on more than a million images.[5] This network contains 18 layers and can classify images into 1000 object categories, where the input layer refers to the input images of a size of 224 × 224 × 3 pixels. Figure 5 shows the GoogleNet architecture (Guo et al., 2017).

2.3. Training and testing stages

The prepared images were applied to AlexNet+TL, GoogleNet+TL, ResNet-18+TL, and AlexNet+SVM. For these operations, transfer learning (TL) was applied to three trained deep learning architectures (AlexNet, GoogleNet, and ResNet-18) to get better parameterization of these architectures. Also, in AlexNet+SVM, to classify test images, features extracted from training images were used to train the model.

At this stage, all the legacy network parameters were replaced with our new data (1000 images divided into 10 categories, 80% for the training stage and 20% for the testing stage). Figure 6 shows the stages of using deep learning architectures in AlexNet+TL.

2.3.1. GPU processing and CUDA in MATLAB

MATLAB allows the use of NVIDIA graphics processing units to accelerate the process required by deep learning and other computationally intensive analysis units using CUDA and Parallel Computing Toolbox. Figure 7 illustrates the architecture of using GPU with CUDA code.

[2] https://developer.nvidia.com/cudnn

[3] https://www.mathworks.com/help/deeplearning/ref/alexnet.html

[4] https://www.mathworks.com/help/deeplearning/ref/resnet18.html

[5] https://www.mathworks.com/help/deeplearning/ref/googlenet.html

Table 1. Layers of the AlexNet architecture.

N	Name	Type	Description
1	Data	Image input	227 × 227 × 3 images with 'zerocenter' normalization
2	conv1	Convolution	96 11 × 11 × 3 convolutions with stride [4 4] and padding [0 0 0 0]
3	relu1	ReLU	ReLU
4	norm1	Cross channel normalization	cross channel normalization with 5 channels per element
5	pool1	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0 0 0 0]
6	conv2	Grouped convolution	2 groups of 128 5 × 5 × 48 convolutions with stride [1 1] and padding [2 2 2 2]
7	relu2	ReLU	ReLU
8	norm2	Cross channel normalization	cross channel normalization with 5 channels per element
9	pool2	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0 0 0 0]
10	conv3	Convolution	384 3 × 3 × 256 convolutions with stride [1 1] and padding [1 1 1 1]
11	relu3	ReLU	ReLU
12	conv4	Grouped convolution	2 groups of 192 3 × 3 × 192 convolutions with stride [1 1] and padding [1 1 1 1]
13	relu4	ReLU	ReLU
14	conv5	Grouped convolution	2 groups of 128 3 × 3 × 192 convolutions with stride [1 1] and padding [1 1 1 1]
15	relu5	ReLU	ReLU
16	pool5	Max Pooling	3 × 3 max pooling with stride [2 2] and padding [0 0 0 0]
17	fc6	Fully connected	4096 fully connected layer
18	relu6	ReLU	ReLU
19	drop6	Dropout	50% dropout
20	fc7	Fully connected	4096 fully connected layer
21	relu7	ReLU	ReLU
22	drop7	Dropout	50% dropout
23	fc8	Fully connected	1000 fully connected layer
24	prob	Softmax	Softmax
25	output	Classification output	crossentropyex with 'tench' and 999 other classes

3. Results and discussion

3.1. Accuracy in the three pretrained networks

Table 3 shows the training iterations of using the AlexNet+TL architecture with GPU in MATLAB. It is clear that as the iteration number increases, the accuracy of the image classification goes up while the loss decreases. Similar outcomes can be witnessed from Figures 8–10. The experimental studies have shown that the total detection accuracy of this system reaches 92.5%, 87.4%, 85.0% and 85.1% when we use AlexNet+TL, ResNet-18+TL, GoogleNet+TL and AlexNet+SVM respectively.

In our proposed system, ten different groups were classified (nine types of diseases and one healthy group) with an accuracy rate of 92.5% by AlexNet+TL. Figure 11 shows the confusion matrix of using AlexNet+TL is the most successful technique to test on our dataset.

Table 4 shows the number of correctly classified images, incorrectly classified images and accuracy in the testing stage.

Looking at Table 4, one can see that high classification accuracy rates are obtained with the AlexNet+TL architecture. There are different accuracy figures, changing between 85% and 100% with a noticeable average value of 92.5%. These discrepancies may be due to the image contrast and similarities for some diseases in the dataset. Taking into consideration the nature of the image dataset, we obtain a high classification accuracy rate that can be useful for farmers and agricultural engineers. Also, the AlexNet may be applied to different images for different situations. In our study, CUDA code was used to speed up the processing in GPU by accelerating the processing of deep learning frameworks. In practice, the GPU takes 3:46, 3:07, 6:55, 1.35 min in AlexNet+TL, ResNet-18+TL, GoogleNet+TL and AlexNet+SVM respectively for individual training sessions. On the other hand, CPU needs more than 10 h to complete the exercise of GPU.

3.2. Performance metrics

We use the receiver operating characteristics (ROC) and area under the curve (AUC) to validate the classification

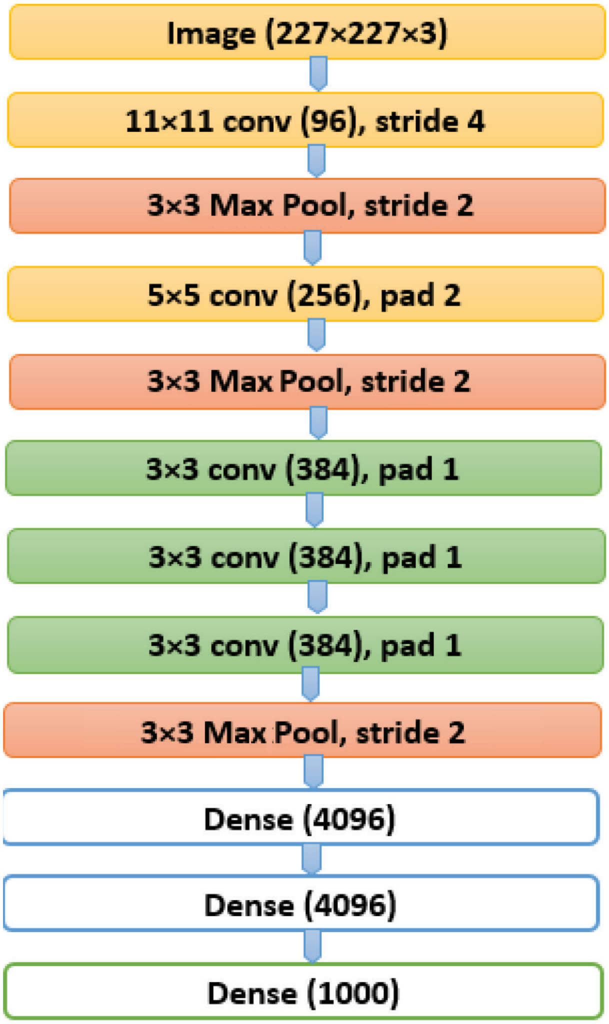

Figure 4. AlexNet architecture.

Table 2. ResNet-18 architecture.

Layer name	Output size	ResNet-18
conv1	112 × 112 × 64	7 × 7, 64, stride 2
conv2x	56 × 56 × 64	3 × 3 max pool, stride 2
conv3x	28 × 28 × 128	$\begin{bmatrix} 3 \times 3.64 \\ 3 \times 3.64 \end{bmatrix} \times 2$
conv4x	14 × 14 × 256	$\begin{bmatrix} 3 \times 3.128 \\ 3 \times 3.128 \end{bmatrix} \times 2$
conv5x	7 × 7 × 512	$\begin{bmatrix} 3 \times 3.256 \\ 3 \times 3.256 \end{bmatrix} \times 2$
Average pool	1 × 1 × 512	$\begin{bmatrix} 3 \times 3.512 \\ 3 \times 3.512 \end{bmatrix} \times 2$
Fully connected	1000	7 × 7 average pool
Softmax	1000	512 × 1000 fully connection

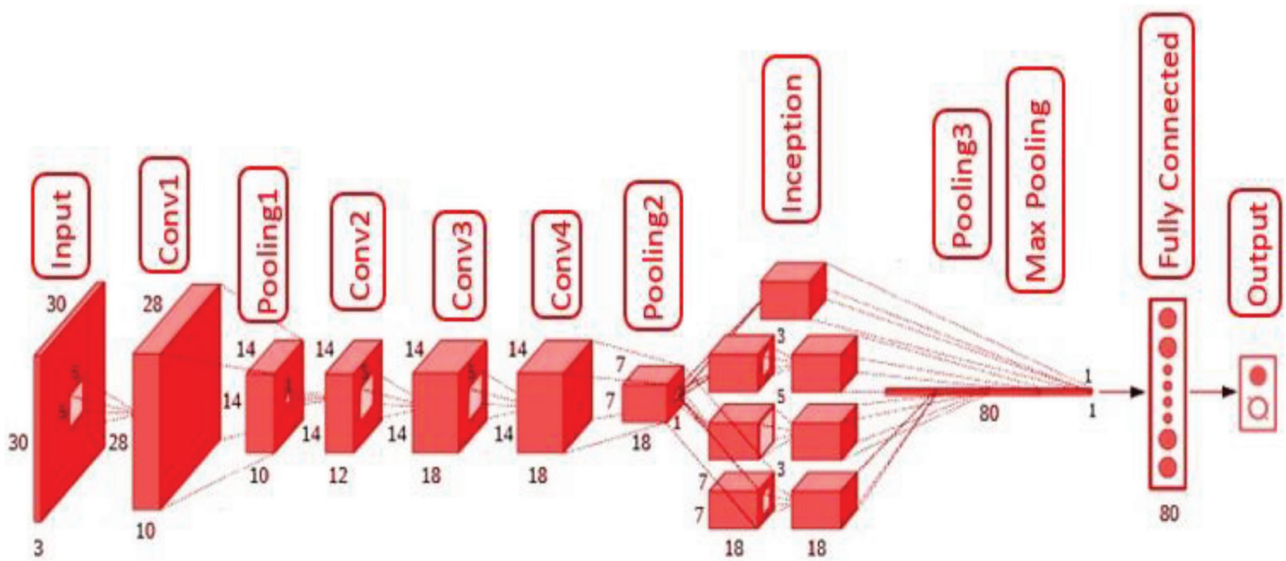

Figure 5. GoogleNet architecture.

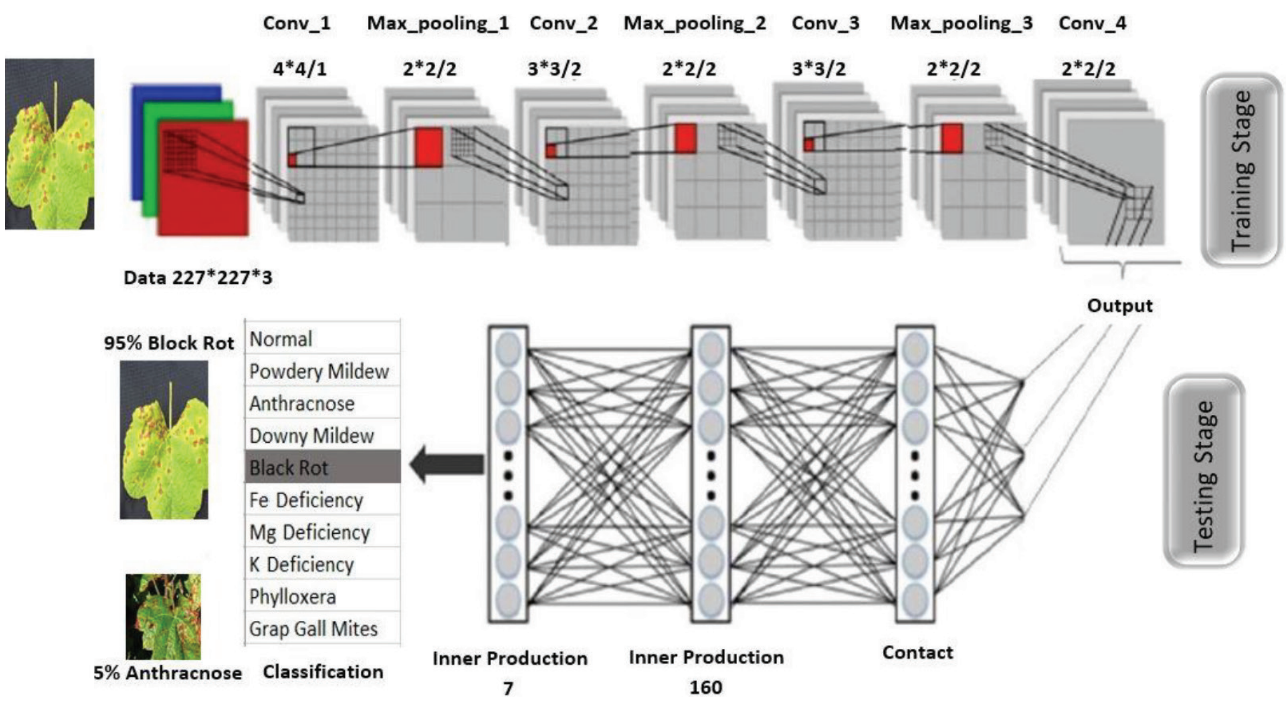

Figure 6. Stages of disease detection in vine leaves by deep learning in AlexNet+TL.

model's performance and find out the best pretrained network in terms of accuracy and efficiency. These classification performance results are given in Figures 12 and 13.

Figure 12 shows that AlexNet+TL is of the best accuracy and highest AUC value for the automatic detection of diseases of vine leaves. This success can also be seen in Figure 13 by examining the calculated AUC values.

In this study, disease diagnosis was made using image processing-based hybrid deep learning from grape leaves. The results obtained by comparing the achieved achievements with similar studies conducted with different plant leaves in the literature are summarized in Table 5. When the table is examined, it can be seen that the obtained results in the current study give high accuracy and AUC values that can contribute to the literature.

4. Conclusion

The use of smart technology in agriculture is increasing every day depending on the technological developments,

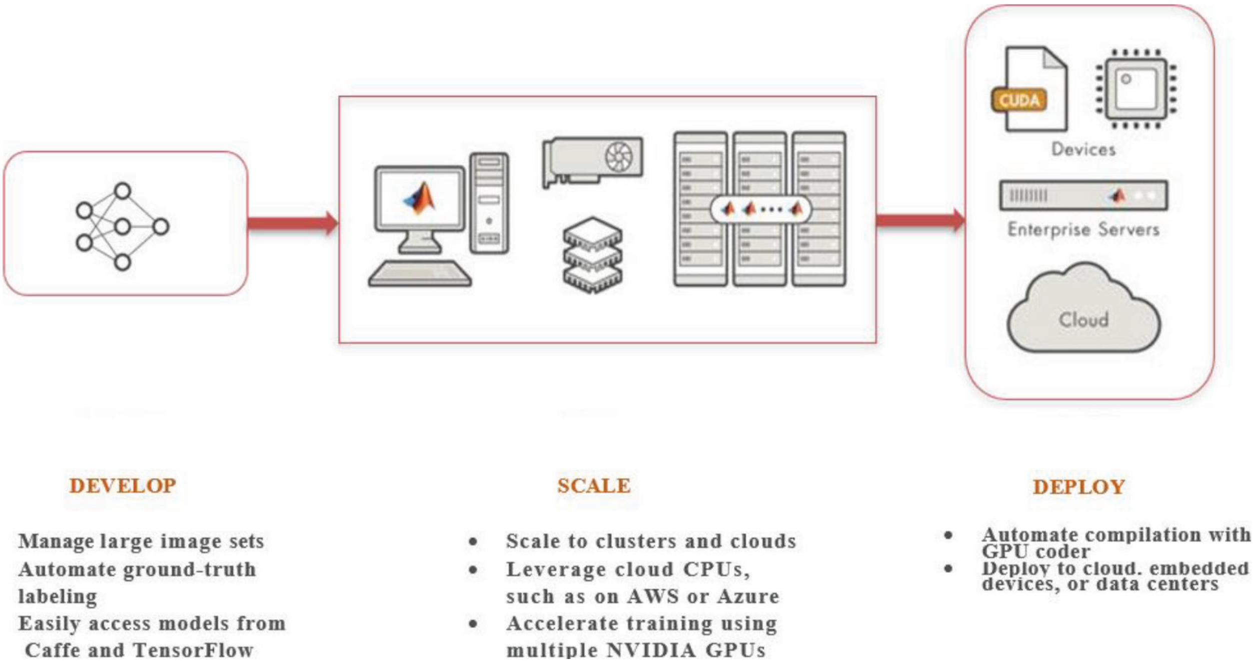

Figure 7. GPU pathway.

Table 3. Training stage for Alexnet+TL with GPU.

Training on single GPU					
initializing image normalization.					
Epoch	Iteration	Time elapsed hh:mm:ss	Minibatch accuracy	Minibatch loss	Base-learning Rate
1	1	00:00:00	20.31%	2.2581	0.0010
9	50	00:00:18	100%	0.0264	0.0010
17	100	00:00:36	100%	0.0085	0.0010
25	15	00:00:55	100%	0.0009	0.0010
34	200	00:01:14	100%	0.0024	0.0010
42	250	00:01:33	100%	0.0004	0.0010
50	300	00:01:52	100%	0.0005	0.0010
59	350	00:02:11	100%	0.0011	0.0010
67	400	00:02:30	100%	0.0011	0.0010
75	450	00:02:49	100%	0.0004	0.0010
84	500	00:03:08	100%	0.0008	0.0010
92	550	00:03:27	100%	0.0008	0.0010
100	600	00:03:46	100%	0.0002	0.0010
Accuracy = 0.9253					

especially artificial intelligence. In this study, we developed a hybrid deep learning based experimental system for automated detection of nine different diseases in vine leaves using. Four different deep learning based hybrid techniques are employed. The highest vine leaf disease detection rate is achieved by using AlexNet+TL algorithm with the rate of 92.5% accuracy. This system can detect/recognize diseases automatically and rapidly, and hence our proposed system will be helpful for the farmers and scientists that study in practice. In a future study, we plan

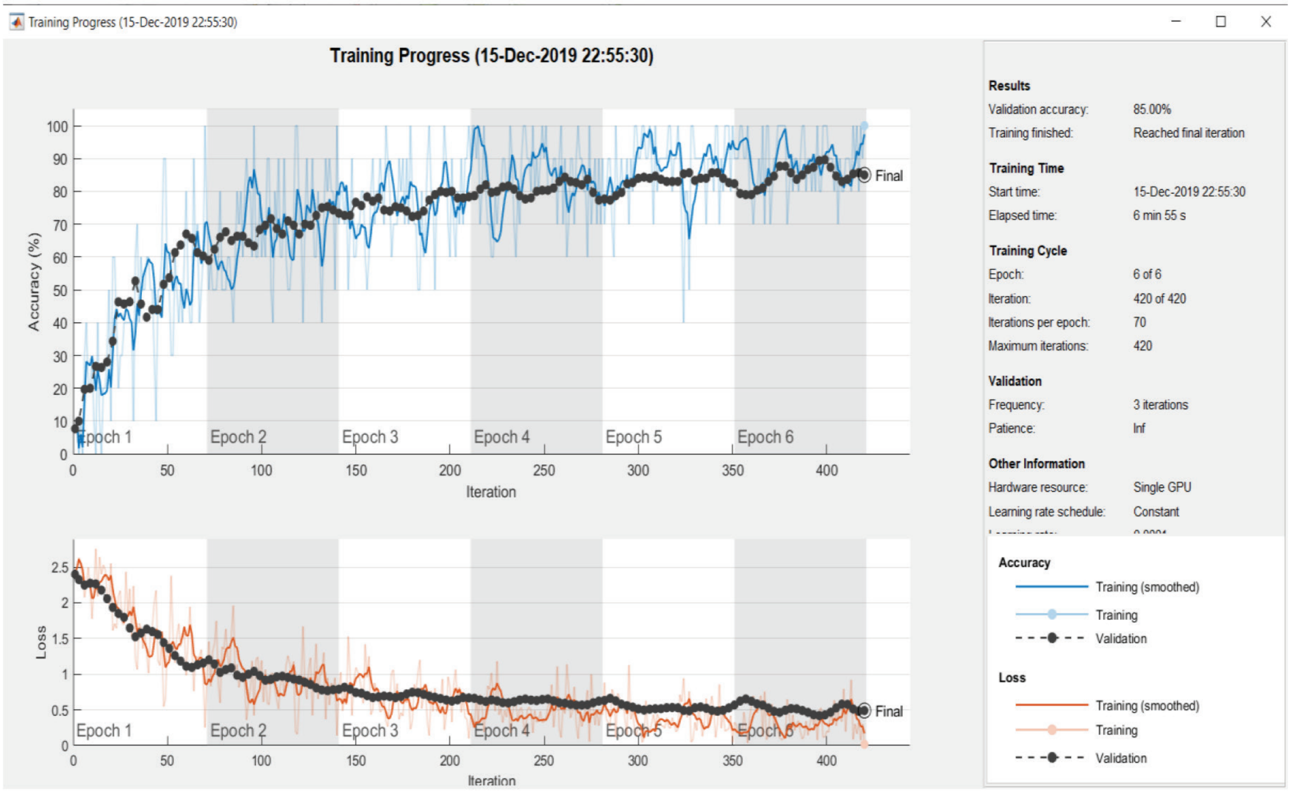

Figure 8. Training stage for ResNet-18+TL with GPU.

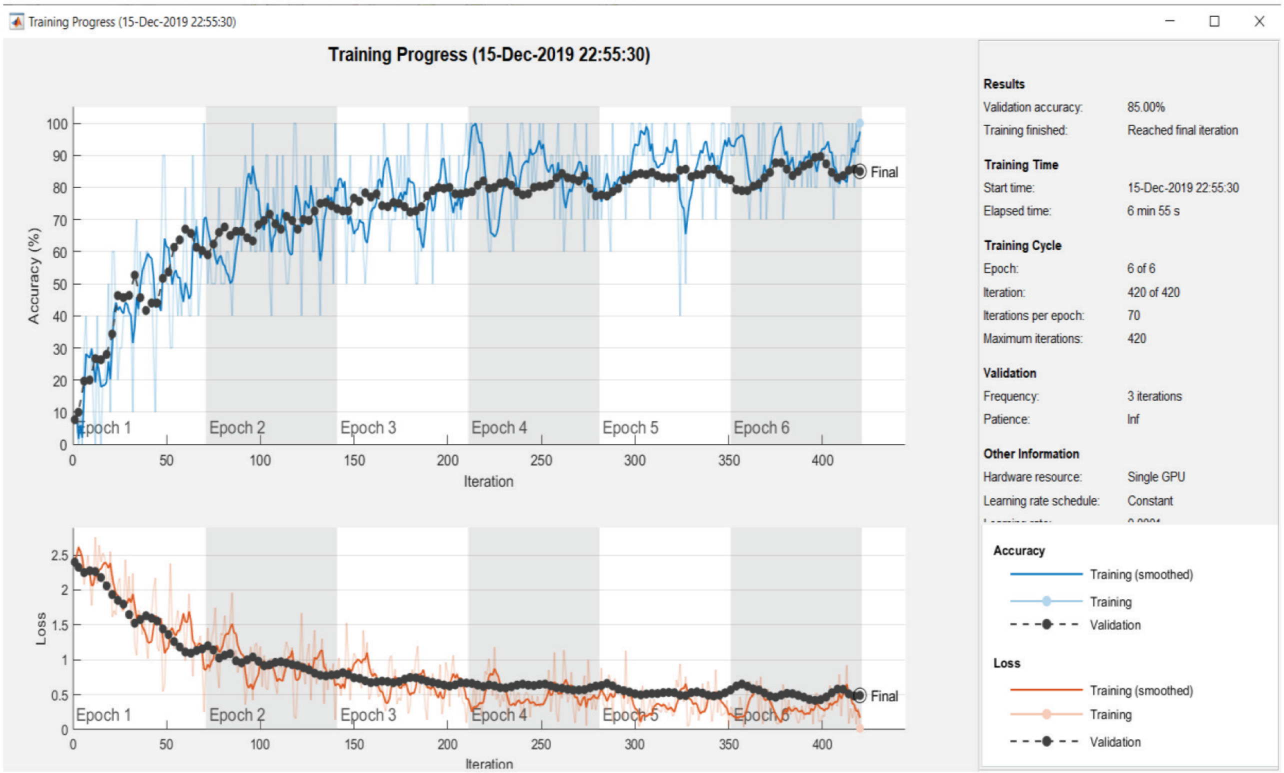

Figure 9. Training stage for GoogleNet+TL with GPU.

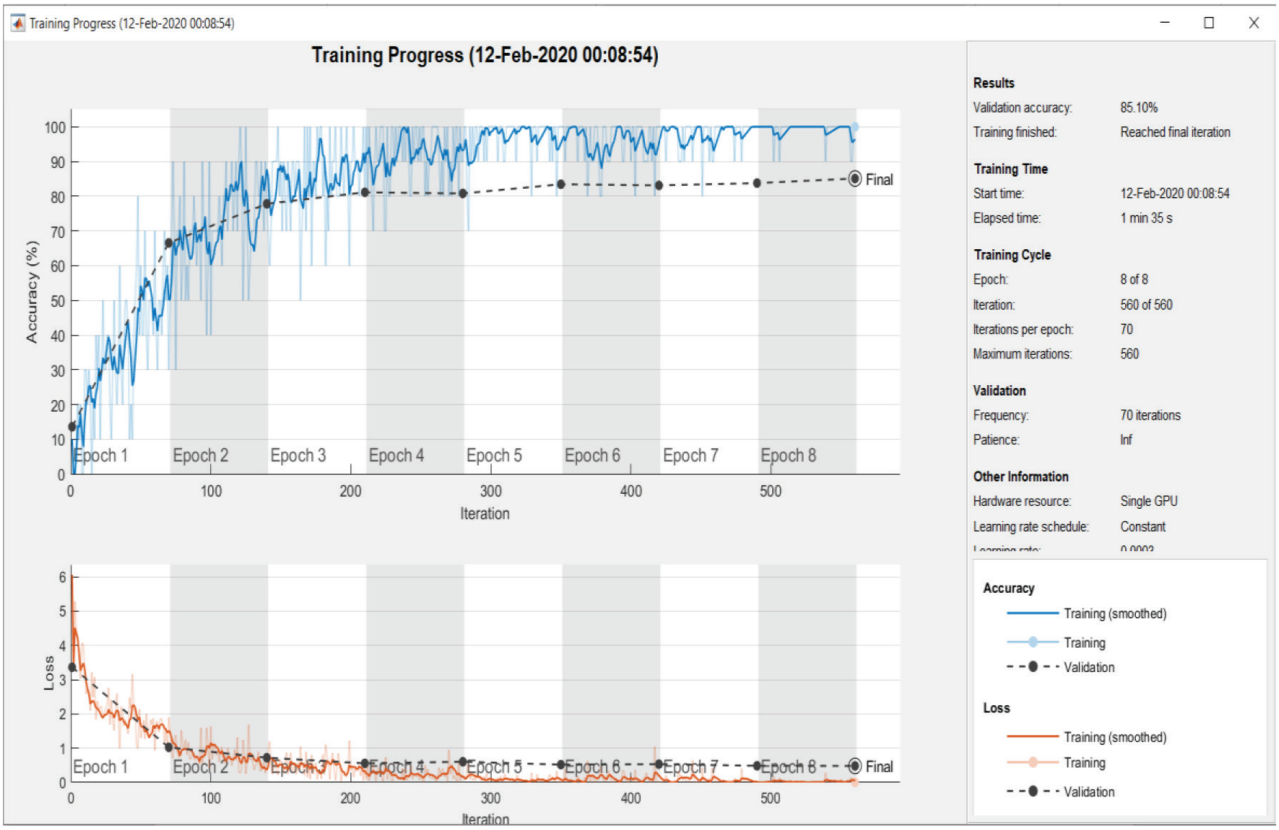

Figure 10. Training stage for AlexNet+SVM with GPU.

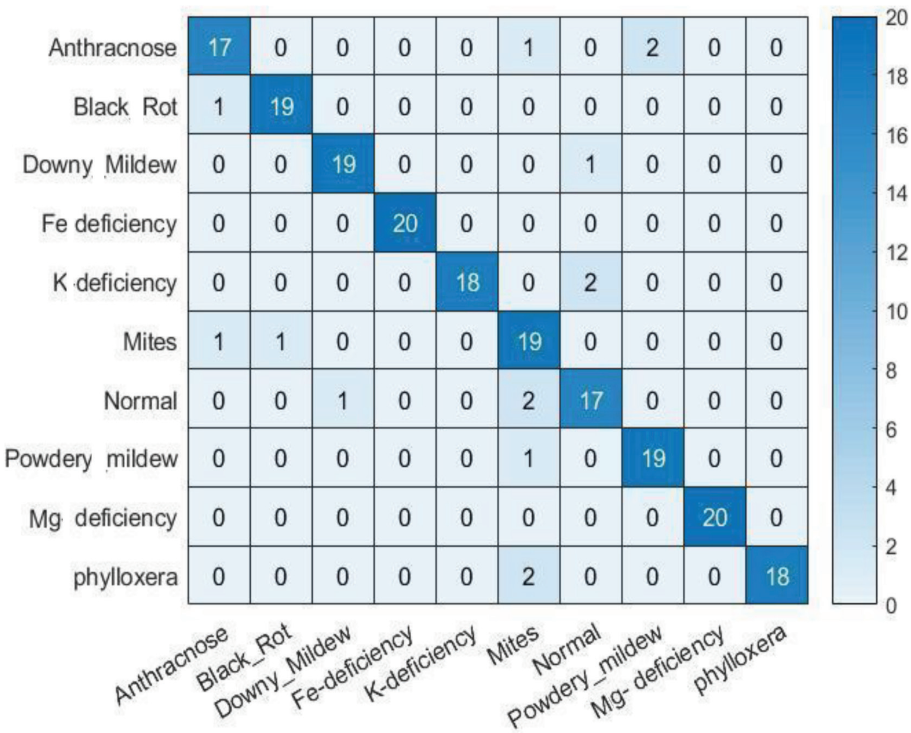

Figure 11. Confusion matrix by Alexnet+TL.

Table 4. Types of diseases and detection accuracy for each class in AlexNet+TL.

Type of diseases	Number of images tested	Number of correct detections	Number of incorrect detections	Accuracy
Anthracnose	20	17	3	85%
Black rot	20	19	1	95%
Downy mildew	20	19	1	95%
Powdery mildew	20	19	1	95%
Mites	21	19	2	90.47%
Phylloxera	20	18	2	90%
Fe-deficiency	20	20	0	100%
K-deficiency	20	18	2	90%
Mg-deficiency	20	20	0	100%
Normal	20	17	3	85%
Total	201	186	15	92.53%

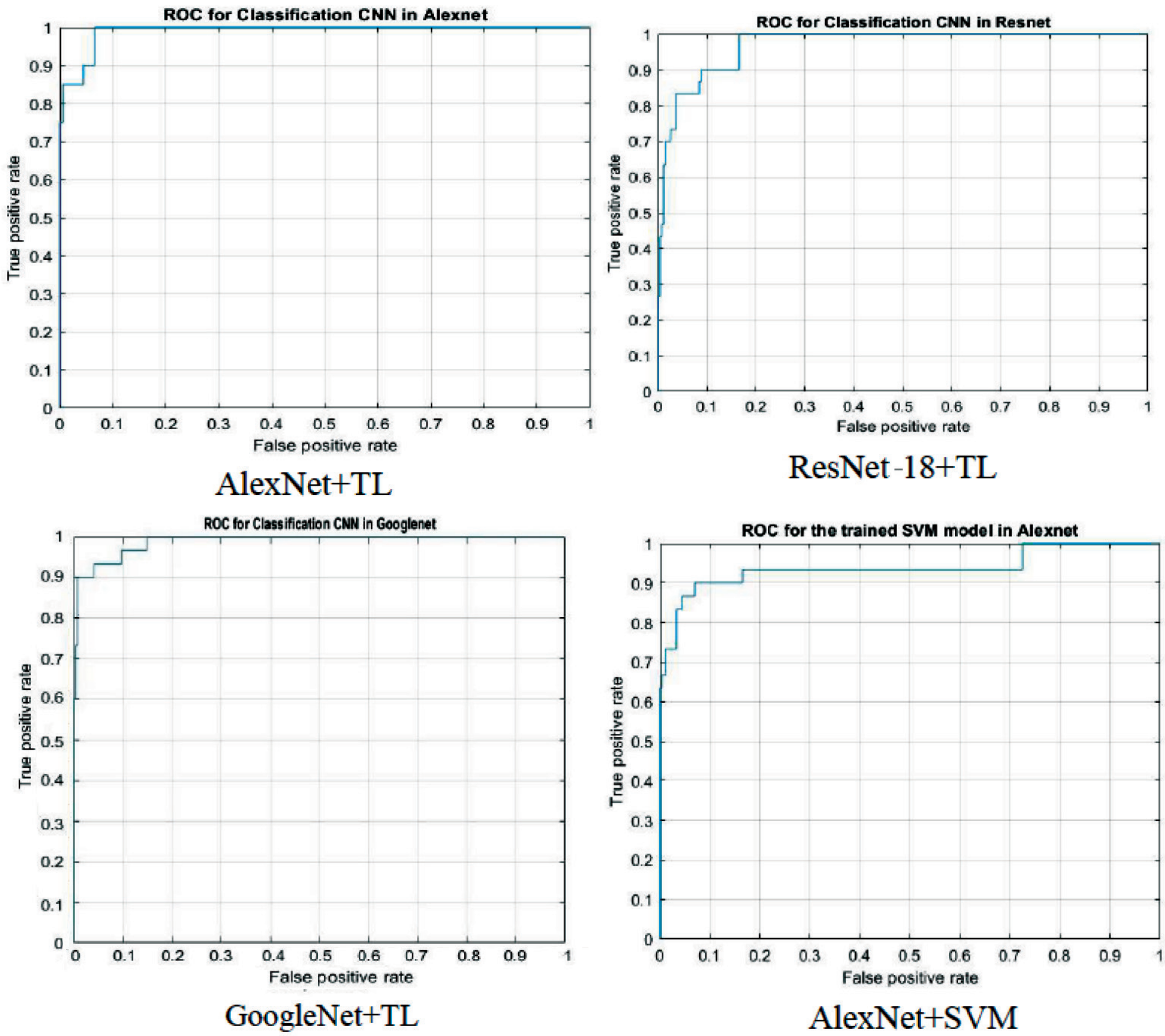

Figure 12. ROC for classification in the four models

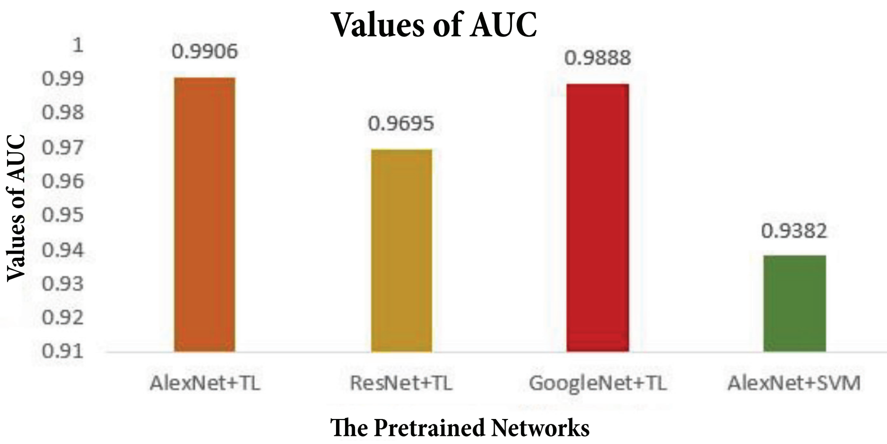

Figure 13. Values of the AUC for the three pretrained networks+TL and AlexNet+SVM.

Table 5. Comparison of the obtained results with the recent literature.

Study	Plant	Dataset sources	Models of methods	Accuracy	AUC
Muthukannan et al., 2015	Bean leaf and bitter gourd leaf.	The agricultural field	FFNN LVQ RBF	0.9067 0.5677 0.7118	NA
Islam et al., 2017	Potato leaf	PlantVillage public source	MSVM	0.95	NA
Pukkela, P et al., 2017	Rice leaf	NA	SVM	NA	NA
Xiang, R. et al., 2018	Tomato	The agricultural field	I Image segmentation based on PCN	0.9167	NA
Current study	Vine leaves	The agricultural fields collected by expert and from internet	AlexNet+TL ResNet-18+TL GoogleNet+TL AlexNet+SVM	0.925 0.874 0.85 0.851	0.9906 0.9695 0.9888 0.9382

to develop a mobile application that will allow farmers to automatically segment and capture images of grapevines by using a portable device to examine the condition of the vine leaves on site.

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