



Deep Learning Convolution Neural Network to Detect and Classify Tomato Plant Leaf Diseases

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Abstract

The tomato crop is an important staple in the market and it is one of the most common crops daily consumed. Plant or crop diseases cause reduction of quality and quantity of the production; therefore detection and classification of these diseases are very necessary. There are many types of diseases that infect tomato plant like (bacterial spot, late blight, sartorial leaf spot, tomato mosaic and yellow curved). Early detection of plant diseases increases production and improves its quality. Currently, intelligent approaches have been widely used to detect and classify these diseases. This approach helps the farmers to identify the types of diseases that infect crop. The main object of the current work is to apply a modern technique to identify and classify the disease. Intelligent technique is based on using convolution neural network (CNN) which is a part of machine learning to obtain an early detection about the situation of plants. CNN method depends on feature extraction (such as color, leaves edge, etc.) from input image and on this basis the decision of classification is done. A Matlab m-file has been used to build the CNN structure. A dataset obtained from plant village has been used for training the network (CNN). The suggested neural network has been applied to classify six types of tomato leaves situation (one healthy and five types of leaf plant diseases). The results show that the convolution neural network (CNN) has achieved a classification accuracy of 96.43%. Real images are used to validate the ability of suggested CNN technique for detection and classification, and obtained using a 5-megapixel camera from a real farm because most common diseases which infect the planet are similar.

Subject Areas

Agricultural Science, Artificial Intelligence, Computer Engineering

Keywords

Convolution Neural Network (CNN), Tomato Plant Leaf Diseases, Machine

1. Introduction

Agriculture has a major impact on the nation's economy, in addition to being the backbone of people's lives. The tomato crop is one of the most important plants, and it directly affects human life. Recently, plant diseases (such as bacteria, late blight, leaf-leaf spot, tomato mosaic, and yellow curved) are wide spread and badly affecting plant growth and causing reduction of quality and quantity of the production [1]. 80% - 90% of plant diseases occurred on the leaves [2]. The process of monitoring the farm and identifying the different types of diseases that affected plants due to the farms is time consuming and requires a long time. In addition, the determination of the type of plant disease by farmers may be inaccurate, and as a result of this decision, the protection mechanisms adopted may be ineffective and sometimes harmful to the plant. It is important to find a smart technology that aims to detect and classify diseases that affect tomato plants with high accuracy.

Deep Learning Neural Network (DLCNN) technology is widely used to detect and classify plant leaf diseases as it achieves high-resolution. The general form of this technique is applied to the tomato plant, **Figure 1(a)**, **Figure 1(b)**. It shows infected and healthy types of tomato plant diseases.

The tomato plant diseases became a domain interesting for many researchers due to both wide-spread and manufacturing important requirements.

Zhang *et al.* [3] discussed how to identify tomato leaf disease by using deep learning convolution neural network (CNN). The paper had used many pre-trained networks such as (AlexNet, googleNet and ResNet) with the accuracy of 97.19%.

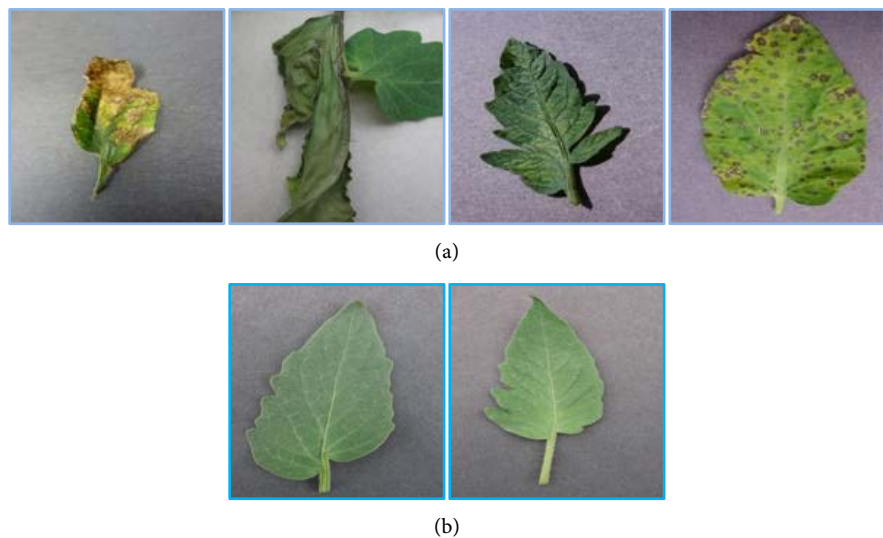


Figure 1. (a) Types tomato plant leaf diseases; (b) Healthy tomato plant leaf.

Prajwala TM *et al.* [4] suggested a method to detect and classify tomato plant leaf diseases using convolution neural network (CNN) based on using a pre-trained network model called (LeNet). The achieved accuracy was 94% - 95%.

Santosh Adhikari *et al.* [5] had created a system containing Raspberry Pi microcontroller (RPM) with a convolution neural network model to detect and classify tomato plant leaf diseases with 89% accuracy achieved.

H. Sabrol *et al.* [6] proposed approach to identify tomato plant disease by using Tree classifier model (TCM). Five types of diseases and one healthy were classified which used 382 images and 97.3% accuracy achieved.

Vetal *et al.* [7] introduced a method to find solution for classifying four types of diseases using Kurtosis, skewness filters and multi-class support vector machine (SVM) classifier model with the accuracy of 93.75% achieved.

Ishak *et al.* [8] had discussed approach to analyze the plant leaf quality, the process started from image acquisition, image processing and classification. Image acquisition was done by using 8-mega pixel smart phone camera, the samples of images then were divided into fifty for healthy and fifty for unhealthy. The image processing method consists of three components, contrast enhancement, segmentation and feature extraction. The classification method has been done using artificial neural network, uses multi-layer feed forward neural network, then comparison between two types of network structures which are Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF). RBF network performance achieved result better than MLP network. The search classifies the plant leaf images to only healthy and unhealthy, it can't detect the type of disease.

Sabrol *et al.* [9] had discussed approach to identify and classify tomato plant leaf. CIE XYZ color space analysis, color moment, histogram, and color coherence are used. The best classification accuracy achieved is 87.2%.

Rangarajan *et al.* [10] proposed a feasible solution to classify tomato crop diseases using tow pre-trained (AlexNet and VGG16 net). The best classification accuracy achieved with number of image 13,262 using AlexNet and VGG16 net was 97.49%.

Coulibaly *et al.* [1] implemented a system to detect and diagnose the diseases that infect millet crops. Their approach was used to extract leaf's features based on the transfer learning technique of the CNN model. A pre-trained network VGG16 model had been used to transfer its learning ability to their suggested neural network, where the best accuracy achieved 95%.

de Luna *et al.* [11] designed a convolution neural network to detect and classify tomato plant leaf's diseases using transfer learning as a training mechanism with deep learning CNN based Alexnet. This approach was used to classify four types of tomato plant diseases. A 4932 of images is used, where it is divided into 80% for training and 20% for testing, and the achieved accuracy is 95.75%.

Mortazi *et al.* [12] had built their own net which used to detect and classified five different types of tomato plant diseases. Their work depends on constructing a network consisting of several layers and requires a short time for training

compare with related previous works based on pre-trained networks like (AlexNet, LeNet, ... etc.). These neural networks consist of any numbers of layers and hyperparameters (learning rate bias and weight, the size of minibatch, the classification precision and accuracy in addition to the time required for execution). This is the main reason for building our network instead of using the pre-trained network.

The suggested CNN are in this paper capable of categorizing 5 different diseases classes in tomato crop using 6202 images with an accuracy of 96.34%. **Table 1** shows a summary of all relevant work that used.

The paper is organized as follows: Section 2 is the description of the proposed methodology. Simulation analysis is given in Section 3. Section 4 explains the results and discussion. Finally, conclusions are stated in Section 5.

2. Proposed Methodology

The structure of classifier model in **Figure 2** consists of four major stages. In the first stage, the plant Village dataset is obtained. All images in the dataset necessary are resized, in the second stage which are split and classified in the third and fourth stages respectively using deep learning convolution neural network (DLCNN), which consist of many layers such as (input layer, convolution layer, batch normalization layer activation function layer, max pooling layer, fully connected layer, soft max layer, and classification layer). As shown in **Figure 3**.

2.1. Dataset

The dataset used in proposed system obtained from plant village dataset [13]. The dataset contains 6202 images used, divided into six groups (five groups for

Table 1. Summary for related work.

Reference	algorithm	Dataset size	Type of image	Dataset size	Accuracy
[4] Prajwala <i>et al.</i>	LeNet	18,160	JPG	Plant village	94% - 95%
[1] Solemane Coulibaly <i>et al.</i>	VGG16	835	RGB	ImageNet	95%
[11] Robert G. de Luna <i>et al.</i>	AlexNet	4923	Colored images	ImageNet	95.75%
[5] Santosh Adhikari, Santosh <i>et al.</i>	CNN	520	Colored images	ImageNet	89%

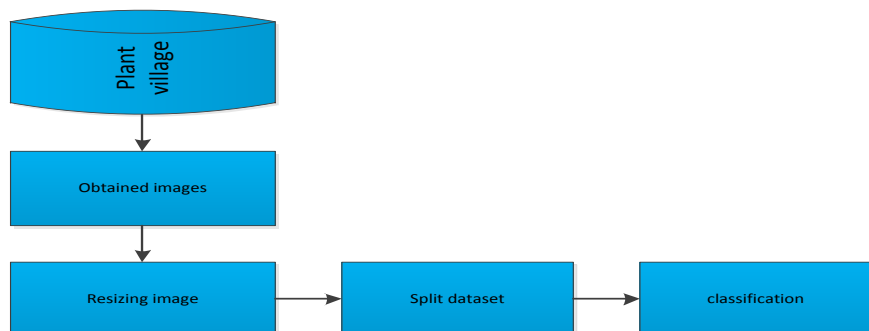


Figure 2. Classifier model.

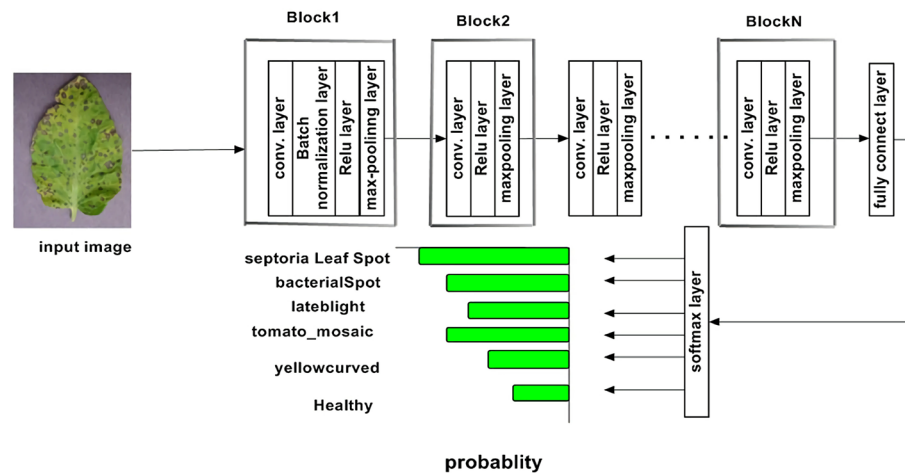


Figure 3. Architecture of proposed network.

inflected plant leaves and the last one is for healthy leaves). The common diseases types are distributed as (bacterial Spot 591, late blight 460, sartorial Leaf Spot 591, tomato mosaic 372, yellow curved 3597 and healthy 591) are used in this work. All images are in RGB color space, its format JPG and PNG.

2.2. Resizing Dataset

(145 × 145 × 3) image size is proposed in this approach to reduce the training time and increase the accuracy. The size of the image depends on the size of network and graphic processing unit (GPU).

2.3. Split Images

The offline neural network must be trained in a set of data to improve the accuracy of the network before testing it with real data, and, accordingly, the data set should be divided into training and testing groups, to avoid increased relevance. The data set can be divided (60% - 80%) for training and (40% - 20%) [14]. for testing, and sometimes increases training data in order to increase the efficiency of the network. In this paper, the images in the dataset are divided into 70% for training and 30% for testing. **Table 2** shows the training and test data that correspond to the accuracy of the network.

2.4. Classification

Deep learning convolution neural network (DLCNN) can be used to detect and classify tomato plant leaf diseases. The proposed approach is a simple model from DLCNN that consist of many convolution layers, batch normalization, activation, max-pooling, fully connect, softmax, and classification. The proposed network architecture consists of three blocks, the first one includes convolution, batch normalization, activation function, max-pooling. The remaining blocks include convolution, activation function, max-pooling followed by fully connected layer, softmax layer and classification layer as shown in **Figure 3**.

Table 2. Split dataset with efficiency of network.

Training data	Testing data	Accuracy
50%	50%	64.25%
60%	40%	89.96%
70%	30%	96.43%
80%	20%	96.77%

Convolution operation is used to extract features such as color and edges from the image. In current work, the size of the filter is fixed in all convolution layers, but the number of filters is changed. In the first convolution layer, the number of filters is 8, while in the second and third convolution layer are 16 and 32 respectively. The function of these layers is extract features such as color and shape from the input image.

Batch normalization layer used to speed up the training of convolution neural networks and reduce the sensitivity for network initialization.

Activation function Rectified Linear Unit (Relu) layer is to eliminate negative value, which can be represented by Equation (1) and **Figure 4**.

$$f(x) = \begin{cases} x, & |x > 0 \\ 0, & |x \leq 0 \end{cases} \quad (1)$$

Max pooling layer contains parameters such as number of filters and number of step size is used to reduce the samples by select the maximum value and eliminate the remaining value, as shown in **Figure 5**. The features extracted from convolution1, Relu1, maxpolling1, convolution2, batch normalization1, Relu2, maxpolling2, Convolution3, Relu3, maxpolling3, see **Figure 6**.

Fully connected layer (FCL) refers to the number of classes, which is 6 classes of tomato plant leaf diseases in this work. Number of class represents the number of neurons is used to connected each input to all neurons.

Soft max layer its function used to calculate the probability of each six target class with a range from 0 to 1 and the sum of all the probabilities will be equal to one. It returns the probabilities of each class and the target class will have a high probability.

Classification layer, is the output layer (final layer) in deep learning convolution neural network. It is responsible for determining the image's affiliation with a specific category.

Pre-trained networks like (AlexNet, RasNet, LeNet, googleNet... etc.) have a large number of layers and millions of parameters, therefore it consumed huge time during training, also its parameters cannot be changed, therefore building an own network with a limited number of layers and other training parameters consider a best choice for solving the problems of pre-trained networks.

3. Simulation Analysis

Matlab software has been used to simulate the suggested 14-layers neural network

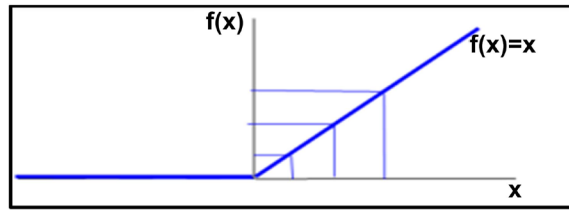


Figure 4. Function of Relu.

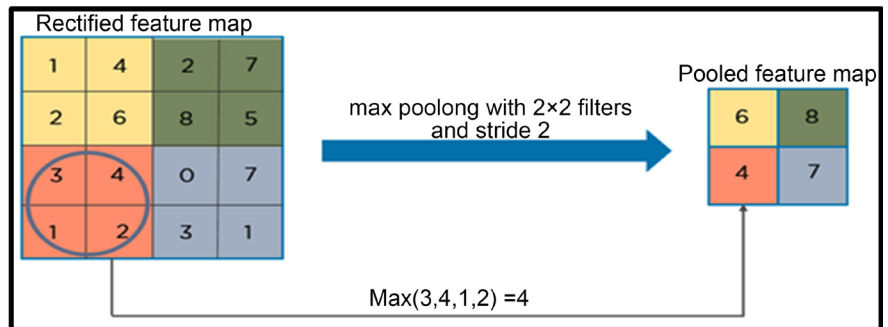


Figure 5. Max pooling function.

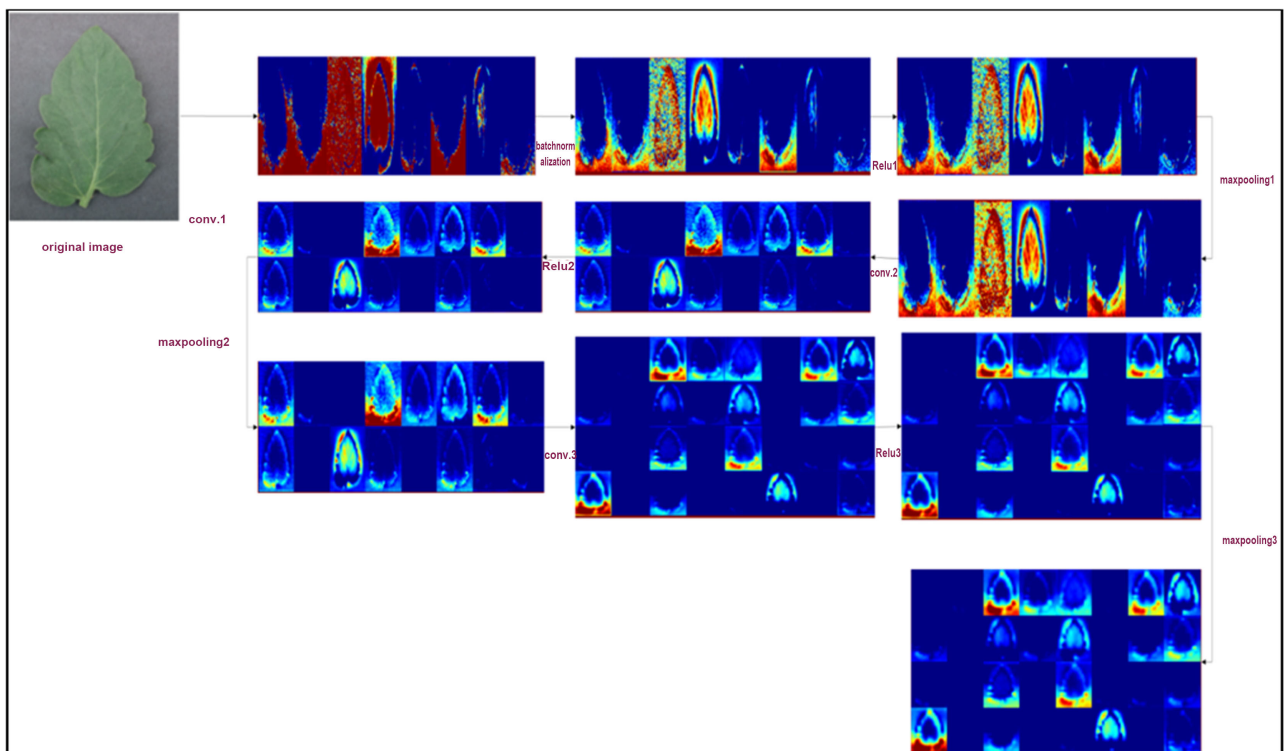


Figure 6. Features extracted.

based on deep learning algorithm. The proposed DLCCN method has been trained using the dataset obtained from plant village for tomato plant leaf diseases. 6202 images divided into six different classes. It is split to 4342 image for training and 1860 for testing. The training options used in this experiment are shown in **Table 3**.

Table 3. Training parameters of the suggested neural network.

Parameter	Description
Solver	Adam (adaptive moment estimation)
Maximum number of epoch	10
Validation Frequency	30
Validation Patience	7
MiniBatch Size	64
Learning rate	reduce by factor 0.5

4. Results and Discussion

The proposed classification system (deep learning convolution neural network) achieves good results to detect and classify dataset of the tomato plant leaves diseases obtained from plant village. Plant's diseases are divided into five categories in addition to a healthy type. These dataset passed in many stages such as resize image and split into training images, testing images and classified using DLCNN. **Figure 7** illustrates the relation between training and validation of the network (DLCNN), through the relationship between accuracy and the number of epochs. The total number of epochs is 10 with 67 iterations per epoch, so the total number of iterations is 670.

The operation process of the neural network consumes about 21 minutes for training and validation. **Figure 8** shows the loss diagram of training and validation, during each step time. Increasing the accuracy of training and validation corresponding to decrease of the training and validation loss. The classification accuracy achieved by proposed network is 96.34%, while the achieved training accuracy is 99.36%.

In addition a confusion matrix method (CMM) has been applied to evaluate the accuracy of classification for each class, also it can be easily used to decide the True Positive Rate (TPR) and False Positive Rate (FPR) according to equations given in Equation (2) and Equation (3) [15] [16] [17].

$$TPR = \frac{TP}{TP + FN} * 100\% \quad (2)$$

$$FPR = \frac{FP}{FP + TN} * 100\% \quad (3)$$

The confusion matrix method is used to compare network output (predicated) and target (actual) output, then calculates classification and error percentage for each class in a test dataset, it describes the performance of the neural network model. **Table 4** and **Figure 9** illustrate.

5. Conclusions

Plant diseases have a bad effect on farmer budgets and the economy of many countries. If these diseases are not discovered in early infected stage time, the treatment will be very expensive and generate a reduction in crop production.

Table 4. Classification accuracy percentage for each class.

Class NO.	Class name	Accuracy (%)
1	Healthy	100%
2	bacterial Spot	87.6%
3	late blight	91.3%
4	sartorial Leaf Spot	94.4%
5	tomato mosaic	87.5%
6	yellow curved	99.1%

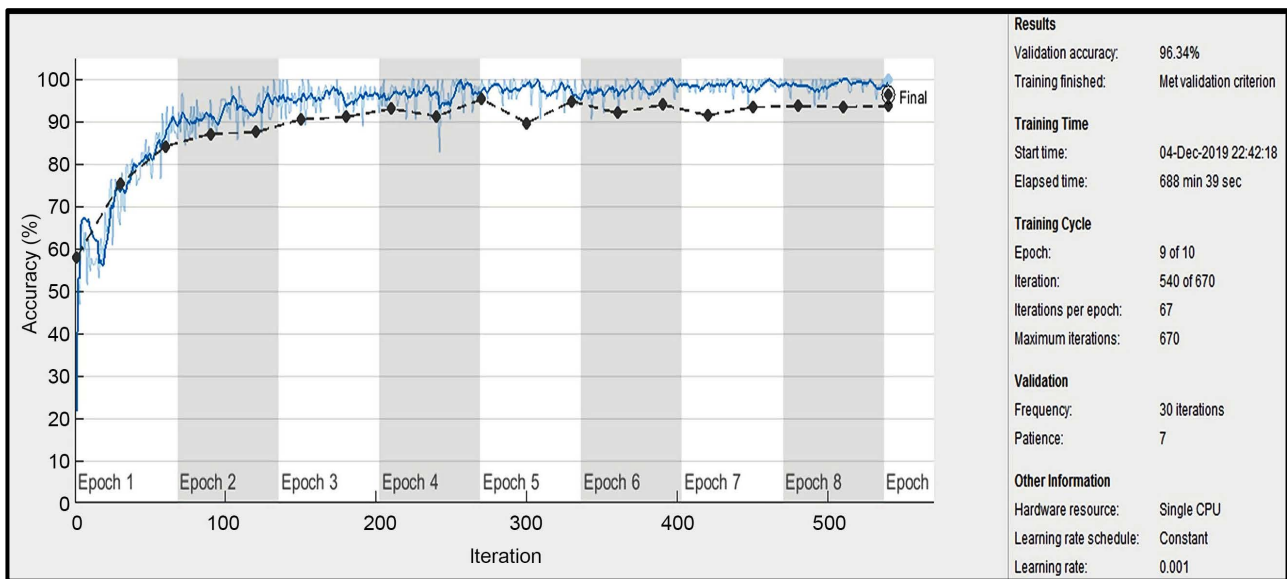


Figure 7. Training and validation accuracy.

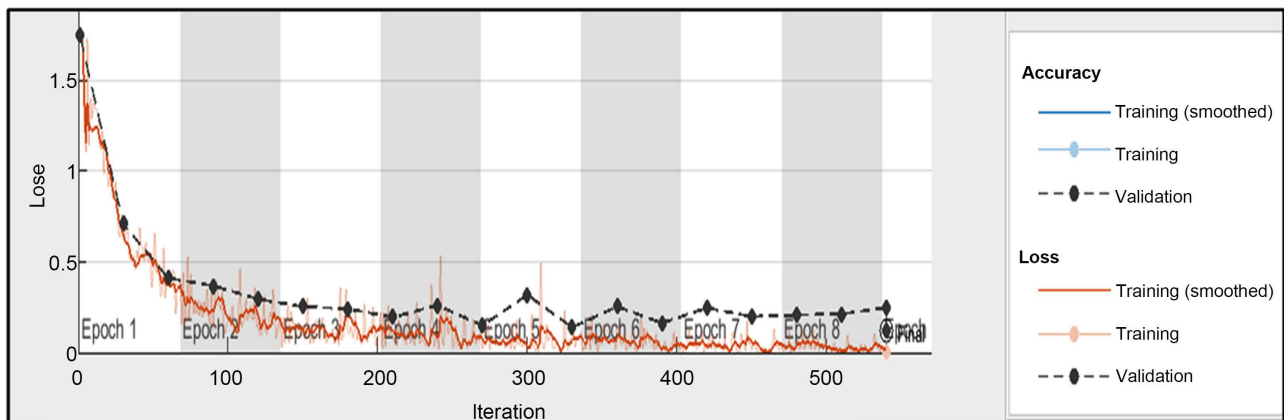


Figure 8. Training and validation loss.

Thus, this work focuses on detecting the primary infection on the plant, where neural network has been trained to monitor any change in color or shape of the leaves. The deep learning approach is considered a modern technique for recognizing and detecting the variation occurring in color and shape of images, also it

		Confusion Matrix							
Output Class	Healthy	177 9.5%	3 0.2%	2 0.1%	2 0.1%	0 0.0%	0 0.0%	96.2%	3.8%
	bacterialSpot	0 0.0%	155 8.3%	1 0.1%	0 0.0%	0 0.0%	6 0.3%	95.7%	4.3%
	lateblight	0 0.0%	7 0.4%	126 6.8%	1 0.1%	0 0.0%	3 0.2%	92.0%	8.0%
	septoriaLeafSpot	0 0.0%	0 0.0%	7 0.4%	167 9.0%	3 0.2%	0 0.0%	94.4%	5.6%
	tomato mosaic	0 0.0%	0 0.0%	2 0.1%	2 0.1%	98 5.3%	1 0.1%	95.1%	4.9%
	yellowcurved	0 0.0%	12 0.6%	0 0.0%	5 0.3%	11 0.6%	1069 57.5%	97.4%	2.6%
			100% 0.0%	87.6% 12.4%	91.3% 8.7%	94.4% 5.6%	87.5% 12.5%	99.1% 0.9%	96.3% 3.7%
		Target Class							
		Healthy	bacterialSpot	lateblight	septoriaLeafSpot	tomato mosaic	yellowcurved		

Figure 9. Confusion matrix.

can be successfully used to identify the diseases of plant leaves. Deep learning convolution neural network has been learned to recognize and detect all these changes in a short time. Because the pre-trained neural networks consist of a huge number of layers and elements, in addition, it needs a very long time to obtain the results; a neural network that used in current work has been built to reduce the drawbacks of these neural networks. A new simple structure of a convolution neural network has been suggested by authors with a minimum number of layers, which consists of 14 layers. DLCNN limitations are: requiring the amount of dataset, needing a long time during training and determining the resolution of an accepted input image.

This network has been trained using a dataset obtained from plant village (6202 images) for tomato plant leaves based on 70% for training and 30% for testing. There is no rule for determining the number of images to the training network, but a lot of images in the dataset will increase network efficiency.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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