Plant Leaf Disease Detection and Classification based on CNN with Tomato Stem Optimization Algorithm

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Abstract — The early detection of diseases is important in agriculture for an efficient crop yield. The bacterial spot, late blight, septoria leaf spot and yellow curved leaf diseases affect the crop quality of tomatoes. Automatic methods for classification of plant diseases also help taking action after detecting the symptoms of leaf diseases. This paper presents a Convolutional Neural Network (CNN) model and TSOA (Tomato Stem Optimization Algorithm) algorithm based method for tomato leaf disease detection and classification. The dataset contains 500 images of tomato leaves with four symptoms of diseases. We have model CNN for automatic feature extraction and classification. Color information is actively used for plant leaf disease researches. In our model, the filters are applied to three channels based on RGB components. The TSOA has been fed with the output feature vector of convolution part for training the network. The experimental results validate that the proposed method effectively recognizes four different types of tomato leaf diseases.

Keywords *–Leaf Disease Detection, Leaf Disease Classification, Convolutional Neural Network (CNN), Tomato Stem Optimization Algorithm(TSOA).*

I. INTRODUCTION

Plant diseases affect the growth and crop yield of the plants and make social, ecological and economical impacts on agriculture. Recent studies on leaf diseases show how they harm the plants. Plant leaf diseases also cause significant economic losses to farmers. Early detection of the diseases deserves special attention. Plant diseases are studied in the literature, mostly focusing on the biological aspects. They make predictions according to the visible surface of plants and leaves. Detection of diseases as soon as they appear is a vital step for effective disease management. The detection is traditionally carried out by human experts. Human experts identify diseases visually but they face some difficulties that may harm their efforts. In this context, detecting and classifying diseases in an exact and timely manner is of the great importance [1]. Advances in artificial intelligence researches now make it possible to make automatic plant disease detection from raw images [2]. Deep learning can be thought as a learning method on neural networks. One of the advantages of deep learning is that it can extract features from images automatically. The neural network learns how to extract features while training. CNN is a multi-layer feed-forward neural network and is the popular deep learning model. In recent years, CNN models have been widely used in image classification problems. Lee at al. [3] introduces a hybrid model to extract contextual information of leaf features using CNN and Deconvolutional Networks (DN). Konstantinos at al. [4] performed several pre-trained CNN models on a large open leaves dataset. Their studies show that CNN is highly suitable for automatic plant disease identification. Durmus at al. [5] also used AlexNet and Squeeze pre-trained CNN models on tomato leaves from an open dataset to detect diseases. Atabay at al. [6] fine-tuned a pre-trained model and designed a new CNN model to perform tomato leaf disease identification. Their study indicates that custom CNN model gives better results than the pre-trained model. Setting a suitable CNN model is a challenging issue to produce higher accuracy values. Zhang at al. [7] proposed a three-channel CNN model based on RGB colors to detect vegetable leaf diseases. Plant leaf images are complex with its background and the color information extracted from a single color component is limited. It causes the feature extraction method to give lesser accuracy results. Using different color components is promising instead of single one. In the proposed paper we developed a CNN model based on RGB components of the tomato leaf images on Plant Village dataset [8]. We preferred TSOA (Tomato Stem Optimization Algorithm algorithm as classifier due to its topology and adaptive model. The paper is organized as follows: section II gives details of CNN. Section III describes TSOA algorithm. Section IV provides the proposed method for plant leaf disease detection and classification. Section V evaluates experimental results. Finally, section VI concludes the paper.

II. CONVOLUTIONAL NEURAL NETWORK

Deep learning is a class of machine learning algorithms that has sequential layers. Each layer uses the output of the preceding layer as input. The learning process can be unsupervised, supervised or semi-supervised. LeCun et al. define the deep learning as a representation learning method [9]. Representation learning algorithms makes optimizations to find the most convenient way to represent the data [5]. Deep learning does not have to divide the feature extraction and the classification because the model automatically extracts the features while training the model. It is used in many research areas such as image processing, image restoration, speech recognition, natural language processing and bioinformatics. CNN is preferred as a deep learning method in this study.CNN, which can easily identify and classify objects with minimal pre-processing, is succesful in analyzing visual images and can easily separate the required features with its multi-layered structure. It consists of four main layers: convolutional layer, pooling layer, activation function layer and fully connected layer. Fig. 1 shows a general CNN architecture.

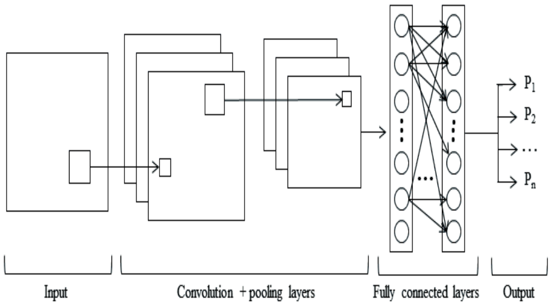


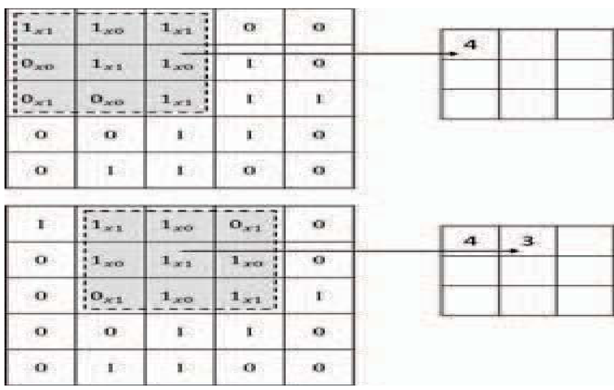
Fig. 1. A general CNN architecture.

A. Convolutional Layer

CNN takes its name from the convolution layer. In this layer, a series of mathematical operations are performed to extract the feature map of the input image [10]. The input image is reduced to a smaller size using a filter. The filter is

Fig. 2. Convolution operation for 5x5 input image and 3x3 filter.

shifted step by step starting from the upper left corner of the image. At each step, the values in the image are multiplied by the values of the filter and the result is summed. A new matrix with a smaller size is created from the input image. Fig. 2 shows the



convolution operation in the convolution layer for a 5x5 input image and a 3x3 filter.

B. Pooling Layer

The pooling layer is usually applied after the convolution layer. The size of the output matrix obtained from the convolution layer is reduced in this layer. Although filters of different sizes can be used in the pooling layer, generally 2x2 size filter is used. Several functions such as max pooling, average pooling and L2-norm pooling can be used in this layer. In this study, max pooling filter with stride 2 has been applied. Max pooling is done by selecting the largest value in the sub windows and this value is transferred to in a new matrix. Fig. 3 shows an example pooling operation.

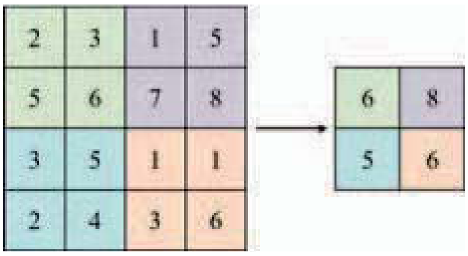


Fig. 3. Max pooling with 2x2 filters and stride 2.

C. Activation Layer

In artificial neural networks, the activation function gives a curvilinear relationship between the input and output layers. It influences the network execution. Non-linear learning of the network happens through the activation function. Several activation functions, like linear, sigmoid, hyperbolic digression, exist, however the nonlinear ReLU (Rectified Linear Unit) activation function is normally utilized in CNN. In ReLU, values less than zero are changed to nothing, while values greater than zero are unchanged by (1).

$$f(x) = \begin{cases} 0, if x < 0 \\ x, otherwise \end{cases} \quad (1)$$

D. Fully Connected Layer

The last acquired matrix, subsequent to completing the convolution, pooling and activation operations, is taken care of into the completely connected layer as input. Recognition and classification are acted in this layer. In this TSOA algorithm has been utilized for preparing the information classification. All layers are not completely connected in this concentrate because of the structure of TSOA utilize a completely connected structure.

III. Tomato Stem Optimization Algorithm (TSOA)

Tomato stem optimization algorithm was motivated by conduct of stem work in tomato High velocity, low degree of calculation, and straightforward execution are the principle benefits of proposed algorithm. This algorithm is a populace based EA. It's anything but an altogether new idea inside the area however enhancements as far as speed of assembly just as getting away from neighbourhood minima are proposed in this method. The algorithm possesses incredible flexibility just as adequate speed in examination with other optimization algorithms to a great extent. The limit of tomato stem to be appealing is additionally one more huge part of the algorithm. The beginning populace is fixed, while in this algorithm, populace is given in ranges with the goal that algorithms can bring populace up in continuous way emphasis till ideal arrangement is reached.

Initial matrices that are comprised of problem parameters, which are tomato stem characteristics which are inherent, are created. For instance, multi-dimensional characteristic may be defined as the capacity of tomato stem to transform to tomato stem and so on. Initial matrices are given by:

$$SC_i = [SC_{i1}, SC_{i1}, \ldots, SC_{i1}] \quad (2)$$

$$i = 1, 2, \ldots, S \quad (3)$$

Where in S means all out quantity of cells participating in execution strategy of this rule while D alludes to issue space measurements introductory populaces are picked with the end goal that appropriations are uniform just as self-assertively stretched out in issue spaces. Measure work is used to discover cost of each tomato stem. The tomato stem is the one having the most reduced expense for the main emphasis. District savvy tomato stems is picked. Worldwide memory stores the expense and area of cells, all things considered, and from this tomato stems are chosen and used in following iterations.Cost functions for all cells are given by:

$$cost(SC_i) = \begin{cases} \frac{1}{a+f_i} & f_i \geq 0 \\ 1+|f_i| & f_i > 0 \end{cases} \quad (4)$$

IV. THE PROPOSED METHOD FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

In this study, 400 training and 100 test tomato leaf images have been used from PlantVilliage dataset. The images in the selected dataset have been cropped to the size of 512x512. The intended leaf diseases to classify in this study are bacterial spot, late blight, septoria leaf spot and yellow leaf curl [15]. Five different classes have been used, four of them are for leaf diseases and one of them is for healthy leaves. Bacterial Spot: Symptoms of bacterial spot begin as small, yellow-green lesions or as dark, water soaked, greasyappearing lesions on leaves. Bacterial spot disease spreads very quickly and is very difficult to control. Therefore it is one of the most dangerous tomato diseases. This disease can cause damage to the tomato plant and its marketability. Late Blight: It is first seen as large brown spots with green gray edges on old leaves. As the disease matures, the spots become darker. Eventually the disease infects the whole plant and causes the plant to be seriously damaged. Septoria Leaf Spot: It first appears in the lower leaves of the plant. The symptoms are round, yellow, water-soaked spots that occur under the leaves. It causes small brown or black spots on the leaves. The size of the spots varies between 1.5 mm and 6.5 mm. Yellow Leaf Curl: It causes the plant to become dwarfed and stunted. The leaves are rolled inwards and upwards. It usually causes the leaves to bend downwards. Leaves become stiff, thicker than normal and have a leathery skin texture. Young and diseased leaves become slightly yellowish. Fig. 5 shows sample images of diseased leaves and a healthy leaf.Fig.

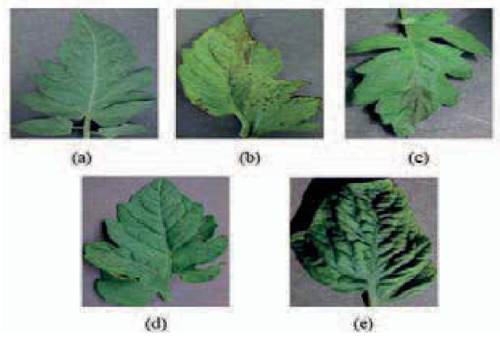


Fig. 5. (a) Healthy Leaf (b) Bacterial Spot (c) Late Blight (d) Septoria Leaf Spot (e) Yellow Leaf Curl.

Three different input matrices have been obtained for R, G and B channels to start convolution for every image in the dataset. Each input image matrix has been convoluted and reLU activation function has been implied four times, respectively. Then the max pooling operation has been implied to the output matrix three times. A 9x9 filter has been used in the first and second convolutions, and a 5x5 filter has been used in the third and fourth convolutions. After these implications, three different 3x3 matrices have been obtained for R, G and B channels separately. As a result of these operations applied to an RGB feature image, three different 3x3 matrices have obtained from R, G and B channels separately.

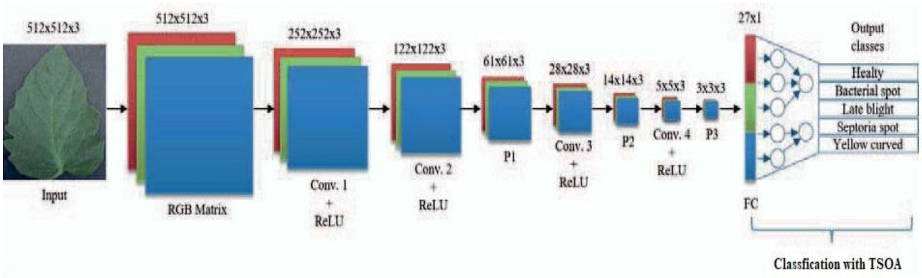


Fig. 6. Architecture of the proposed method.

TABLE I

CLASSIFICATION RESULTS AS CONFUSION MATRIX.

Leaf Disease	Healthy	Bacterial spot	Late blight	Septoria spot	Yellow curved	Accuracy
Healthy	18	0	0	0	2	90%
Bacterial spot	0	18	0	0	2	90%
Late blight	0	0	17	0	3	85%
Septoria spot	1	0	0	16	3	80%
Yellow curved	0	0	0	3	17	85%
Average						86%

V. EXPERIMENTAL RESULTS

To verify the performance of the proposed method, we have conducted a set of experiments on healthy and diseased tomato leaf image databases and have performed classification. One of the main challenges in disease detection and classification for this study is that the leaves with different diseases are very similar to each other. Therefore, this similarity can cause some leaves to be folded into to wrong classes. The classification results are shown in Table I as confusion matrix. 20 images have been used for each class. As seen in the table, leaves ranging from 16 to 18 of 20 for each class have been correctly classified from these test data. Only a few leaves have been incorrectly classified for every classes, and it can be seen in which classes these wrong classifications have been folded in the table.

VI. CONCLUSION

In this paper, a tomato leaf diseases detection and classification method is presented based on Convolutional Neural Network with Learning Vector Quantization algorithm. The dataset consist of 500 tomato leaves images. Three different input matrices have been obtained for R, G and B channels to start convolution for every image in the dataset. Each input image matrix has been convoluted. reLU activation function and max pooling have been implied to the output matrix. Total 500 feature vectors which obtained from original images have been used for training and testing operations in the TSOA algorithm. The experiments have been carried out on healthy and diseased leaf images to perform classification. It is concluded that the proposed method effectively recognizes four different types of tomato leaf diseases. To improve recognition rate in classification process different filters or different size of convolutions can also be used.

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