Double Channel CNN Based Tomato Plant Leaf Disease Detection

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Abstract

Early blight, late blight, bacterial spot, leaf mold, spider mites, yellow leaf curl virus and Septoria leaf spot are the most common diseases of tomato plant which cause major loss to agriculture sector. Diagnosis and prognosis at early stage are prime challenges to save life of tomato crop. This research presents a state-of-the-art Double-Channel Convolution Neural Network (D-CNN) model for diagnoses of 8 different Classes of Tomato Plant Leaves. The proposed model integrates two separate Convolutional Neural Network (CNN) channels with similar number of Conv Layers and Parameters. One Channel processes the pre-processed Red-Green-Blue (RGB) data, whereas the second channel processes the region segmented data obtained by applying a Multi-Otsu Thresholding algorithm. We verified the proposed model on the Plant Village dataset which consists of more than 16,000 images of tomato plant leaves. The proposed model attains an overall accuracy of 94% after 200 iterations, comparatively 3.2% faster than Support Vector Machine (SVM), 2.2% faster than Probabilistic Neural Network (PNN), and 8% faster than Residual Neural Network (ResNet-50).

Keywords—Tomato Leaf Diseases, Convolutional Neural Network (CNN), Double-Channel Neural Network (D-CNN), Deep Learning, Multi Otsu Thresholding, Plant Disease Detection.

1 Introduction

Since dawn of time, edible plants have been the main reason for human survival. Throughout ages humanity has learned to cultivate such plants. Nowadays in 21st Century such plants have become a necessity not only for daily life cooking but to be used for industrial and medicinal purposes. Among such plants Tomatoes are the most popularly consumed fruit around the world and third most harvested fruit in PAKISTAN and world's leading fruit for industrial processing. Tomato crop provides rich nutrition, unique taste, and various health benefits. According to Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) 2018 report presented by Agriculture Marketing Information Service (AIMS), Pakistan ranks at 37th place in Country Wise Area and Production of Tomato where Sindh and Punjab are the top provinces for production of such commodity, 146th place out of 174 Countries in Tomato yield in the World, Pakistan is at 11th place in World Tomato Imports and 27th at World Tomato Exports [1]. Same as other plants tomato plants are also susceptible to various plant diseases. Early Blight, Late Blight, Leaf Mold, Bacterial Spot, Yellow Leaf Curl Virus, and many others. Detection of such diseases at early stages is extremely important. In 2013 Pakistan experienced Yellow Leaf Curl Virus in tomato crops which caused the crop to go bad and prices to hike, also by the end 2019 to mid of 2020 Pakistan experienced shortage of Tomatoes and price hike due to various problems. Whereas in winter season in Punjab Province and other cold regions tomato crop is highly likely to be affected by Spider Mites as the mites grow under the Plant Leaf and go unnoticed and spread at higher rates. Eventually, the useful Human Computer Interfaces exist throughout the world, Pakistan still relies on manual human expertise to detect such diseases and ensure safety of our crops. With increasing demands there is also increment in plant-based diseases making it a key factor for introduction of autonomous, easy to use and swift means for detecting such diseases at earlier stages.

ISSN: *2523-0379 (Online), ISSN: 1605-8607 (Print)*
DOI: https://doi.org/10.52584/QRJ.1902.01

2 Related Work

Expert system innovations that aid the agricultural and economic aspects which include advanced machine learning algorithms or deep neural network models are becoming a part of our daily life work which are now replacing the image processing techniques and traditional means of identifying plant leaves diseases.

In [2], the authors have briefly discussed the pros and cons of the traditional direct and indirect methods, also the potential of Biosensors for detecting Plant Leaves Diseases. According to their findings although traditional direct methods like Polymerase Chain Reaction (PCR), Fluorescence in-situ Hybridization (FISH), Enzyme Linked Immunosorbent Assay (ELISA), Immunofluorescence (IF) and Flow cytometry (FCM) are widely used for Plant Disease Detection yet they are relatively hard to operate [3], time taking and require constant expert supervision, also they do not provide real-time results. Whereas traditional indirect methods that use imaging techniques like (Gas Chromatography GC-MS), Thermography [4] and Fluorescence Imaging [5] have proved to be effective in field of Plant Disease Detection but are susceptive to environmental conditions and change in properties of all type of plant diseases. Furthermore, the usage of biosensors is proving to be promising in disease identification but the sensors that provide the real time data are costly, require very specific and accurate data to generate accurate results.

Computer Image Processing Techniques and Machine Learning algorithms such as k-Nearest-Neighbors (KNN), PNN, especially SVM and many others are proving to be successful in field of Plant Leave Disease Classification. The researchers in [6], proposed a method in which they segmented the data by using multi thresholding algorithm then used Gray-Level Co-occurrence Matrix (GLCM) for feature extraction and at last used the SVM classifier for classifying 4 different classes of Tomato Plant Leaf Disease. In [7], the researcher conducted a study to identify best machine learning algorithm that could classify 5 classes of tomato leaves (4-diseased and 1-healthy). The research methodology consists of 4 stages: Image acquisition in which data was collected manually, Image Preprocessing in which images were resized to 400x400 pixels, Image Segmentation in which features were identified by the gradient of images intensity and edge detection intensity values and at last Image Classification was carried out by using Random Forest (RF), SVM, KNN, Naïve Bayes (NB) and Decision Tree (DT) classifiers that provided the respective accuracies of 89%, 83%, 82%, 81% and 77%. Another Tomato Plant Leaves Disease Classification study conducted by authors in [8], proposed a different approach by introducing a two-step method. In the first step the features are extracted from dataset and provided to KNN, it classifies them into healthy and unhealthy. In later step, the Unhealthy classified data is again preprocessed using RGB to Hue-Saturation-Value (HSV) color space conversion, then various filters are applied that are Sobel and Morphological image filters, after that the data is sent to PNN for classification which then can classify 5 different diseases with accuracy of 91.88% as compared to KNN that provides the accuracy of 78.76% as per the study.

Since their creation, Neural Networks have been known to identify various features like edges, shapes and different intensities from Image based datasets. Not only they are used in the field of Deep Learning and Artificial Intelligence but now are being used to create various faster means for disease detection and classification in Medical Field and for Analyzing, Forecasting in Environmental based fields. The proposed research study in [9], used Faster Region based Convolutional Neural Network (R-CNN), Region based Fully Convolutional Neural Network (R-FCN) and Single Shot Detector (SSD) models as base feature extractors from the manually collected dataset of Tomato Plant Leaves in which diseased parts are manually annotated and then augmented. After base feature extraction, the data is moved for classification through multiple neural network deep feature extractors and classifiers. The proposed method was able to classify 9 different classes with 85.9% for R-FCN - ResNet-50, 83% for Faster R-CNN - Visual Geometry Group (VGG-16) and 82.5% for SSD - ResNet-50, also the study presented that augmented data could be classified more accurately than non-augmented data. The authors in [10], used a typical CNN model for identifying 4 classes of Apple Plant Leaf Diseases. At first the researchers resized the data to 60 x 60 pixels and then augmented the data. After that data was provided to CNN model in which a dropout layer of 0.2 (20%) was added at each block of the model. The model achieved the accuracy of 98.54%.

3 Proposed Methodology

The proposed methodology comprises of 3 stages. A. Data Acquisition B. Data Preprocessing C. Classification.

3.1 Data Acquisition

Initially, the first step undertaken in this research is Data Acquisition. We acquired the required data from the largest publicly available dataset called “The Plant Village” which is available on Kaggle [11]. This dataset contains a total of 50,000 plus images of more than 14 Different Crops and also it contains pre-processed images (segmented images) of each different crop. As for the Tomato Crop there are a total of 10 different classes (1 Healthy Class - 9 Diseased Class) with more than 18,000 images and from the available classes we have used 8 Tomato Plant Leaf Classes (1 Healthy Class - 7 Diseased Class), also we have only used the non-pre-processed image dataset. The resolution of the images present in the dataset is 256 x 256 pixels.

3.2 Data Description

3.2.1 Early Blight

These are small brown lesions in a bull's-eye pattern turning surrounding tissues yellow.

3.2.2 Late Blight

Leaf lesions appear small, dark, and water-soaked spots. These spots will quickly enlarge and a white mold will appear at the margins of the affected area.

3.2.3 Bacterial Spot

The symptoms consist of numerous small, angular to irregular, water-soaked spots on the leaves and may have a yellow halo also centers dry out and frequently tear.

3.2.4 Leaf Mold

Initial symptoms are pale green or yellowish spots on the upper leaf surface, which enlarge and turn a distinctive yellow and lower surface gray.

3.2.5 Spider Mites

Spider mites prefer the undersides of leaves, severe infestation will occur on leaf surfaces. Spider mites spin silk threads that anchor them and their eggs to the plant.

3.2.6 Yellow Leaf Curl Virus

The symptoms are the upward curling of leaves, yellow leaf margins, smaller leaves than normal [12].

3.2.7 Sectorial Leaf Spot

Usually occurs on the lower leaves near the ground. Numerous small, circular spots with dark borders and leaves turn yellow.

3.3 Dataset Partition

After the required dataset is acquired, manual filtration is performed to take out Redundant, Corrupt Anomalous Data (bad lighting, noisy/grainy, smoothened) which affects the classification accuracy. After the filtration process, a dataset of Tomato Plant Leaf has been obtained, and it includes 16,383 images. Then the dataset is divided into three parts Training, Validation and Testing in ratio of 6:2:2, we get 1,591 Healthy Leave Images, 1,000 Early Blight Images, 1,909 Late Blight Images, 2,127 Bacterial Spot Images, 952 Leaf Mold Images, 1,676 Spider Mites Images, 5,357 Yellow Leaf Curl Virus Images and 1,731 Septoria Leaf Spot Images.

4 Data Pre-Processing

The images present in obtained dataset have resolution of 256 x 256 pixels which are resized to 150 x 150 pixels for faster processing.

Inspired by the architectures and performances of classical CNN Models, R-FCN - ResNet-50 and Faster R-CNN - VGG-16 [9], and CNNs multi-channel approach we have created a Multi-Channel CNN based model, namely Double-Channel Convolutional Neural Network (D-CNN), for diagnosis of eight classes of tomato plant leaves. As the name suggests, this model requires two separate inputs. For the First Input the pre-processed RGB data is used whereas for the Second Input the whole the data set presented in TABLE I will be processed by applying a thresholding algorithm.

4.1 Preparing Second Channel Input

4.1.1 Thresholding

This technique is mostly used for performing segmentation on Image based Dataset, which detect and extract object and features invisible to naked eye that help in distributing background from foreground. Thresholding is usually taken out by using a histogram of the image, that is distribution of gray level pixels within the image [13].

4.1.2 Our Method

Global Adaptive Binarization Algorithm or commonly known as Otsu's Method is widely used for Image Segmentation. This algorithm takes maximum between-class variance between object of interest (foreground) and background (non-region of interest). It performs this division based on gray level characteristics of the Image [14] as expressed in Eq.1.

$$\sigma_{B^2} = \omega_b \omega_f (\mu_b - \mu_f)^2 \tag{1}$$

It finds the largest variance between the clusters. Larger the inter-class variance lowers the chance of misclassification. The problem occurs when this algorithm encounters images with multiple regions of interest as is the case with the acquired dataset in Figure 1.

Class	Training Images	Validation Images	Testing Images
Healthy Leaves	1,191	200	200
Early Blight	600	200	200
Late Blight	1,509	200	200
Bacterial Spot	1,727	200	200
Leaf Mold	552	200	200
Spider Mites	1,276	200	200
Yellow Leaf Curl Virus	4,957	200	200
Septoria Leaf Spot	1,371	200	200

TABLE 1: Dataset Partition

Class	Regions	Thresholds
Healthy Leaves	3	2
Early Blight	4	3
Late Blight	5	4
Bacterial Spot	4	3
Leaf Mold	3-4	2-3
Spider Mites	4-5	3-4
Yellow Leaf Curl Virus	5	4
Septoria Leaf Spot	4	3

TABLE 2: Multi Otsu identified regions and thresholds

4.1.3 Multi Otsu Algorithm

To address the problem at hand researchers in [15], came up with a Fast Algorithm for Multilevel Thresholding commonly known as Multi Otsu Thresholding. We have used this algorithm to prepare second input for our Double Channel CNN model. This algorithm separates pixels of an input image into several different classes. By default, this algorithm can obtain three classes / two thresholds automatically as expressed in Equation 2.

$$(\sigma B)^2(t_1, t_2, , t_i, \ldots, t_{M-1}) = H(1, t_1) + H(t_1 + 1, t_2) + \ldots + H(t_{M-1} + 1, L) \quad (2)$$

Initially, a set of 50 images each from 8 classes were tested on the default approach of the algorithm. From the results we found out that only Healthy class and a few cases from Leaf Mold class provided required results on default approach. So, to get optimal results in remaining classes we defined number of desired classes manually. On doing so we found out the overall number of classes were between 3 - 5 as it could be seen in Table 2. Furthermore, a color mapping technique is applied on the obtained regions to separate image data from Multi Otsu algorithm and subsequently data is forwarded as second input for our proposed model in Figure 1.

5 Classification Model Construction

5.1 Convolutional Neural Network Architecture

CNNs have proved to be effective in field of Computer Vision and Artificial Neural Networks. They work well with data that has spatial relationship [16]. Preliminary, the CNN are go-to choice for problems involving Image Classification, Image Semantic Segmentation, Classification and Regression Prediction and Object Detection. Although not specifically developed for non-image-based data they have proved successful in sentiment analysis, time-series based temperature and weather prediction and also object detection and labeling [17]. A typical CNN architecture involves Convolutional Layers, Pooling Layers, Dropout Layers and Fully Connected Layers. In this work two classical CNN Architectures are used to be compared with various CNN and Machine Learning (ML) based models.

5.2 Double Channel Convolutional Neural Network

The concept of Multi-Channel CNNs has been used since the creation of AlexNet which was created using two separate CNNs. These are used to access different views of the data, enabling CNNs to learn more features (edges, shapes, color intensities) thereby improving the classification accuracy of the model, also each separate CNN channel should have same number of convolution layers and parameters [18]. Both separate CNN channels eventually merge into one in the later stages of the network. Our Double-Channel CNN model is a four-block sequential feed forward CNN model. The layers involved in our model are as follows.

Convolution Layer: It is a layer which performs convolution operation on input image using n filters and generates an output called Feature Map or Activation Map.

Max Pooling Layer: It is used to reduce dimensionality of activation map by selecting a pixel value based on filter size.

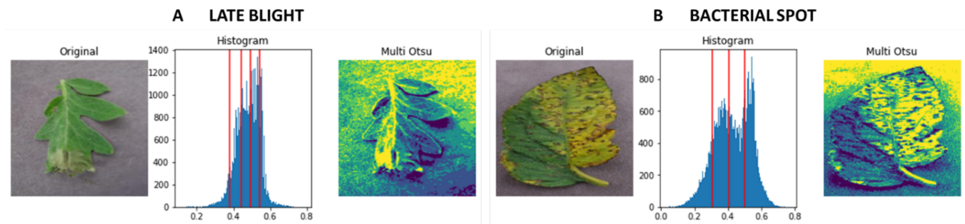

Fig. 1: Multi Otsu & Color Mapped Tomato Leaf Dataset (A) Late Blight 4-Thresholds (B) Bacterial Spot 3-Thresholds

Dropout Layer: Used to drop a specified percentage of features from model to overcome the problem of overfitting.

Dense Layer (Full Connected): Used to aggregate information extracted from previous layers activation maps. Operates on flattened inputs.

Softmax Layer: Also known as the classification layer [19].

As specified earlier our model gets two different inputs for both of its Channels for Channel 1 (CH1) - RGB data and as for Channel 2 (CH2) - Otsu Threshold and Color Mapped data. Each channel consists of four Convolution (CONV) Layers with increasing depths from 32, 64 to 128 and 128, a filter size of 3 x 3 with default value for stride and ReLU (Rectified Linear Unit) activation function. After each CONV layer we have placed Max Pooling Layers because in other pooling types it is difficult to find important information such as edge of interested regions whereas the former takes the most active neuron or in our case the pixel with highest value of each region in feature maps [20] and to reduce dimensionality and enhance extracted features. Each Max Pooling layer has a filter size of 2 x 2. At first the model gets input of 150 x 150 pixels to begin with, upon acquiring the input it is sent to CONV layer where a filter is applied to input and generates feature map of size 148 x 148 pixels with 32 depth then to complete the block a Max Pooling Layer of defined filter is applied to all generated feature maps which reduced its size to exactly half 74 x 74 pixels where the depth remains the same because these layers are also known as non-learning layers. This process continues for another 3 consecutive blocks and at end we are left with feature map of size 15 x 15 pixels with 128 depth but here when max pooling layer is applied the filter size isn't exactly halved but a floor function is applied and we get the end output of 7 x 7 pixels with 128 depth because when facing the odd feature map, the Keras automatically leaves the last column of the feature map if padding is not performed. To counter the problem of Overfitting that is the model learns the details and noise in training data to the extent that it negatively impacts the performance of model on new data. As there is no sort of segmentation being done, the model starts to learn patterns and noise present in the background and on regions of non-interest. So, we placed a Dropout Layer of 0.2% after the fourth CONV block as in Figure 2. After the four CONV blocks outputs from both channels CH1 and CH2 are flattened and fused together. By fusion, it is meant that the flattened identified/extracted features provided by CH1 and CH2 are summed together using Keras Merge Layer Techniques, which are then forwarded towards a Hidden Full Connected Layer with 512 neurons and ReLU activation. After which the fused features are forwarded towards the final Full Connected Layer with 8 neurons and Softmax Classifier for the purpose of classifying 8 different classes of Tomato Plant Leaves. As mentioned in TABLE III, the model uses Adaptive Moment Estimation (Adam) optimizer which provides a faster and more direct approach with minimum loss and is often suitable for smaller runs as we have used it along with 200 epochs.

Parameters	**Values**
Batch Size	32
Epochs	200
Optimizer	Adam
Classifier	Softmax

TABLE 3: Model Parameters

6 Results & Comparative Analysis

Successively, in this research we present the results obtained by our proposed Multi Channel CNN based architecture namely Double-Channel CNN model. The hardware required by proposed model involved Intel Core i5 10th Generation processor, NVIDIA GTX 1660ti 6gb and the model was developed using TensorFlow and Keras libraries in Python language using Anaconda IDE. For Evaluation, we have used Precision, Recall F1 Score and Overall Accuracy based on Confusion Matrix.

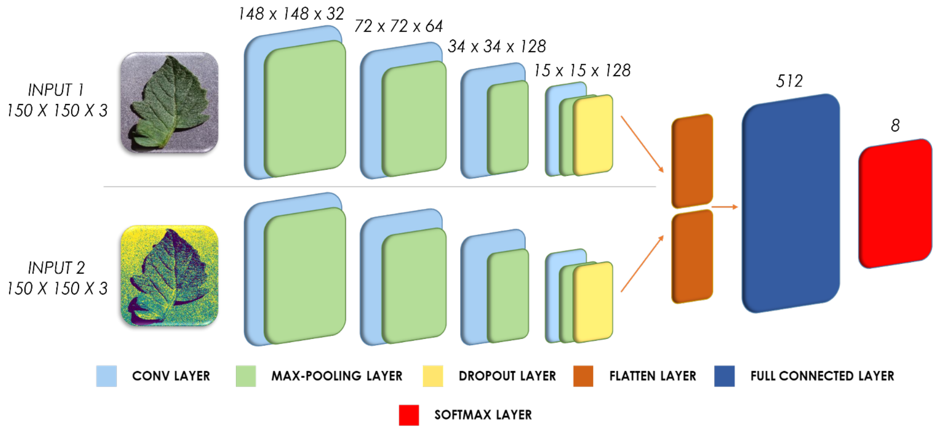

Fig. 2: The proposed Double-channel Convolutional Neural Network (D-CNN) architecture

Our model achieved the Overall Accuracy of 94% by successfully classifying test dataset of total 1600 images of Eight Different Tomato Plant Leaves Classes as described in Table 1, with F1 accuracy equal to and greater than 93% for each class. The recognition performance of our proposed Double-Channel CNN model as shown in Figure 3a, shows that our model Training Accuracy slope moves close to 1.0 (100%) within 25 epochs out of 200 epochs whereas the model Testing Accuracy slope move close to 1.0 (100%) within 20 epochs out of 200 epochs.

From Figure 3b, it is clearly visible that our proposed model trained very well with loss curve moving towards 0 within 25 epochs and keeps on decreasing as our models iterates more. Furthermore, to provide comparative analysis we have compared our model with various Machine Learning and Neural Network Models which both require high level and complex pre-processing techniques to be carried out first onto the acquired dataset. The conducted analysis is both research study based and experimental. By comparing with the study taken out on PNN and KNN in our model is 3% and 11% more accurate [8] in classifying 8 different classes whereas the PNN and KNN were able to classify only 5 different type of Tomato Plant Leaves Diseases, their model construction involved 2 complex steps to carry out classification at first they performed pre-processing on dataset which involved a series of operations first RGB TO HSV conversion then applying Sobel edge detection to identify edges of the leaf and diseased areas in the leaf and at last applying morphological operations which are basically performed to fill the space between detected edges with white pixels to create a mask that can be used for segmentation then to carry out first classification GLCM was to extract features an to classify KNN classifier was used which gave the Binary result of Healthy and Unhealthy after that unhealthy data is then forwarded for second classification where GLCM is used once again and PNN classifier is used to classify 5 different disease classes. Whereas in [9], Faster R-CNN - VGG 16 and R-FCN - RESNET 50 models are 11% and 9% less accurate in identifying 10 plant diseases, their models require pre-processed data which first involves manually annotating the acquired dataset with bounding boxes where each box represents diseased area. Then data augmentation is performed on the data to increase the size of dataset after that they used defined pre-existing models to identify 10 tomato plant diseases. From both studies it is visible that our model requires less complex operations to perform classification.

7 Conclusion

In this work we have proposed a deep learning based robust real-time Tomato Plant Leaves Disease Detection Multi Channel Model named Double-Channel CNN. The proposed Model accepts RGB Data and Otsu Threshold data as Two Inputs Channels. To obtain more information and topological structures from Diseased area on leaves. Activations from both channels are fused together at a Hidden Full Connection Layer. The dataset on which the classification is taken out is called Plant Village Dataset locally available on Kaggle.

For future work improve our model accuracy to compete with state-of-the-art CNN models like GoogleNet, United Model and, increase number of classes and use different optimizers.

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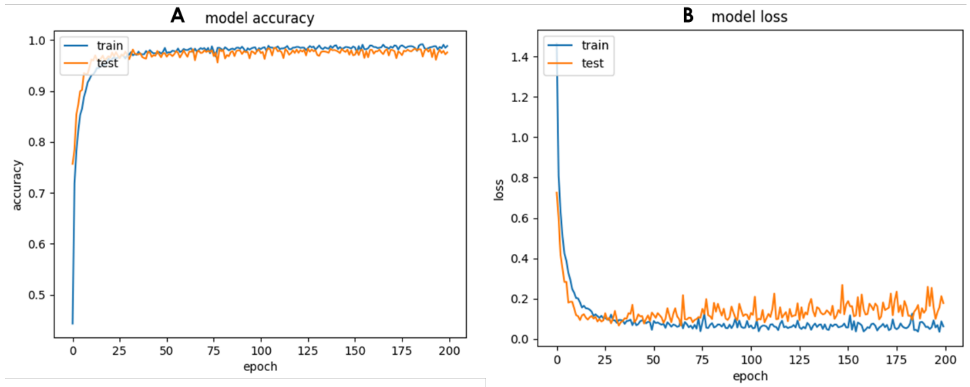

Fig. 3: a) D-CNN Train - test accuracy graph per 200 epoch, b) D-CNN train - test loss graph per 200 epoch.

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