DETECTION OF PLANT LEAVES DISEASE USING CNN AND IMPROVED TECHNIQUES

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ABSTRACT

Current crops have always been important for food use so in order to keep the plants healthy and edible, we should feel the leaves of plants that are not affected by disease and use the Tomato crop as a test of our model. The tomato plant is an important base in the Indian market with a high commercial value and is produced in large quantities. Diseases are harmful to the plant's health and contribute to its growth. To ensure the minimal loss of the cultivated crop, it is important to monitor its growth. There are many types of tomato diseases that target the leaves of a plant at an alarming rate. This paper acknowledges a small variation of the convolutional neural network model called LeNet to detect and diagnose diseases in tomato leaves. The main purpose of this proposed project is to find a solution to the problem of tomato leaf disease using a simpler method while using smaller computer resources to obtain comparable results with state-of-the-art techniques. Neural network models use automatic feature extraction to help split the input image into successive disease stages. The proposed system achieved an average accuracy of 94-95% indicating the possibility of a neural network pathway even under adverse conditions.

Keywords: *leaf detection, neural network, convolution, LeNet*

1. INTRODUCTION

India is a country with a large population dependent on the agricultural sector. Tomatoes are the most widely used vegetable in India. The three most important antioxidants that are vitamin E, vitamin C and beta-carotene are found in tomatoes. They are also rich in potassium, minerals that are essential for good health. The tomato farm in India covers about 3,50,000 hectares and the production area reaches 53,00,000 tons, making India the third largest producer of tomatoes in the world. Climate sensitivity to plants has caused disease to spread to the tomato plant at all stages of its growth. Disease-affected plants make up 10-30% of the total crop losses. The identification of these diseases in the plant is very important in preventing significant losses in yield and value of agricultural production. Monitoring plant diseases personally is a daunting task because of their complex nature and time-consuming process. Therefore, there is a need to minimize the effort required to perform this task, while making accurate forecasts and confirming that the lives of farmers are not a problem.

Visible patterns that seem difficult to define by a single look, leading many farmers to make erroneous assumptions about the disease. As a result, preventive measures taken by farmers may be ineffective and sometimes dangerous. Farmers often congregate and use conventional methods of disease prevention, as they do not have expert advice on how to deal with their crop infections [2]. There have been cases where due to insufficient information or misinterpretation of the disease, excessive use or ingestion of pesticides has resulted in crop damage. This is the basic motivation for the proposed method aimed at accurately identifying and diagnosing diseases in the tomato plant.

The proposed method is based on the most common diseases found in tomato plants such as, Bacterial leaf spot and Septoria leaf spot, Yellow Leaf Curl among many others. Any leaf image given as an implant can be classified as one of the stages of the disease or can be considered healthy. The site used for testing is part of Plant Village [6], a repository containing 54,306 photographs of 14 plants infected with 26 diseases. The subset includes some 18160 photographs of tomato leaf diseases.

In general, the proposed method consists of three main steps: data acquisition, pre-processing, classification, and feature removal. Pictures for use of the proposed method are derived from a publicly available database called Plant Village, as mentioned earlier. In the next step, the images are resized to a normal size before being included in the partition model. The final steps in the separation of input images is using a small variant of the standard deep learning convolutional neural network (CNN) model called LeNet which contains fully converted, open, integrate and fully integrated layers.

The paper is structured as follows: Phase II focuses on the key work done in relation to the sector concerned. Section III sets out the proposed methodology and the model used and the steps taken to obtain the required results. Phase IV deals with the outcomes and analysis of the proposed performance. Section V covers the end of the paper and provides the scope for future work.

2. LITERATURE SURVEY

It is important to note the previous research done in this field so that you can move forward in the right direction. The discovery of plant leaf diseases has been a major area of study where both image processing and in-depth reading methods have been widely used in their precise classification. In this paper, we discuss methods that are often included in the text in the appropriate paragraph. Two common diseases of tomato plants look like those shown in Fig. 1 and Fig.2 and Fig. 3 are healthy tomato leaves

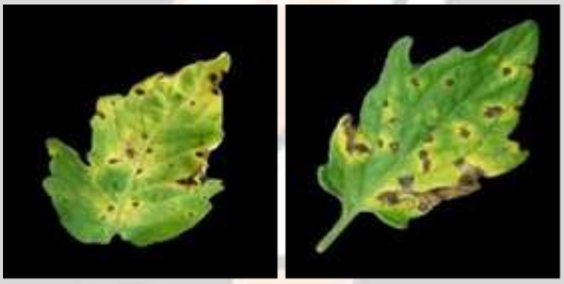


Figure 1: Septoria leaf spot

Figure 2: Yellow Leaf Curl

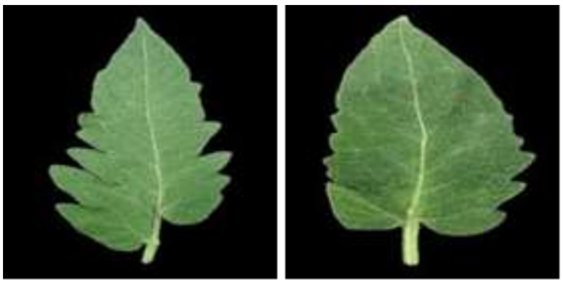


Figure 3: Healthy

Monitoring a large vegetable garden is tedious, if done in person. It is necessary to minimize the human effort made in plant protection. So this is a popular research center that attracts many researchers. Several activities related to plant diseases appear in the literature.

The authors of the paper [7] have proposed a practical approach to determining whether a tomato leaf is healthy or infected. The image provided as an insert was first processed by removing the background and the existing noise was eliminated with the help of an erosion method. The Gray Level Co-occurrence Matrix (GLCM) was used to extract the texture element from the enhanced image. The Support Vector Machine (SVM) filter was trained using a variety of kernel functions and performance was tested using the N-fold cross-country verification method. The proposed system achieved 99.83% accuracy using line kernel function with SVM filter. Although the accuracy obtained is high, it is not enough to predict or differentiate between healthy or diseased leaves. Also, the type of disease has not been identified

To overcome the problem of the page above, the authors [in 3] proposed a variety of classification, feature-classification and classification techniques that identify the type of disease using a diseased image to form a distinction. The leaf image provided to the system input is pre-processed by smoothing or enhancing the image by performing histogram measurements. To determine the affected area, various classification methods such as K-Means clustering are proposed. Features are then extracted from a separate area and calculated using GLCM. After removing the feature, infections can be detected with the help of Artificial Neural Networks (ANN) or Back Propagation Neural Networks. The image classification effect using K-Means clustering was that the proposed process was slightly automated as the user had to clearly select a collection containing the infected component.

Paper [8] describes a method that uses the Gabor wave transformation technique in order to eliminate the factor that contributes to the diagnosis of tomato leaf disease. The extracted components were an input into the SVM training filter which then determined the type of infected tomato leaf disease. Image resizing, audio editing and background removal were performed in the previous processing phase. This paper has used Gabor modification to identify text-sensitive text patterns and extract relevant features. Disease classification is performed using SVM with different kernel functions and performance has been tested using the opposite validation method. 99.5% accuracy was shown to be achieved in accordance with the test results of the proposed program. The great disadvantage of using Gabor modification to remove a feature is that it is computer-generated.

In [9], the authors used a simple method of dividing sick tomato leaves into various classes namely Tomato blight late, Septoria spot, Bacterial spot, Bacterial canker, Tomato leaf curl and Healy. A database of 383 photos taken using a digital camera was used for implementation purposes. Otsu's method of image classification was applied to the database. Color features were obtained using RGB color components while color features were obtained using regional props function and texture elements were obtained from GLCM. All extracted components are integrated to form an output module. Supervised learning strategies used for classification by training decision tree divider. Although the accuracy is high, the decision tree has its own set of drawbacks - over-installing in the event of a loud data and the amount of user control over the model is relatively small.

Deep convolutional neural networks are trained [6] to diagnose 26 diseases in 14 different plant species. Authors use standard Alex Net[4] and Google Net [10] for properties for this purpose. A public repository containing 54,306 images of both diseased leaves and healthy plant leaves has been used for this purpose. Database is created by collecting images of the plant and leaving it in a controlled environment.

The authors performed performance analysis on both of these structures by performing model training in two ways. It is done from the beginning in the first case and the second through readingtransfer.

Transfer learning corresponds to the method of adapting pre-trained weights obtained by training models on the ImageNet dataset. The model implementation has been administered using the Caffe framework giving an accuracy of 99%. This portrays the feasibility of this approach. However, on testing the trained model against a bunch of sample test images obtained from online public data sources which are quite different from the set, the model accuracy falls to 31.4%. this is often a typical problem faced in neural networks owed to the train and test

3. PROPOSED METHODOLOGY

The proposed method includes the three important stages namely: Data Acquisition, Data pre-processing & Classification. Flow chart is shown in Fig. 4 and current section includes the brief discussions of an identical.

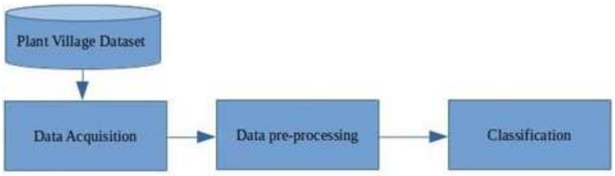


Figure 4: Proposed methodology

3.1 Data Acquisition

The tomato disease images are taken from the Plant Village repository [5]. Images for the diseases were downloaded employing a python script. The acquired dataset consists of around 16108 images belonging to 10 different classes. The dataset includes images of all major kinds of leaf diseases that might affect the tomato crop. Each of the downloaded images belongs to the RGB color space by default and were stored within the uncompressed JPG format.

3.2 Data pre-processing

The acquired dataset consisted of images with minimal noise and hence noise removal wasn't a necessary pre-processing step. the pictures within the dataset were resized to 60*60 resolution so as to hurry up the training process and make the model training computationally feasible.The process of standardizing either the input or target variables tends to hurry up the training process. this is often done through improvement of the numerical condition of the optimization problem. it's also made sure that the several default values involved in initialization and termination are appropriate. For our purpose, we normalize the photographs to urge all the pixel values within an equivalent range by using the mean and thus the variance . In machine learning terms, it's called because the Z-score.

3.3 Classification

Convolutional neural networks (CNN) are often used for the creation of a computational model that works on the unstructured image inputs and converts them to corresponding classification output labels. They belong to the category of multi-layer neural networks which can be trained to seek out the required features for classification purposes. They require less pre-processing as compared to sets belonging to different distributions.

The authors of [1] propose an method where they identify and classify banana leaf diseases namely Banana sigatoka and Banana speckle. they need performed the training of deep learning models under certain challenging conditions. These conditions comprise of different images resolution, illumination, size, orientation and complex background. They effectively demonstrate the accuracy of this approach and thus the very less computational efforts required.

traditional approaches and perform automatic feature extraction which provides better performance. For the aim of tomato disease detection, we've experimented with several standard deep learning architectures like AlexNet [4], Google Net [10] and thus the simplest results might be seen with the utilization of a variation of the LeNet architecture [5].

LeNet could also be an easy CNN model that consists of convolutional, activation, pooling and fully connected layers. The architecture used for the classification of the tomato leaf diseases may be a variation of the LeNet model. It consists of an extra block of convolutional, activation and pooling layers as compared to the primary LeNet architecture. The model utilized during this paper been shown in Fig. 5.

Each block consists of a convolutional, activation and a m a x pooling layer. Three such blocks followed by fully connected layers and SoftMax activation are utilized during this architecture. Pooling and convolutional layers are used for feature extraction whereas the fully connected layers are used for classification. Activation layers are used for showing non-linearity into the network.

Convolutional layer applies convolution operation for getting of features. With the rise thorough , the complexity of the extracted features increases. the dimensions of the filter is fixed to 5*5 whereas number of filters is increased progressively as we move from one block to a special . the amount of filters is 20 within the first convolutional block while it's increased to 50 within the second and 80 within the third. This increase within the number of filters is important to catch up on the reduction within the size of the feature maps caused by the utilization of pooling layers in each of the blocks. The feature maps are also zero padded so on preserve the size of the image after the appliance of the convolution operation. The max pooling layer is employed for reduction in size of the feature maps, speeding up the training process, and making the model less variant to minor changes in input. The kernel size for max pooling is 2*2. ReLU activation layer is employed in each of the blocks for the introduction of non-linearity. Also, Dropout regularization technique has been used with a keep probability of 0.5 to avoid overfitting the plaything . Dropout regularization randomly drops neurons within the network during each iteration of coaching so on reduce the variance of the model and simplify the network which aids in prevention of overfitting. Finally, the classification block consists of two sets fully connected neural network layers each with 400 and 8 neurons respectively. The second dense layer is consecutively followed by a SoftMax activation function to form the probability scores for the ten classes.

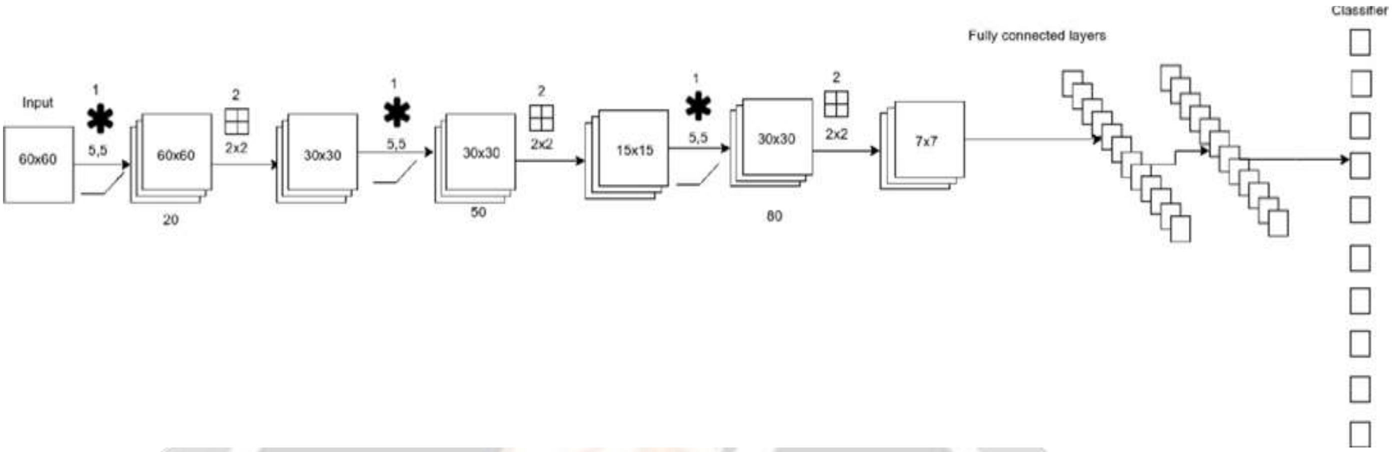


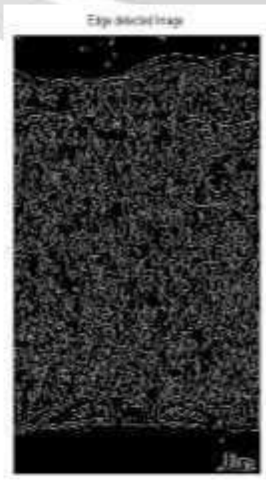
Figure 5: Model architecture

3.4 Feature extraction

In feature extraction, we making use of Gabor filter to extract texture features of image. With the assistance of Gabor filters, we are considering GLCM features for our feature extraction of leaf, Contrast, Area, Perimeter Energy, Homogeneity, minor length, major length, mean of gray level, these are common features we are extracted[5].

Gabor Filter:

Texture features that are helped the local power spectrum obtained by a bank of Gabor filters are evaluated. Here we are focused to extract texture features like Contrast, Area, Perimeter Energy, minor length, major length, mean of gray level. The filter is characterized by a preferred orientation and a preferred spatial frequency. When a min-area patch features a wide variation of indications of discrete gray tone, the major property of that area is texture.

Step1. Edge Detectedimage 	**Step2.** Centroid Image 

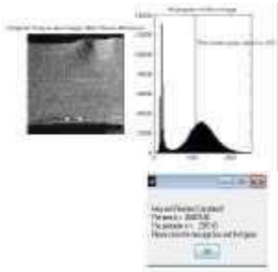
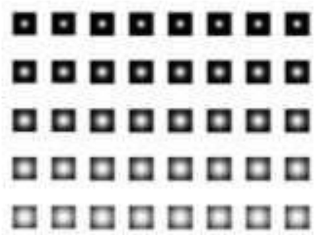
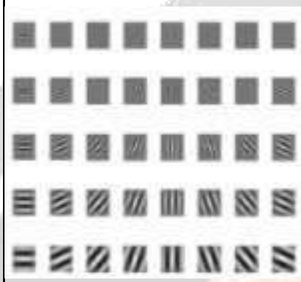
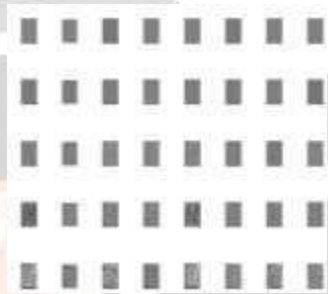
Step3. Histogram Graph ofImage: 	**Step4:** Magnitude of Gaborfilter 
Step5: Real parts of Gabor filter 	**Step 6:** Real parts of Gabor filter with angular rotation 

TABLE 1: How Feature Extraction work

4. EXPERIMENTAL SETTINGS

The implementation of the proposed methodology has been administered on the Plant Village dataset. It consists of around 16108 images belonging to 8 different classes of tomato leaf diseases. Keras, a NN API written in Python, has been used for the model implementation. Out of the 16108 images, 4800 images were put aside for testing and 13360 images were used for training. In order to increase the dataset, automatic data augmentation techniques have been used by randomly rotating the images by a small amount of 20 degrees, horizontal flipping, vertical and horizontal shifting of images. The optimization was administered using Adam optimizer with categorical cross entropy because the loss functions. Batch size of 20 has been used and therefore the model has been trained for 30 epochs. The initial learning rate has been set to 0.01 and it's reduced by an element of 0.3 on plateau where the loss stops decreasing. Early stopping has also been utilized in order to watch the validation loss and stop the training process once it increases. All the experiments were performed on Intel i5-8010U CPU.

5. RESULTS AND ANALYSIS

No. of epochs	Accuracy	Precision	Recall	F1-Score
10	0.9041	0.9012	0.9012	0.9012
20	0.9452	0.9449	0.9449	0.9449
30	0.9485	0.9481	0.9481	0.9481

TABLE 2: RESULTS AND ANALYSIS

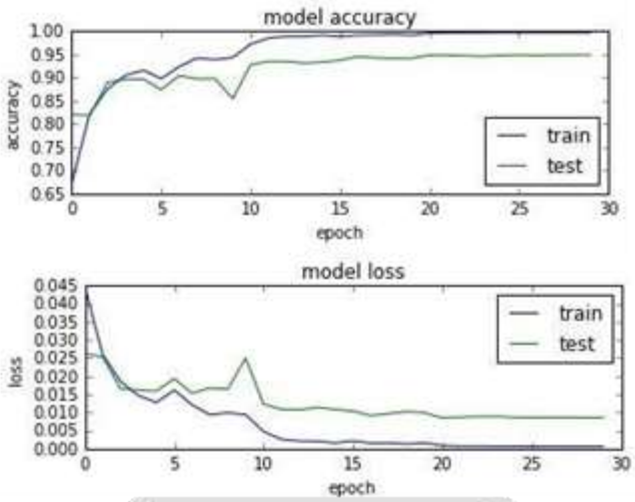


Figure 6: Plots of loss against epochs & accuracy

30 epochs of training, while a high 99.3% of training accuracy was reported. An average validation accuracy of 95% has been obtained. This is an efficient measure of the classification made by the deep learning model. The plots of train and test loss against the epochs and accuracy in Fig. 6 provide a way of visualization and indication of the speed of model convergence. It are often seen that the model has stabilized around 20 epochs and therefore the metrics don't show a significant improvement within the last 10 epochs The results show that the model performs well on the dataset and may be used as a way for classification of the ten tomato leaf diseases with minimum resource requirements. The implementation process requires minimum hardware requirements unlike large neural networks which generally have high computational resource requirements or the utilization of a Graphics Processing Unit. This is due to a smaller number of training parameters owed to the presence of fewer layers with less filter sizes and smaller train size images. Distinct other state of the art models, the model implementation can be carried out on Computer Processing Unit with less time owing to the simplicity. Also, the variation of the LeNet model adopted is straightforward to know and straightforward to implement. The model thus, provides an easy and effective way of solving the matter of disease detection with results comparative to [6], where the authors affect plant diseases of multiple crops. With less resource constraints and minimal data, the model gives comparative results to traditional state of the art techniques.

6. CONCLUSION AND FUTURE WORK

Agricultural sector is still one of the most important sectors over which the majority of the Indian population relies on. Detection of diseases in these crops is important to the growth of the economy. Tomato is one among the staple crops which is produced in large quantities hence; this paper aims at detection and identification of 10 different diseases within the tomato crop. The proposed methodology uses a convolutional neural network model to classify tomato leaf diseases obtained from the Plant Village dataset. The architecture used may be a simple convolutional neural network with minimum number of layers to classify the tomato leaf diseases into 10 different classes. Different learning rates and optimizers could even be used for experimenting with the proposed model as a neighborhood of the longer term work. It could also include experimentation with newer architectures for improving the performance of the model on the plaything . This model can be made use of as a decision tool to help and support farmers in detecting the diseases that can be found in the tomato plant. With an accuracy of 95-96% the methodology proposed can make an accurate detection of the leaf diseases with little computational effort.

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