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CLASSIFICATION AND DETECTION OF TOMATO LEAF DISEASE

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Abstract:
The tomato crop is a significant staple with a high commercial value on the Indian market and is produced in enormous quantities. Diseases are harmful to the health of the plant, which has an impact on its growth. It is essential to monitor the progress of the farmed crop to ensure minimal losses. Many different tomato diseases attack the crop's leaves at frightening rates. The primary goal of the proposed effort is to identify a simple method for detecting tomato leaf disease while employing limited computational resources to produce outcomes that are comparable to state-of-the-art. Automatic feature extraction is used by neural network models to help categorize the input image into the appropriate illness classifications. The average accuracy of this suggested system is between 94 to 95 percent, demonstrating the viability of the neural network approach even in challenging circumstances.

Keywords: Agriculture, Convolution Neural Network, machine learning, Support Vector Machine.

Introduction

Farmers are now very well aware of use the engineering science and technology for farming management. The agriculture related technological skills required for agricultures development. Usually crops health's and growth depends on environment condition, which is probably uncertain at maximum times [1-3]. Therefore great initiatives require for fast development agriculture life cycle. The use of technology always helps in agriculture sectors to adopt practices that are profitable, environmentally sound, and contribute to quality of farmer life [4]. Some machine vision application developed in agriculture like remote sensing for natural resource assessments, post harvesting product quality, safety detection, classification, sorting, process automation and precision farming [5-6]. Machine vision predicts the size, shape, colorant texture of object, it mostly support for numerical attributes of the objects. Computer Vision play important role in the image processing to extract the useful information image and to enhance it. The removal of noise is the key steps in image processing. Noise added in the image during the process of storing, transmitting the images [7]. The various noise like gaussian, salt ,speckle and pepper etc., to remove these the superior model are require to prevent the image from noise. Image processing in main fundamental aspects of computer vision. Image processing converts image into digital equivalent from extraction of features get enhanced the original image version [8]. The main challenges in the image processing is the de-nosing images which removal and suppresses all kinds of noise from noisy image. Noise added in the image due to unwanted signals, varying brightness, colors contrasts, which form tiny speckles, grains or multicolored pixels [9].The detection of tomato leaf disease accurately, fast and reliable with the use of Convolution Neural Network (CNN) is novel approach. The work done has been developed with CNN in agriculture field for yield detection and automated harvesting [10]. A state-of-art in object detection methods use faster Region-based CNN with transfer learning approach. Faster Region-based CNN is the combination of modalities Color (RGB) and Near-Infrared (NIR). Different types of leaf disease has been identified as shown in Fig. 1

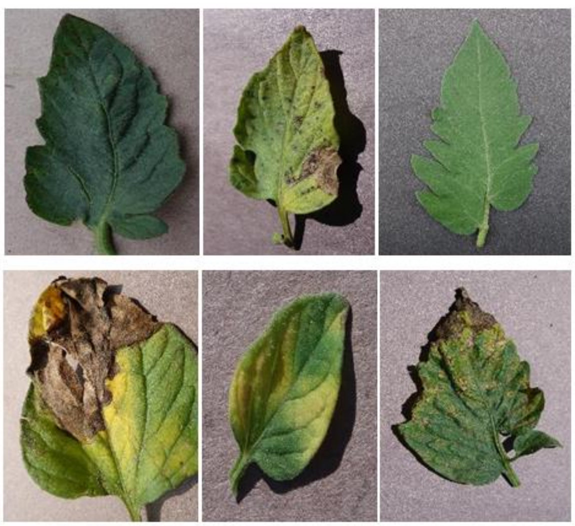

Fig. 1 Different Leaf diseases

In the proposed method authors of suggest a CNN based method for identifying and categorizing the tomato leaf disease that affect banana leaves. They worked under some difficult circumstances to develop deep learning models. These circumstances include lighting, a complicated background, various image resolutions, sizes, and orientations. They successfully illustrate the precision of this method and the negligibly high computational effort needed.

Methodology: The three crucial phases of the suggested methodology are data acquisition, data pre-processing, and classification. The flow diagram is depicted in Fig. 2, and the current part contains a quick explanation of it.

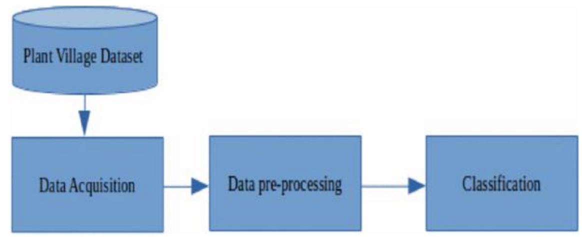

Fig. 2 Different Leaf diseases

Data Set: The Plant Village repository [5] is where the images of tomato leaf disease were obtained. A Python script was used to download the illnesses images. There are roughly 18160 photos in the obtained dataset, divided into 10 different classes. Images of all the main leaf diseases that potentially harm the tomato crop are included in the dataset. Each image that was downloaded was saved in the uncompressed JPG format and by default uses the RGB color space.

Data Pre-Processing

The collected dataset was made up of mostly noise-free images; hence noise removal was not required as a preprocessing step. To speed up the training process and make the model training computationally possible, the images in the dataset were downsized to a required resolution of the model.

CNN model : The main component of the proposed model is CNN. The different layers which are used in the proposed model are given in Fig. 3.

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_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 31, 31, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 29, 29, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 14, 14, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 12, 12, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 128)         0
_________________________________________________________________
dropout_2 (Dropout)          (None, 6, 6, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 64)                294976
_________________________________________________________________
dense_1 (Dense)              (None, 128)               8320
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 405,450
Trainable params: 405,450
Non-trainable params: 0
_________________________________________________________________
```

Fig. 3: Proposed CNN model

Results and Discussion

In image processing applications, the available data must be validated and labelled by experts in order to be useful in any development. This section presents the datasets used in recent works related to deep learning for the detection of leaf disease.The number of sample images used for training and testing in each category is shown in Fig. 4 and Fig. 5 respectively.

Classification accuracy is a metric that summarizes the performance of a classification model as the number of correct predictions divided by the total number of predictions.It is easy to calculate and intuitive to understand, making it the most common metric used for evaluating classifier models. This intuition breaks down when the distribution of examples to classes is severely skewed.

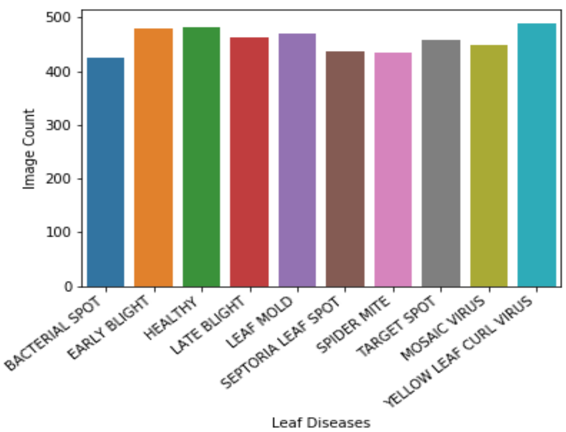

Fig. 4: Training images

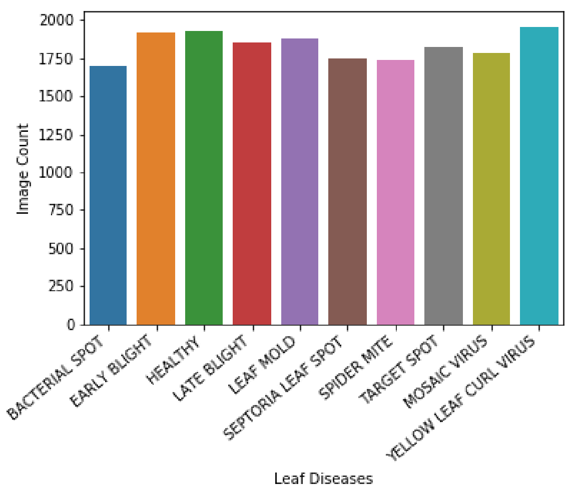

Fig. 5: Testing images

Classification accuracy is a metric that summarizes the performance of a classification model as the number of correct predictions divided by the total number of predictions. It is easy to calculate and intuitive to understand, making it the most common metric used for evaluating classifier models.

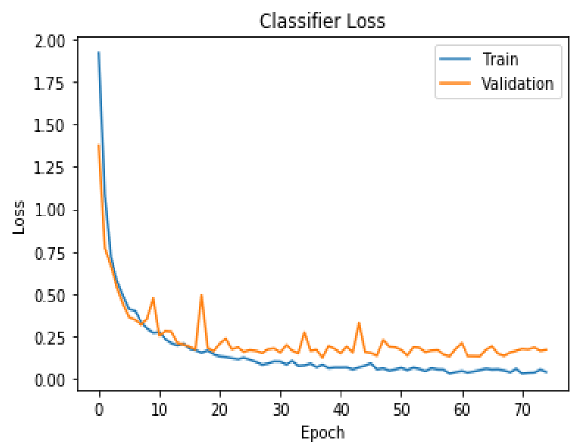

Fig. 6: Loss curve

The Loss curve and classification accuracy through epochs is as shown in Fig. 6 and Fig. 7 respectively.

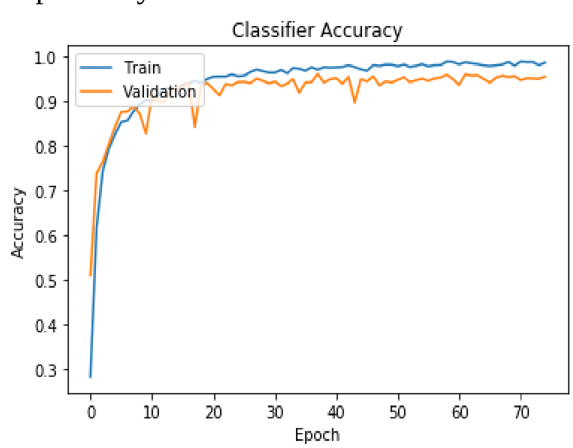

Fig. 7: Classification accuracy

A confusion matrix is a matrix that summarizes the performance of a machine learning model on a set of test data. It is often used to measure the performance of classification models, which aim to predict a categorical label for each input instance. The matrix displays the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) produced by the model on the test data. The confusion matrix generated is as shown in Fig. 16.

	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Spider Mite	Target Spot	Mosaic Virus	Yellow Leaf Curl Virus
Bacterial Spot	420	4	0	0	0	0	0	0	0	1
Early Blight	8	419	0	25	1	17	2	7	1	0
Healthy	2	0	476	0	0	0	0	3	0	0
Late Blight	3	12	1	436	1	8	1	0	0	1
Leaf Mold	0	0	0	3	449	14	4	0	0	0
Septoria Leaf Spot	0	2	0	2	5	423	1	1	2	0
Spider Mite	0	0	2	0	1	2	417	11	0	2
Target Spot	0	2	13	0	0	7	13	414	8	0
Mosaic Virus	0	0	0	0	0	1	0	0	447	0
Yellow Leaf Curl Virus	4	2	0	3	0	1	6	0	0	474

Fig. 8: Confusion matrix

Conclusion

The agricultural industry continues to be one of the most crucial industries on which most of the Indian people depends. Therefore, spotting diseases in these crops is essential to the expansion of the economy. One of the staple crops that is widely cultivated is the tomato. Therefore, the purpose of this paper is to discover and characterize 10 distinct illnesses in the tomato crop. A convolutional neural network model is used in the suggested methodology to categorize tomato leaf diseases found in the Plant Village dataset. To categorize tomato leaf illnesses into 10 separate classifications, a straightforward convolutional neural network with a minimal number of layers was utilized as the architecture. As a result, farmers can utilize the aforementioned model as a decision-making tool to assist and support them in recognizing diseases that can affect tomato plants. The proposed methodology may accurately identify the leaf diseases with an accuracy of 94–95% and minimum computational work.

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