

Tomato Plant Disease Detection and Diagonosis using CNN

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Abstract

The tomato crop is an important staple in the Indian market with high commercial value and is produced in large quantities. Diseases are detrimental to the plant's health which in turn affects its growth. To ensure minimal losses to the cultivated crop, it is crucial to supervise its growth. There are numerous types of tomato diseases that target the crop's leaf at an alarming rate. This paper adopts the convolution neural network model to detect and identify diseases in tomato leaves. The main aim of the proposed work is to find a solution to the problem of tomato leaf disease detection using the simplest approach while making use of minimal computing resources to achieve results comparable to state of the art techniques. Neural network models employ automatic feature extraction to aid in the classification of the input image into respective disease classes. This proposed system has achieved an average accuracy of 96-97% indicating the feasibility of the neural network approach even under unfavorable conditions.

Keywords—Convolutional Neural Network, Deep Learning, Leaf Disease Detection

I. INTRODUCTION

In the world of agricultural need, the automatic detection of plant diseases using plant leaves is of major importance. Additionally, the early and timely detection of plant diseases improves agricultural production and quality. So, it is very important to finding the solution in short period. India is an agriculture dependent country.70% of Indian economy depends

on agriculture. Tomatoes are essential due to their high market demand and nutritional value. These antioxidants are very important for our overall health.

Early plant disease detection plays a significant role inefficient crop yield. Plant diseases like early blight, bacterial spot, target spot etc. affect the growth, crop quality of plants and economic impacts in the agriculture industry. To avoid the impact of these diseases, expensive approaches and the use of pesticides are some solutions the farmers usually implement. The use of chemical means damages the plant and the surrounding environment. In addition, this kind of approach intensifies the cost of production and major monetary loss to farmers. Early discovery of diseases as they occur is the most important period for efficient disease management. To treat diseases on tomato plants by hand, farmers need to know about the disease. Farmers face many problems every year when they try to grow healthy crops. Insects and other pests damage the production line. Manual disease detection through human experts to identify and recognize plant diseases is a usual practice in agriculture. In contrast, manually diagnosing tomato diseases is a time-consuming and difficult process. So, the use of a machine can find diseased tomato plants, figure out what kind of disease they are affected by, and provide a remedy to that disease by use that information to help the rest of the crop grow more efficiently. With the improvements in technology, automatic detection of plant diseases from raw images is possible through computer vision and artificial intelligence researches. A convolutional neural network (CNN) is a deep learning model that is widely used in image processing. The methodology in the study involves three key stages: acquisition of data, pre-processing of data and image classification. In this study, the researchers were able to investigate plant diseases and Pest's infestation that affects the leaves of the plants.

CONVOLUTIONAL NEURAL NETWORK

Deep learning is a subsection of Artificial Intelligence and machine learning that uses artificial neural networks (ANN). Training the deep learning models divides the feature extraction and extracts its features for classification. There are several applications of deep learning which include computer vision, image classification, restoration, speech, video analysis, etc. A convolutional neural network with nominal process can simply detect and categorize. It is efficient in evaluating graphical images and extracts the essential features through its multi-layered structure. As shown in Fig. 1, the CNN involves four layers, that is: input image, convolutional layer and pooling layer, fully connected layers, and output.

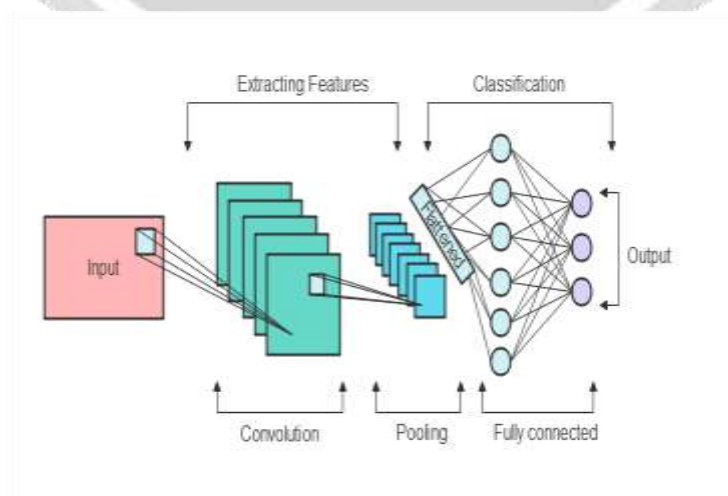


Fig1. Convolutional Neural Network (CNN) Architecture

A. Convolutional Layer

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter ($M \times M$). The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image. The convolution layer in CNN passes the result to the next layer once applying the convolution operation in the input. Convolutional layers in CNN benefit a lot as they ensure the spatial relationship between the pixels is intact.

B. Pooling Layer

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. It basically summarizes the features generated by a convolution layer.

In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

This CNN model generalizes the features extracted by the convolution layer, and helps the networks to recognize the features independently. With the help of this, the computations are also reduced in a network.

C. Activation Layer

Utilizes a non-linear ReLU (Rectified Linear Unit) activation layer in every convolution layer. The application of dropout layers to prevent overfitting is also applied in this layer.

D. Fully Connected Layer

This layer is used to analyze the class probabilities and the output is the input of the classifier. Softmax classifier is the well-known input classifier and recognition and classification of sugarcane diseases are applied in this layer.

II. PREVIOUS RELATED WORK

Plant leaf diseases are a major significant risk to food security. In many situations the agriculture production may be reduced, which consequently reduces the nation's economy, if the crops get affected due to diseases. Generally, diseases affect the leaves of the crops which should be identified in the early stage so that the quality and quantity of the produce may

be increased [1]. So, there is a need for an automatic system for leaf disease recognition that identifies and classifies the leaf diseases at an early stage.

Traditional machine learning techniques like Support Vector Machines, Random Forests, K-Means Clustering have gained traction and have shown considerable accuracy - SVM most commonly of all. In SVM model[6], enhanced hybrid method consisting of three pipeline procedures namely box filtering, Gaussian and Median filters is labored for image and spot enhancement, color differentiation, smoothing and noise removal. Each disease can have a different color, texture and scale, which is identified using SCP[6] and EM[6] algorithms highlighting the spots. SVM classifier then uses these extracted features.

Random forests classifier[4] is flexible in nature and can be used for both classification and regression techniques. Compared to other machine learning techniques like SVM, Gaussian Naïve bayes, logistic regression, linear discriminant analysis, Random forests gave more accuracy with less number of image data set. The feature vectors are extracted for the test image using HoG feature extraction. These generated feature vectors are given to the saved and trained classifier for predicting the results[4].

Convolutional neural networks (CNN) can be used for the creation of a computational model that works on the unstructured image inputs and converts them to corresponding classification output labels. LeNet is a simple CNN model that consists of convolutional, activation, pooling and fully connected layers. The architecture used for the classification of the tomato leaf diseases is a variation of the LeNet model. It consists of an additional block of convolutional, activation and pooling layers in comparison to the original LeNet architecture.

III. PROPOSED SYSTEM

The existing method for plant disease detection is simply naked eye observation by experts through which identification and detection of plant diseases is done. For doing so, a large team of experts as well as continuous monitoring of plant is required, which costs very high when we do with large fans. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact to experts. Due to which consulting experts even cost high as well as time consuming too. In such conditions, the suggested technique proves to be beneficial in monitoring large fields of crops.

We can reduce the attack of pests by using proper pesticides and remedies. We can reduce the size of the images by proper size reduction techniques and see to it that the quality is not compromised to a great extent. We can expand the projects of the earlier mentioned authors such that the remedy to the disease is also shown by the system. The main objective is to identify the plant diseases using image processing. It also, after identification of the disease, suggest the name of pesticide to be used. It also identifies the insects and pests responsible for epidemic. Apart from these parallel objectives, this drone is very time saving. The budget of the model is quite high for low scale farming purposes but will be value for money in large scale farming. It completes each of the process sequentially and hence achieving each of the output.

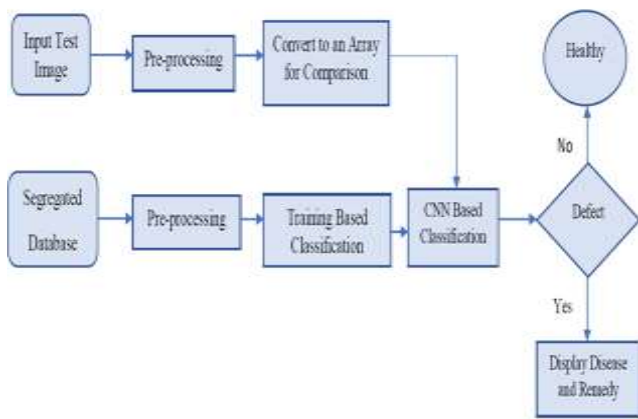


Fig2. Flow Diagram for Proposed System

IV. RESULTS

A 96% accuracy rate was achieved using 50 epochs during the training of the model. The model also achieved a maximum accuracy rate of 100% when testing random images of plant varieties and diseases. The visualization of plots of train and test accuracy is described in fig 3. shows the model is effective in detecting and recognizing plant diseases.

Fig. 4 shows of detection and recognition of a tomato plant with 100% accuracy and it shows an accuracy rate of 100% recognition of healthy plant leaf. Fig. 5 shows affected with bacterial spot disease the result of 96.95% accuracy of detecting and recognizing a tomato plant .Fig.6 it shows a 97.40% accuracy rate that it is infected with a the tomato mosaic virus disease . Fig. 7 shows a 100% result of detection and recognition of an early blight disease at 98% accuracy rate.

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Epoch 50/100
1/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
2/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
3/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
4/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
5/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
6/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
7/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
8/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
9/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
10/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
11/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
12/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
13/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
14/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
15/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
16/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
17/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
18/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
19/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
20/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
21/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
22/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000
23/23 [.....] - ETA: 4s - batch: 8,000/8000 - size: 8,000 - loss: 8.607 - accuracy: 1.000

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Fig 3. Tracking the validation accuracy during training.

V.CONCLUSION

The use of CNN techniques in tomato leaf disease detection has the potential to be a powerful tool in managing and controlling these plant pathogens. The ability of CNN algorithms to analyze a collection of data, to identify patterns, and make predictions can be leveraged to improve the accuracy and efficiency of tomato leaf disease detection. Tomato leaf diseases are a critical component of tomato crop management and plays major role in protecting the health and productivity of tomato plants. Early detection allows for prompt action to be taken to prevent or limit the spread of disease, minimizing the potential for yield and quality losses.

VI.FUTURE WORK

Creating a practical application for tomato plant disease detection and diagnosis using Convolutional Neural Networks (CNNs) is a valuable project with the potential for several future improvements and extensions. Here are some future work directions for such an application:

- 1. Mobile Application Development:** Develop a user-friendly mobile application that allows users (farmers or gardeners) to easily capture images of tomato plants and receive real-time disease diagnosis and treatment recommendations. Ensure the app is available on both Android and iOS platforms.
- 2. Data Augmentation and Diverse Datasets:** Expand the dataset to include a more comprehensive range of images representing various tomato plant diseases, plant growth stages, and environmental conditions. Implement advanced data augmentation techniques to make the model more robust.
- 3. User Feedback and Reporting:** Implement features that allow users to provide feedback and report their experiences with the application. Use this feedback to continually improve the system's accuracy and user satisfaction.
- 4. Multi-language Support:** Localize the application for different languages and regions, ensuring that it can be used effectively in diverse agricultural settings worldwide.

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