

## Automatic Pesticide Spraying System with Tomato Leaf Disease Detection

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### ABSTRACT

Agriculture is very important sector and automatic disease detection has been essential part of agriculture research. Numerous methods have been discovered for various plant disease detection. This paper illustrates remote tomato disease detection and pesticide spraying using convolutional neural network with slight variation in LeNet model. The image which is captured by camera will be used for further processing. Raspberry Pi is used as controlling device. The neural network model will automatically extract the feature and will find the disease class from the trained dataset. After detection of disease, the system will provide solution in the form of pesticide spraying and will move forward to monitor the next plant.

**Keywords**– Convolutional neural network, leaf disease detection, LeNet, machine learning, raspberry pi

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### I. INTRODUCTION

Agriculture is important source in India. Only agriculture constitutes about 22% of income in India. For huge population, to meet the rate of demand, farmers use excess pesticides to increase their food production. Plant diseases leads to reduction in quality of production. The solution for this is by spraying pesticides on crop in proper amount. It requires continuous monitoring of crops, but it is not possible by farmers. Most of the diseases are caused by fungi and bacteria. It is difficult for the farmers to identify the type of disease by visually looking at the plant. Also, they lack in the expertise. The process of disease detection needs to be automated. It is necessary to detect the tomato leaf diseases at the early stage to reduce spreading of diseases. It can be done with the help of various image processing and neural network techniques. By comparing affected leaf with the dataset of diseases, it is easy to identify if the plant is affected or not. The system comprises of a robotic vehicle along with the disease detection model. Our approach identifies the diseases which commonly occurs in the tomato plant by using neural network. The neural network model uses characteristics of leaves itself to detect disease. Upon detecting the disease, the robot will spray the pesticide automatically and will move further. Automatic crop disease detection will benefit all the farmers. The approach is much simpler in order to identify the disease quickly. We have taken the dataset from internet and processed it with LeNet model. Any image given input to the system will be classified classes as either diseased or healthy. The database used here is a subset of Plant

Village [1], a public repository that contains 6359 images of tomato diseases with 7 different classes.

### II. LITERATURE REVIEW

Usama Mokhtar et al. [3] have proposed an efficient method that identifies whether a tomato leaf is healthy or infected. The image given as input was first pre-processed by removing the background and then the present noise was eliminated with the help of erosion technique. Grey Level Co-occurrence Matrix (GLCM) was used for texture feature extraction from the enhanced image. Support Vector Machine (SVM) classifier was trained using different kernel functions and the performance has been evaluated using N-fold cross-validation technique. The proposed system has achieved an accuracy of 99.83% using the linear kernel function with the SVM classifier. Even though the obtained accuracy is high, it is not sufficient enough to predict or differentiate between healthy or diseased leaves. Also, the type of disease was not identified.

To overcome the problem, S. D. Khirade and A. B. Patil [2] have proposed various segmentation, feature extraction and classification techniques that identify and detect the type of the disease using the diseased image to make the classification. The leaf image given as input to the system was pre-processed by smoothing it or enhancing the image by performing a technique called histogram equalization. To obtain the affected area, different segmentation techniques like K-Means clustering have been proposed. The features were then extracted from the segmented region and calculated using GLCM method. After feature extraction, the diseases can be detected with the help of Artificial Neural Networks (ANN) or Back

Propagation Neural Networks algorithm. The drawback of segmenting the image using K-Means clustering is that the process proposed was semi-automated as the user should explicitly select the cluster which contains the diseased part.

In [4] H.Sabrol and K. Satish have used a simple approach for the classification of the diseased tomato leaves into various classes namely Tomato late blight, Septoria spot, Bacterial spot, Bacterial canker, Tomato leaf curl and Healthy. A dataset of 383 images which have been captured using a digital camera has been used for implementation. Otsu's method for image segmentation has been applied on the dataset. Color features have been obtained using the RGB color components while shape features have been obtained using region props function and texture features have been obtained from GLCM. All the extracted features have been combined to form a feature extraction module. Supervised learning techniques have been used for classification by training the decision tree classifier. Though the accuracy is high, decision tree has its own set of disadvantages – over fitting in case of noisy data and the amount of control that the user has over the model is relatively less.

Sharada P Mohanty, David P Hughes, and Marcel Salath' e [5] trained The Deep convolutional neural networks for the identification of 26 diseases in 14 different crop species. The authors make use of the standard AlexNet and GoogleNet architectures for this purpose. A public repository which contains 54,306 images of both diseased leaves and healthy plant leaves has been used for this purpose. The dataset has been created by collecting the images of the plant leaves in a controlled environment. The authors have conducted a performance analysis on both these architectures by carrying out the model training in two ways. It is performed from scratch in the first case and by using transfer learning in the second. Transfer learning corresponds to the process of adapting pre-trained weights obtained by training models on the ImageNet dataset. The model implementation has been carried out using the Caffe framework giving an accuracy of 99%. This shows the feasibility of this approach. However, on testing the trained model against a set of sample test images obtained from online public data sources which are quite different from the train set, the model accuracy falls to 31.4%.

With above literature survey, we have found that deep neural network approach has been more feasible in the case of accuracy. Hence, we have used LeNet model [1] based on neural network for processing.

### III. SYSTEM OPERATION

Block diagram of the whole system is as shown in Fig. 1.

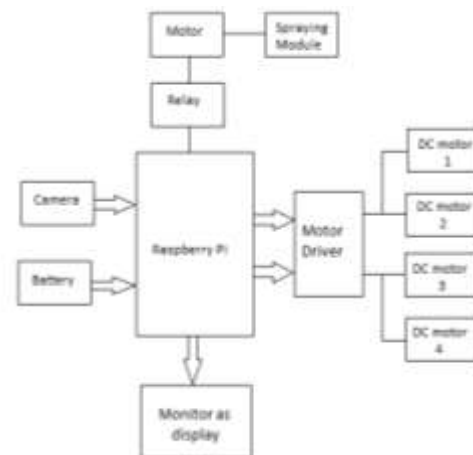


Fig.1 block diagram of whole system

The block diagram of proposed system is as shown in figure. It has various devices and components connected it. This system requires 5V, 1A power supply for raspberry pi and 12V, 7A supply for dc motors. The raspberry pi model B has the special connection provided onboard. Using that USB connection, the power supply can be provided. Camera is used to capture the image of crops; it is directly connected to the raspberry Pi 3 Model B+. There are two ways to connect camera to raspberry Pi 3 model B+. First one is through USB port and second is between audio port and the HDMI port provided for camera interface of raspberry Pi3. We have connected the camera through USB port. Raspberry Pi is small module like a small computer. The image captured by camera is sent to the Raspberry Pi. Using various libraries like OpenCV, Keras and deep learning architectures, the Raspberry Pi will process the image and will give the result. The L298N is a dual H-Bridge motor driver which allows speed and direction control of two DC motors at the same time. The module can drive DC motors that have voltages between 5 and 35V, with a peak current up to 2A. Four dc motors are being used to drive the vehicle. These motors are driven by motor driver and operates on 12V dc supply. The relay is the device that open or closes the contacts to cause the operation of the other electric control. The relay will drive the dc motor pump which is connected to spraying module. The monitor is used to display the detected disease name.



of the features. Various pooling layers used for extraction of features. ReLu layer used for normalization of components as well as rounding off the parameters. fully connected neural network layers are introduced with 500 and 10 neurons. Finally, the SoftMax classifier used for classification into subclasses.

## V. RESULT



Fig.5 test input 1



Fig.6 test input 2

Here we have taken two test inputs for observing the results. The Test input 1 is the leaf having septoria and the Test input 2 is the healthy leaf having no disease. Septoria leaf spot requires pesticide D to be sprayed whereas healthy leaf doesn't require any. The results are obtained as follows and it has shown the correct possible disease each time when testing the data from test files.

Respective output results have shown below in fig.7 and fig.8, however for field images the accuracy is not much achieved.

```
Using TensorFlow backend.  
[[[-5.9994766e-04  5.9473048e-05  2.0464917e-02  2.3778077e-03  9.1187946e-01  
  9.8657897e-04  8.3442201e-02]]  
4  
septoria1_leaf_spot  
Spraying the pesticide D  
*** |
```

Fig.7 test output 1

```
Using TensorFlow backend.  
[[[-2.4485460e-15  1.0001009e+00  2.3824551e-12  3.3464618e-16  5.1862692e-13  
  7.3066342e-19  1.2489097e-15]]  
2  
healthy  
*** |
```

Fig.8 test output 2

## VI. CONCLUSION

The detection and classification of tomato plant disease is very important for the successful productivity and this can be done using our proposed system. It is used to find the diseases which can be identified at early stage or the initial stage and it provides the proper amount of pesticides required by particular disease. Further automation of the drive system will enable to robot autonomously navigate the entire greenhouse. Improvements to the spraying system will allow the precise application of pesticide spray at varying dosages. Improvements to the spraying hardware will enable improved coverage with reduced over-spray. CNN is a most popular deep model that works on an image domain. Further work on the software model will allow high accuracy in disease detection of field images and also in remote monitoring and overall operation.

## ACKNOWLEDGEMENTS

An acknowledgement section may be presented after the conclusion, if desired.

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