

## LEAF DISEASE DETECTION USING CONVOLUTION NEURAL NETWORK

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### ABSTRACT

This paper helps in identification of plant disease which can be used as a defense mechanism against the disease. The database obtained from the Internet is properly segregated and the different plant species are identified and are renamed to form a proper database then obtain test-database which consists of various plant diseases that are used for checking the accuracy and confidence level of the project. Then using training data we will train our classifier and then output will be predicted with optimum accuracy. We use Convolution Neural Network(CNN) which comprises of different layers which are used for prediction. The deep learning algorithm is used in order to estimate the superiority of the leaf. The plant leaf provide us the most important data to distinguish the disease of the plant. The development of the Android app that gives farmers the ability to Identify leaf diseases based on image of plant leaf taken from the camera source. Android mobile application which can automatically identify the plants diseases based on its leaf appearance with convolution neural network techniques. The target group of the user is those who request a free and quick diagnosis on common leaf disease at any time of the day.

### Keywords:

Diseased and Healthy Leaf, Convolution Neural Network, Classification, Training model, Feature extraction, Test database.

### 1.INTRODUCTION

Technology helps human beings in increasing the production of yield. However the production can be affected by number of factor such as climatic change, diseases, soil fertility etc. Out of these, disease plays major role to affect the production of food. Agriculture plays an important role in Indian economy. Leaf spot diseases weaken trees and shrubs by interrupting photosynthesis, the process by which plants create energy that sustains growth and defense systems and influences survival[1]. Over 58% smallholder farmer depends on agriculture as their principal means of livelihood. In the developing world, more than 80 percent of the agricultural production is generated by smallholder farmers, and reports of yield loss of more than 50% is due to pests and diseases are Common. The production is decreasing day by day with various factors and one of them is diseases on plants which are not detected early stage.

There is various work is done in previous years. Bacterial disease reduces plants growth very fastly so to detect this type of diseases, Dheeb Al Bashish, Malik Braik, and SuliemanBani-Ahmad created system which detect the type of disease the plants have using image processing and color space transformation which creates device independent transformation.

Identifying the disease at an early stage and suggesting the solution so that maximum harm can be avoided to increase the crop yield have used ANN and K-means to classify the disease and grade the disease for.

There is a need to design the automatic system to detect the leaf disease with confidence levels. It also checks the health condition of the leaf along with the comparison of the range.

Third section include proposed methodology for leaf disease and recommending pesticide using CNN and Tensor flow technology.

### Example:

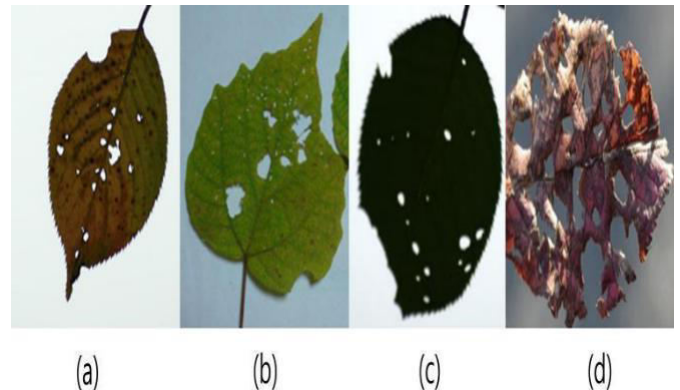


Figure1: Leaf damage: (a) damage 5%, (b) damage 10%, (c) damage 15%, and (d) damage 30%.

## II. LITERATURE SURVEY

**Liu, H.; Lee, S.-H.; Chahl, J.-S. A review of recent sensing technologies to detect invertebrates on crops. *Precis. Agric.* 2017, 18, 635–666.**

Bio security surveillance has been highlighted as a key activity to discover non-native species at the initial stage of invasion. It provides an opportunity for rapidly initiating eradication measures and implementing responses to prevent spread and permanent establishment, reducing costs and damage. In importing countries, three types of bio security activities can be carried out: border surveillance targets the arrival stage of a non-native species at points-of-entry for commodities; post-border surveillance and containment target the establishment stage, but post-border surveillances carried out on a large spatial scale, where as containments carried out around infested areas.

In recent years, several surveillance approaches, such as baited traps, sentinel trees, bio surveillance with sniffer dogs or predatory wasps, electronic noses, acoustic detection, laser micrometry, citizen science, genetic identification tools, and remote sensing, have been developed to complement routine visual inspections and aid in bio security capacity. Here, we review the existing literature on these tools, highlight their strengths and weaknesses, and identify the bio security surveillance categories and sites where each tool can be used more efficiently. Finally, we show how these tools can be integrated in a comprehensive bio security program and discuss steps to improve biosecurity.

**Kurtulus, F.; Lee, W.S.; Vardar, A. Immature peach detection in color images acquired in natural illumination conditions using statistical classifiers and neural network. *Precis. Agric.* 2014, 15, 57–79.**

A “fast normalized cross correlation” (FNCC) based machine vision algorithm was proposed in this study to develop a method for detecting and counting immature green citrus fruit using outdoor color images toward the development of an early yield mapping system. As a template matching method, FNCC was used to detect potential fruit areas in the image, which was the very basis for subsequent false positive removal. Multiple features, including color, shape and texture features, were combined in this algorithm to remove false positives. Circular Hough transform (CHT) was used to detect circles from images after background removal based on color components. After building disks centered in canroids resulted from both FNCC and CHT, the detection results were merged based on the size and Euclidian distance of the intersection areas of the disks from these two methods. Finally, the number of fruit was determined after false positive removal using texture features. For a validation dataset of 59 images,

84.4 % of the fruits were successfully detected, which indicated the potential of the proposed method toward the development of an early yield mapping system.

## III. PROPOSED SYSTEM

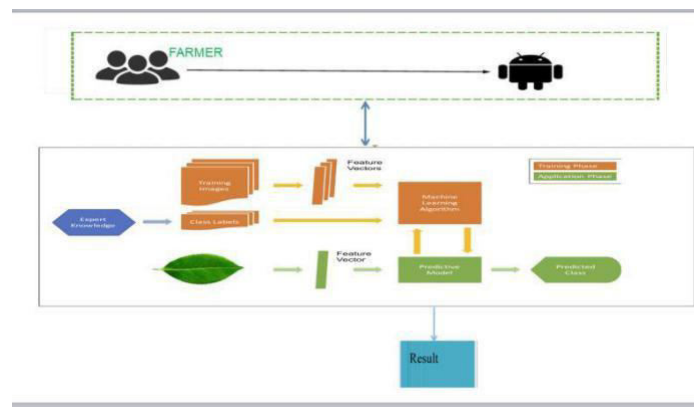
In the proposed system an android app which distinguish and identify the symptoms of disease on plant leaf. our app work on such plants which are infected by many disease that is fungi, viruses to detect, classify plant disease by using machine learning techniques.

And finally we get all information regarding that disease its symptoms, its preventive mechanism and recovery suggestion at very least time and lowcost.

### Advantages of proposed system:

1. Useful to detect the disease of the plant using the smart phone
2. The result is given in short time
3. User friendly and easy to operate.
4. User can calculate the health condition of the leaf.

### Architecture



### System Architecture

### MODULES

There are 4 main modules in this system. They are

1. Training by image data
2. Farmer
3. Feature vector
4. Prediction

#### 1. Training by image data

Image data should be probably be centered by subtracting the per-channel mean pixel values calculated on training dataset. Training data augmentation should probably involve random, rescaling, horizontal flips, perturbations, brightness, contrast, and color, as well as random cropping.

#### 2. Farmer

Farmer can capture the particular leaf acquired using a android camera after successfully installation of this app, then machine learning technique is applied to the acquired image to extract useful results that are necessary for the analysis.

#### 3. Feature vector

A feature vector is a vector that contains information describing an object's important characteristics. A simple feature representation of an image is the raw intensity value of each pixel. However, more complicated feature representations are also possible. Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector.

#### 4. Prediction

The proposed plant disease detection system consists of two phases, in the first phase we establish the knowledge base and this by introducing a set of training samples in a series of processing that include first use pre-processing techniques.

## ALGORITHM

Algorithm used in this paper is "CONVOLUTION NEURAL NETWORK(CNN)".

CNN is a feed forward neural network that is generally used to analyse visual images by processing data with grid like topology. A CNN is also known as "convnet".

### Step 1: Convolution Operation

A convolution layer has a number of filters that performs convolution operation. Every image is considered as a matrix of pixel values.

### Step2: Relu layer

Relu is nothing but activation function layer. In this layer we remove every negative values from the filtered image and replace it with Zero's. This is done to avoid the values from summing up to zero.

### Step3: pooling layer

In this layer we shrink the image stack into smaller

size.

1. pick the window size (usually 2 or 3)
2. Pick a stride (usually 2)
3. Walk the window across the filtered image.
4. From each window take the minimum value

### Flattening

Flattening is the process of converting all the resultant two dimensional arrays from pooled feature map into a single long continuous linear vector.

### Step4: Fully connected layer

The flattened matrix from the pooling layer is fed as input to the fully connected layer to classify the image.

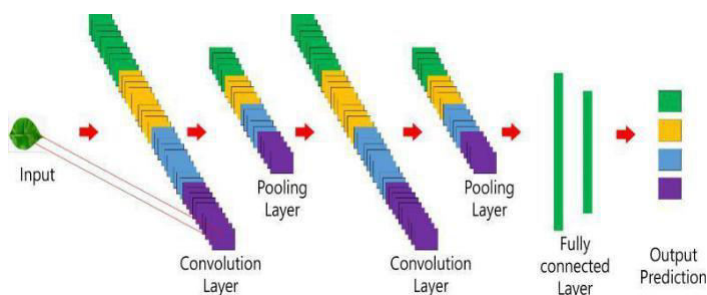


Figure 3. Basic structure of a convolutional neural networks.

## IV. EXPERIMENTAL RESULTS

The two models described above were tested, and Model 2 demonstrated advantages over Model 1. The effect of increasing the number of inception modules in Model 2 to slightly increase performance, is shown in Table 2. However, as shown in Table 2, the difference between Model 1 and Model 2 is small. Experimental images were obtained by using the discolored images in Figure 1 and the distorted

as Figure 7 using different angles.

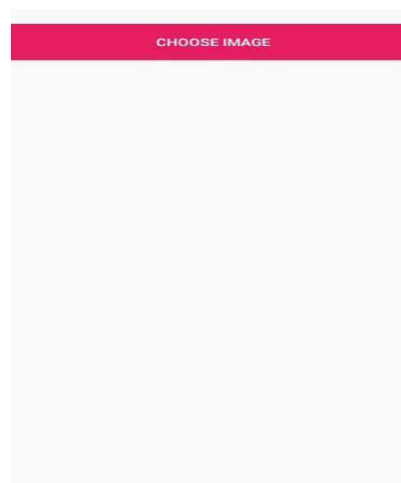


Figure 4: First the image which is captured from camera source is selected from choose an image.

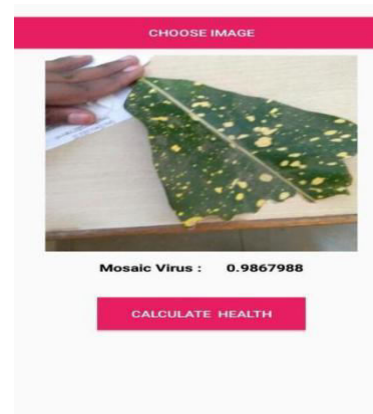


Figure 5: After selecting the image the application will predict the disease name along with the range of the disease affected on the leaf.

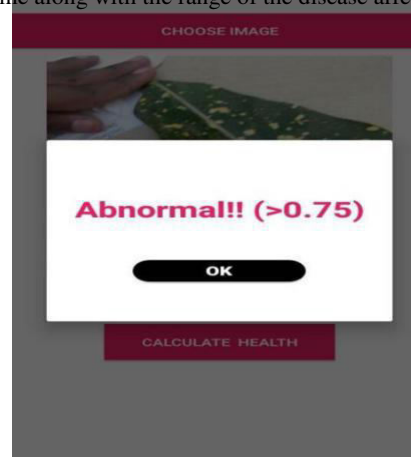


Figure 6: In figure 6 the Health condition of the leaf is calculated comparing with the range as displayed above

## SYSTEM REQUIREMENT SPECIFICATIONS

Recognition of a plant disease in its early stage be performed by specialised h/w equipments and specialised s/w packages. The SRS of the plant disease detection is:

### H/W System Configuration:-

CPU TYPE : Intel I5

CLOCKSPEED : 3.0GHz

RAMSIZE : 8GB

HARD DISK : 1TB

### Software Requirement

OPERATING SYSTEM : ANDROID

LANGUAGE : JAVA

DATABASE : MYSQL

IDE : ANDROID STUDIO

The training images were divided into eight types of 3,767 images, and the test images were chosen by randomly selected 100 images. The deep learning framework used was Tensor Flow r0.10.

## EXPERIMENTAL METHOD

Two CNN models were selected and tested. The chosen two models were GoogleNet and a variant of GoogleNet, and changes in performance were checked when the layers were added. The size of the each image used in the experiment was adjusted from  $1600 \times 1200$  to  $229 \times 229$  to fit the model. We also tested color changing or deforming of leaves by creating leaves that were cut or pitted randomly, as is common in nature. The leaf images used in the test are shown in Figures 1 and Figure 7.

Training of CNN is performed using Tensorflow at the backend, which is a deep learning framework. pixel values were divided so that the range within  $[0.0, 1.0]$ . The network was initialized with random weights. After a successful training of the CNN, the feature extraction layers were optimized to capture specific features from the image for the diagnosis of the plant disease.

Table 1. Type and number of leaves

Leaftype	Number of images
Lanceolate	568
Oval	554
Acicular	612
Linear	439
Oblong	374
Reniform, kidney-shaped	580
Cordate, heart-shaped	379
Palmate leaf	361

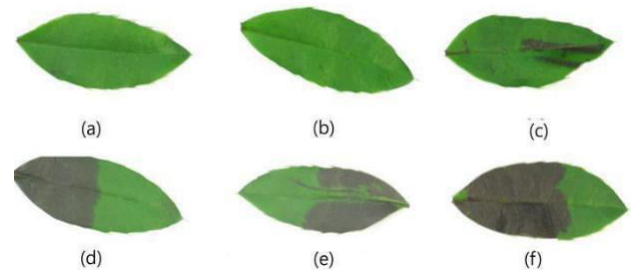


Figure 7. Color change: (a) input image, (b) discoloration 5%, (c) discoloration 10%, (d) discoloration 30%, (e) discoloration 50%, and (f) discoloration 60%.

Figure 6 : Shows the discoloration ratio of the input leaf images.

Figure 7 : shows images of damaged leaves.

The images in the Flavia dataset are displayed vertically, horizontally, and at an angle of  $45^\circ$ , which are all angles not necessarily found in nature. We therefore examined all possible leaf directions by rotating them by  $90^\circ$ . Using the methods described above, 10,000 training sessions were conducted and the performance of the two models was compared.

According to the above results, the recognition rate of our system was above 94% when using the CNN, even when 30% of the leaf was damaged. Our system therefore improves upon previous studies, which achieved a recognition rate of approximately 90%. Leaves that were cut or pitted randomly, as is common in nature. The leaf images used in the test are shown in Figures 1 and 7.

Table 2. Type and number of leaves

Leaftype	Number of images
Lanceolate	568
Oval	554

The images in the Flavia dataset are displayed vertically, horizontally, and at an angle of 45°, which are all angles not necessarily found in nature. We therefore examined all possible leaf directions by rotating them by 90°. Using the methods described above, 10,000 training sessions were conducted and the performance of the two models was compared.

## V. CONCLUSION

In this paper, we proposed a new method to classify leaves using the CNN model. We evaluated the performance of each model according to the discoloration of, or damage to, leaves. The recognition rate achieved was greater than 94%, even when 30% of the leaf was damaged.

In future research we will attempt to recognize leaves attached to branches, in order to develop a visual system that can replicate the method used by humans to identify plant types.

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