E-ISSN 2581 – 7957
P-ISSN 2277 – 3916
CVR Journal of Science and Technology, Volume 21, December 2021
DOI: 10.32377/cvrjst2119

A Survey on Leaf Disease Detection Techniques

A.S Neelima[1] and CVS Satyamurty[2]
[1]PG Scholar, CVR College of Engineering/IT Department, Hyderabad, India
Email: alwalneelima@gmail.com
[2]Assoc. Professor, CVR College of Engineering/IT Department, Hyderabad, India
Email: satyamurtycvs@yahoo.co.in

Abstract: **Plants get affected by various diseases, different pathogens, fungus, bacteria, and viruses that affect the plants. Some affect leaves, stems, fruits, flowers, and other parts of the plant. Diseases in plants are one of their kinds in nature. There are a few diseases that can be fought by the plant immune system but there are a few diseases that need to be focused and a little care has to be taken to find the particular disease at an early stage and take an immediate measure. This helps the agriculturists to save time and increase productivity over a relative period of time. To encounter such types of problems automatically, computer science provides various technologies to detect diseases which include machine learning and deep learning algorithms which resolve the problem. The leaves are just as important as other parts of the plant. Mainly the leaf diseases are most common among many plants than the other diseases caused on different parts. Because in general, the leaf is the sensitive part of the plant, the changes in it which can be observed by the naked eye whenever there is a change in the weather, soil, fertilizer, etc. Plant diseases make farmers suffer, which may be any disease related to any part of the plant. Plant diseases are just abnormal effects that disturb the normal functioning of plant life. Thus plants are the most important factors to create ecological balance in the environment. This paper focuses on different diseases caused to leaves. This is a survey paper that represents the disease detection in various leaves, algorithms, and techniques used.**

Index Terms: **Leaf diseases, Deep Convolution Neural Network, GoogleNet, AlexNet, Image Subdivision.**

I. INTRODUCTION

Plants are organisms that have life. Similar to animals they also suffer from different diseases. All the plants including wild, cultivated and organic are prone to various kinds of diseases. Plants indicate their health condition by any of the following ways as shedding leaves, changing the color of leaves, white patch on leaves, and discoloration of the branch, thinning of a stem, bending of the shoot, premature fruits, and flowers drop off, the plant stops its growth. The plant diseases must be found at an early stage so that the plant can be saved. Diseases in plants affect agricultural productivity, huge losses to farmers, the GDP of the country coming from agriculture gets affected as more than 70% of the rural people do farming in India. Most of the diseases are caused on leaves where the pathogen first finds the source as a leaf to start its infection on a plant. There are many sources from which a disease can occur, some of them occur due to fungus, bacteria, virus, and other pathogens, worms, and insects. This survey paper describes the various diseases, techniques implemented on maize, cucumber, mango, and tomato leaves also factors influencing the techniques used. The common diseases caused in leaves are:

A. Southern leaf blight:

It is a fungal disease that is caused by Bipolaris maydis. They are particularly hosted by the maize plant. It forms diamond-shaped lesions with brown borders mostly form at the lower parts of the leaves and slowly move upwards towards the main plant.

B. Brown Spot:

It is caused by fungi known as physoderma maydis. Mostly affect in hot and humid conditions, they form tiny yellow spots which turn to brown later. Mainly develop on stealth, leaf blades. They form like stretched bands on the leaves. These fungi are hosted by the maize plant.

C. Curvularia Leaf spot:

It is caused by Curvularia lunata in the maize plant. It forms round brown border tan lesions with a yellow halo on leaves. They start with fewer lesions on leaves later spread throughout the leaf also these fungi travel through wind or water and affect the other plants.

D. Common Rust:

This is caused by a fungus named Puccinia sorghi. Initially, they form slightly tanned spots later they grow into powdery form and golden brown pustules scattered on both sides of leaves. Usually, the color of the spots changes into black as time progresses. Commonly hosted by maize, sorghum, millet plants.

E. Dwarf mosaic:

It is mainly caused by the maize Dwarf Mosaic Virus This virus has two strains A and B cause the yellowing of leaves followed by red patches along the margins of leaves. The effect of the virus depends on the growth of the plant. Mainly hosts Maize, Sorghum plants.

F. Grey leaf spot:

This is caused by Cercospora zeae-maydis. Initially, they form below the leaves as yellow halos further expand to the leaf veins , they are of many varieties as some of them appear black, yellowish, and brown spots. Sometimes they form silver coloured powdery form.

G. Anthracnose:

Anthracnose disease is a fungal disease that commonly occurs in almost all plants. It mainly affects the trees in general causing the leaves to have small irregular brown or yellow lesions later they develop largely and spread to other leaves as well. Anthracnose spreads fast during the rainy season.

H. Downy mildew:

It is caused by a fungus known as Pernosderospora. It is highly serious effects causing fungi to plants. The plants become brittle, do not develop properly, and thin. These are wind born and spread very quickly through the air and infect other plants.

Received on 16-04-2021, Revised on 04-05-2021, Accepted on 15-06-2021.

I. Bacterial spot:

It is one of the most disturbing diseases caused in tomatoes and pepper. Mostly found in warm and humid places, once the disease is out of control it is not possible to reduce its effect. Plants show yellow lesions later develop into black which would be a serious issue causing, shedding of young leaves, and drying of premature fruits.

J. Leaf mold:

It is caused by a fungus known as Fulvia fulva. This stays alive feeding on the moisture present in plants especially on tomato plants making it dry, weak, and finally make the leaf dead one by one. This makes leaves develop purple color fuzzy texture under the leaves later the leaf starts to wither turning into yellow.

K. Spider mites:

Spider mites are small spiders that look like bugs. They can be noticed in different colors such as yellow, brown, red and green. These spider mites feed on plants mostly in the spring season. They lay hundreds of eggs on leaves which increases their population exponentially and damages the plant.

II. The Evolution of Various Convolution Neural Networks

The most predominant methodology used in detecting leaf disease is convolution neural networks (CNN or ConvNet). The convolution neural network has been used in various applications such as image recognition, image segmentation, object detection, etc. It consists of mainly the following layers: Convolution layer, Pooling layer, Fully connected layer, Dropout and activation functions.

A. The Convolution Layer:

This is the first layer in CNN architecture, it performs the convolution operations and extracts the features from the input image. The convolution is an operation that is performed by sliding an NxM filter on an input image to extract features.

B. Pooling Layer:

The pooling layer is followed by the convolution layer. The pooling layer is used to reduce the convoluted featured image which helps to reduce the computational cost. The pooling operations such as the max-pooling which calculates the maximum of the feature maps, the average pooling calculates the average of feature maps, the sum pooling calculates the total sum of the feature map elements.

C. Fully Connected Layer:

The fully connected layer is placed at last before the output layer. In the fully connected layer, all the neurons are interconnected with each of the other neurons. The flattened vector input is fed into this layer, later the classification process begins at this stage.

D. Dropout:

In the fully connected layer, all the features are very well Connected. This causes over fitting and creates a negative impact on the model performance. The dropout layer drops off few neurons at the time of training which reduces the size of the model enhancing the performance.

E. Activation Functions:

The activation function is the most important parameter in the CNN architecture. It is the main factor that decides which neuron needs to get fired and what neuron must act idle. The common activation functions used such as ReLU, SoftMax, Sigmoid, and Tanh functions.

There are many types of CNN's some of them are: LeNet was introduced by Yan LeCun et al 1998 it was used for the classification of numerics and was used at most of the banks to recognize the handwritten numbers on cheques, it had 7 convolutions layers with 60,000 parameters. AlexNet was introduced by Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever in 2012 which won the ImageNet challenge it is simple and consists of 60 million parameters. ZFNet was introduced by Matthew Zeiler, Rob Fergus in 2013 which is an improved version of AlexNet. Network in Network(NiN) uses multilayer perceptron convolution which adds to increase the depth of the network can be regularized by dropout, always used at the bottleneck of the CNN model. Also, the NiN uses GAP(GlobalAveragePooling) which reduces the number of parameters helps to generate low dimension feature vectors without reducing the dimensions of feature maps. VGG Net(Visual Geometry Group) was introduced by Simonyan Zisserman in 2014 this had a more simple architecture than the AlexNet and ZFNet with 138 million parameters. GoogleNet was introduced by Google in 2014 it consisted of inception modules which in turn has skip connections forming small modules and this forming of small modules are repeated in the whole network GoogleNet uses such nine inception modules and has about 4 million parameters with 22 layers and fewer parameters than VGG and AlexNet. The inception modules used in the GoogleNet architecture are just the 27 layers deep convolution layers. The inception module is the core concept of sparsely connected architecture, comes into the picture when the model is prone to overfitting, also when the number of parameters is more which increase the computational resources. The prerequisite for the inception layer is the Hebbian principle which says that "Neurons that fire together wire together", i.e. when building the subsequent layer one needs to focus on what has been learned in the previous layer. It works as an example, if the deep learning model has learned to identify the individual parts of a leaf it then the next layer must identify the overall complete leaf what kind of symptoms are there any dark spots, lesions or any other patterns are there on the leaf. To do all these the model must be aware of all kinds of appropriate filters which are available in Keras. ResNet(Residual Network)was introduced by Kaiming He in 2015 it consists of 158 layers for computation. FractalNet was introduced by Larsson et al which is based on the fractal design which is an advanced architecture of ResNet. This is based on the drop path which is a regularization approach to design large models. DenseNet was introduced by Gao Huang in 2017 consisting of densely connected CNN layers which are mostly used for feature reuse also by reducing the number of parameters.

Steps for leaf disease detection and classification:

1. Image acquisition
2. Image pre-processing
3. Image segmentation
4. Feature extraction
5. Detection of disease and classification

Image acquisition is the basic step in image processing. It is a process of acquiring an image by any source that may be hardware or software i.e. through the camera or from image dataset sites. These images collected have many disturbances and are unprocessed "Ref.[4]" Image processing is used to remove noise, contrast enhancement, image smoothing, image cropping, filters some of the filters such as average filter, maximum filter, Gaussian filter helps to get good insights for the model to perform well [4]. Image segmentation is mainly done to locate the regions which are more useful for the model than the other parts of the image. Usually, it creates pixel-wise masking to create a more meaningful image to analyse. Used to locate pixel boundaries or objects. Feature extraction plays an important role in image processing as the main features (color, texture, edges, shapes, etc.) of the image needs to be extracted by the model. "Ref. [4]" Color features are extracted by the color histogram, color moments, and color descriptor here refers to leaf color. Disease detection and classification is the last stage of the image processing where the images are classified according to their diseases and labelled accordingly after training and testing of the dataset by the classifiers. Classifiers such as SVM, CNN, ANN, KNN, etc. used for the classification and detection of diseases.

III. Literature Survey

Uday Pratap Singh et al. "Ref. [1]" has proposed a way that mainly focuses on developing a deep learning method which will classify the mango leaves infected by a fungal disease referred to as anthracnose disease. It mainly uses the multilayer convolution neural network for classification inspired by the AlexNet architecture. Two types of dataset repositories were used they are real-time mango leaf dataset and the other is PlantVillage repository. A total of 2200 images were used in the real-time captured are about 1070 images remaining 1130 images were taken from the plant village dataset. They were divided into 4 classes and labeled, given in table I.

The full dataset is divided into training and testing sets with 80%-20%, so for training 1760 images were used and for testing 440 images were used. The convolution neural network(CNN) is used here because it can handle complex pattern recognition and image classification process for large datasets which has been inspired by AlexNet architecture.

A. Methodology:

First, the dataset for both mango and other multiple leaves are collected from plantVillage and real-time mango leaf datasets for both disease and non-disease leaves. All the images are pre-processed by contrast enhancement and rescaling using 2methods such as:

1. Histogram equalization
2. Central square crop method

The histogram equalization is used for assigning uniform intensity values for each pixel, later the images are rescaled to128x128 using the central square crop method.

TABLE I.
Dataset Details

Type Of Image	Class_Label	No. Of Images
Mango Leafs Without Disease	C0	512
Mango Leafs With Disease	C1	558
Multiple Plant Leaf Without Disease	C2	520
Multiple Plant Leaf With Disease	C3	610

The task of the classifier is given in 3 steps they are:
STEP1: To find out whether the leaf is mango leaf or not
STEP2: Later to know if it is diseased or not
STEP3: Then classify is it as a diseased mango leaf or not

There are many different models of cnn they can be named as GoogleNet, AlexNet, ResNet, VGG many more. The convolutional neural network is a deep learning technique that has mainly the following layers to extract the information from the images sent from the input layer:

1. Convolution layer
2. Max pooling layer
3. Fully connected layer
4. Dropout layer
5. Activation functions

The convolution neural network model used in this paper given has:

1. The 1st 2nd layers are convolution layers of 128 filters with 3x3 size followed by Relu activation function after each of them. Next is the max-pooling layer with a size of 2x2 of the convoluted image.
2. The next 2 layers are convolution layers with 256 filters size of 3x3. Followed by a max-pooling layer with a convoluted image with the size of 2x2.
3. Again the next 2 layers are convolutional layers followed by a max-pooling layer with a convoluted image with a size of 2x2. Later followed by flattening layer with convert's images into 1d array.
4. The last two layers are fully connected layers where each neuron is connected with every other neuron.
5. There are about 512 neurons in the first fully connected and 3 output neurons in the last fully connected neuron it uses softmax function. Ultimately classify the image and produce the output class label.
6. There are dropout layers in between the network with the rate of 0.2-0.5.
7. The learning rate is given as 0.01.
8. The backpropagation algorithm or the stochastic gradient descendent is used here for training the network, refer figure 1.

9. The accuracy achieved using multilayer convolution neural networks is 97.13%.

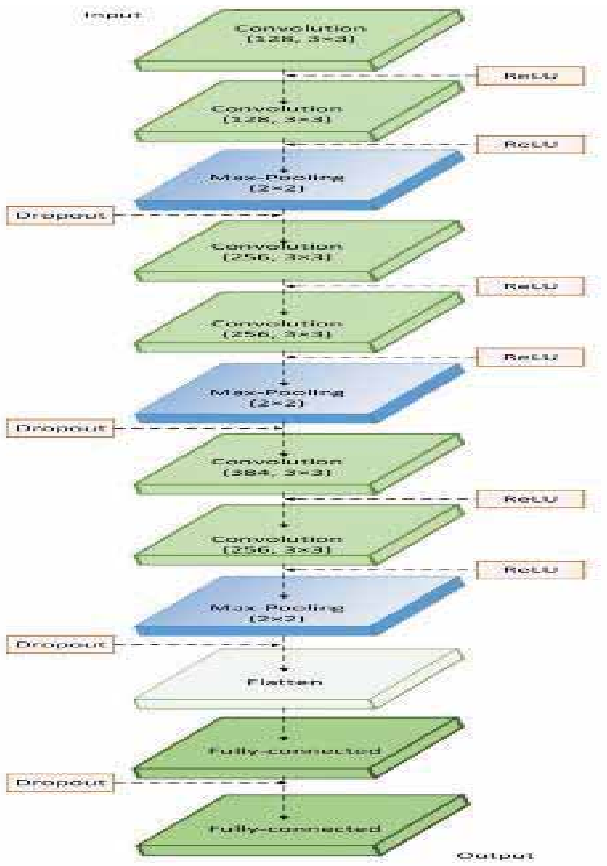


Figure 1. Convolution Neural Networks

Halil Durmuú et al. "Ref. [2]" describes the deep learning methods which have been implemented to recognize the diseases that occur in tomato plant leaves. The tomato Leaves were collected from the plant village dataset, a total of 10 classes of the different diseases was used along with healthy leaves. Only the tomato leaf images were considered which has 10 classes including the healthy leaves given has:

1. Bacterial spot
2. Early blight
3. Healthy leaf
4. Late blight
5. Leaf mold
6. Septoria leaf spot
7. Spider mites
8. Target spot
9. Mosaic virus
10. yellow leaf curl virus

B. Methodology:

Here in this paper 2 networks were used for disease detection AlexNet and Squeeze net. The AlexNet used here is from the Caffe library which is written in C++ language also has python binding which helps in easy implementation. SqueezeNet v1.1 was downloaded from GitHub. The training and testing were done on the NVidia Jetson Tx1. The training was done on GPU or GPU clusters which takes a long time and with a training batch of smaller size(20) which in turn reduced accuracy.

a. AlexNet Architecture :

It has the following layers: -

1. The input layer with image 227x227x3 resolution.
2. This network has 5 convolutional layers where each layer is preceded by the ReLu layer, preceded by the normalization layer, and pooling layer up to the conv2 layer.
3. A convolution layer (conv1) has 96 kernels with a 11x11x3 convoluted image.
4. Conv2 has 256 kernels with a 5x5x96 convoluted image
5. Conv3 has 384 kernels with 3x3x256 convoluted images preceded by Relu(relu3) function.
6. Conv4 has 384 kernels with 3x3x384 convoluted images preceded by Relu (relu4) layer.
7. Conv5 has 256 kernels with 3x3x384 convoluted images preceded by Relu (relu5) layer and the pooling layer (pool5).
8. The $6^{th,}$ 7^{th} layer is the fully connected layer with 4096 neurons preceded by the Relu (relu6, relu7) layer and dropout layer with the rate of 0.5.
9. The 8^{th} layer is the fully connected layer (FC8) helps to find the class probabilities preceded by the softmax function to find which class the image belongs to from the given 10 classes, refer figure 2(a).

b. SqueezeNet Architecture:

The Squeeze Net is introduced to increase the accuracy than the AlexNet which has been used earlier with 50 times fewer weights than AlexNet, also the SqueezeNet is lightweight architecture mainly built on 3 design strategy by reducing the filter size, input channel, and downsampling rate in the network. The input Layer with the RGB image with 227x227x3, refer figure 2(b).

c. Fire module:

The fire module has mainly 2 layers:

1. Squeeze Layer
2. Expansion Layer

d. Squeeze layer:

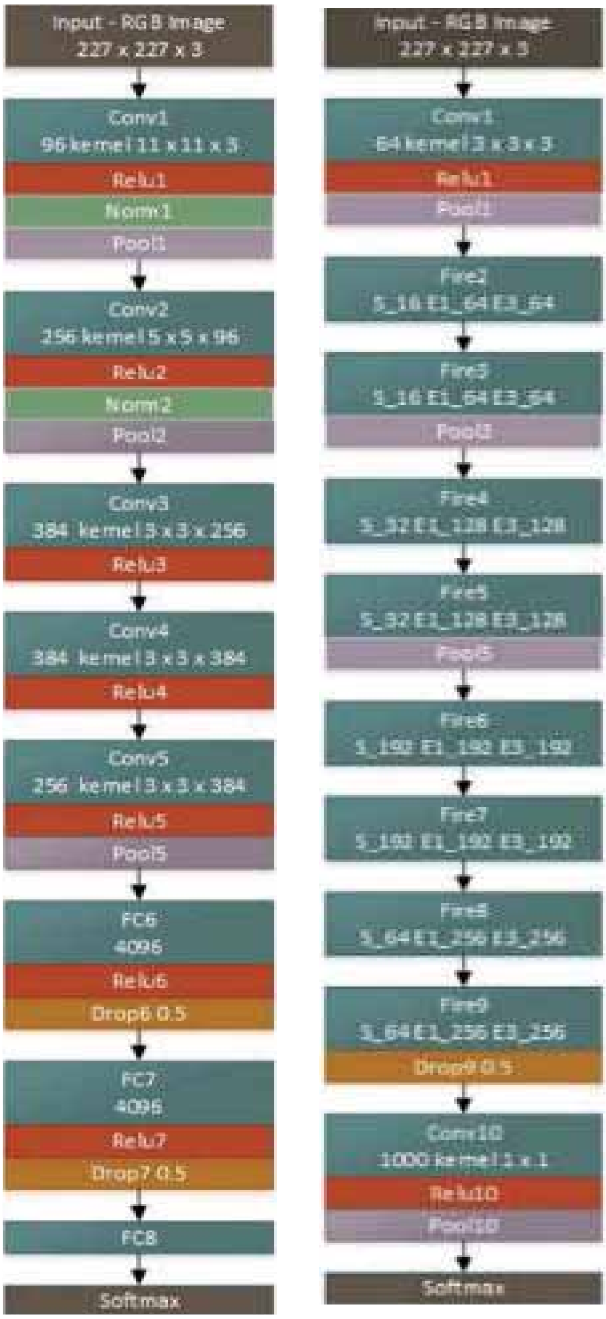
The squeeze layer has 1x1 size filters i.e. reducing the 3x3 filters used earlier in the input channel to reduce the parameters in the network.

e. Expansion layer:

The 1x1 convolutions are combined with the 3x3 convolutions. The 1x1 convolutions mix the earlier channels in various ways as they can't identify the spatial structures. The 3x3 convolutions can identify the structures in the image. By combining the 2 types of convolutions (1x1 and

3x3) reduces the number of parameters and also makes the model expensive. These 2 layers (squeeze layer and expansion layer) are preceded by the ReLu layer.

In this paper, the Squeeze Net module uses 8 fire modules and one convolution layer as input and output layers along with a softmax classifier. The squeeze net uses the global



(a) (b)
Figure 2. (a) AlexNet (b) SqueezeNet

average pooling and the last convolution layer must have as many outputs to represent the output classes."Ref. [3]" Both the AlexNet and Squeeze Net have their area of applications but Squeeze Net achieves the accuracy by 50x fewer parameters than of AlexNet, also benefits for model compression. The accuracy test onset of AlexNet and SqueezeNet is given as 0.9565 and 0.943~ 95.65% and 94.3%.

Juncheng Maa "Ref . [5]" has discussed a method used to recognize the cucumber diseases using DCNN by symptom-wise recognition, which would be useful without the effect of multiple diseases in a single leaf. This recognizes 4 symptom-based cucumber images refer to table II. The dataset was collected from the plantVillage and forestry sites symptom images such as:

1. Anthracnose obtained from the internet.
2. Downy mildew obtained from the internet.
3. Powdery mildew was obtained by using a digital camera.
4. Target leaf spots obtained from the internet.

The resolution of the images was 2592x 1944 pixels later resized to 800x600 pixels, for recognition the images were again resized to 20x20x3 as the symptom images were in little space. Segmentation was done using disease symptom segmentation along with comprehensive color features with region growing technique. The training was done by 80% and the validation by 20% rule. Feature extraction is performed, later segmentation is performed to extract the color and texture features to differentiate the diseases. The color features have mean and variance of the 9 channels from 3 color spaces including R,G,B(RGB space),H,S,V(HSV cpace) and L,a*,b* (CIEL*a*b*) refer figure 3.

The texture features were analysed using GreyLevel co-occurrence matrix for each channel which includes contrast, homogeneity, and correlation for the 9 channels. Confusion matrix prepared to check the performance of the classifier later the precision, sensitivity, f1score were also used to evaluate the performance.

TABLE II.
CUCUMBER LEAF DISEASE IMAGE DATASET

Name Of Disease	Number Of Symptom Images
Anthracnose	229
Downy mildew	415
Powdery mildew	332
Target leaf spots	208

The augmentation method used here doesn't compress the size of the input image, a total of 12 sets of augmented images were produced. By rotating the images to 90,180,270 degrees, flipping horizontally and vertically. From the augmented training set 1600 symptom images were randomly selected from each class, also 400 images were selected from each class of the augmented test dataset. Where 5120 image were used for training, 128 images used for validation and 1600 images used for testing purpose

C. *Methodology:*

The architecture used here is analogous to Lenet5 which is robust, fast for the small image recognition task. The convolution neural networks were implemented in MATLAB.

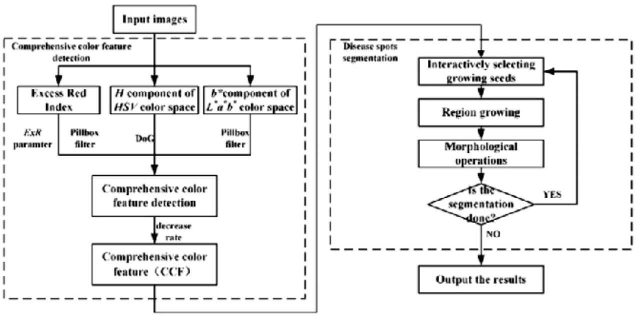


Figure 3. Image Color Feature Segmentation

The architecture is given as in figure 4. The input layer consists of the symptom images (RGB 20x20x3), the weights were optimized using stochastic gradient descendent (SGD) with a momentum of 0.9, and the maximum number of epochs used for training is 800.

The Learning rate was initialized for about 0.001 later reduced for about 20 epochs by a drop rate of 0.1 and the min batch of 128 was used. DCNN (Deep Convolution Neural Network) consists 4 modules such as:

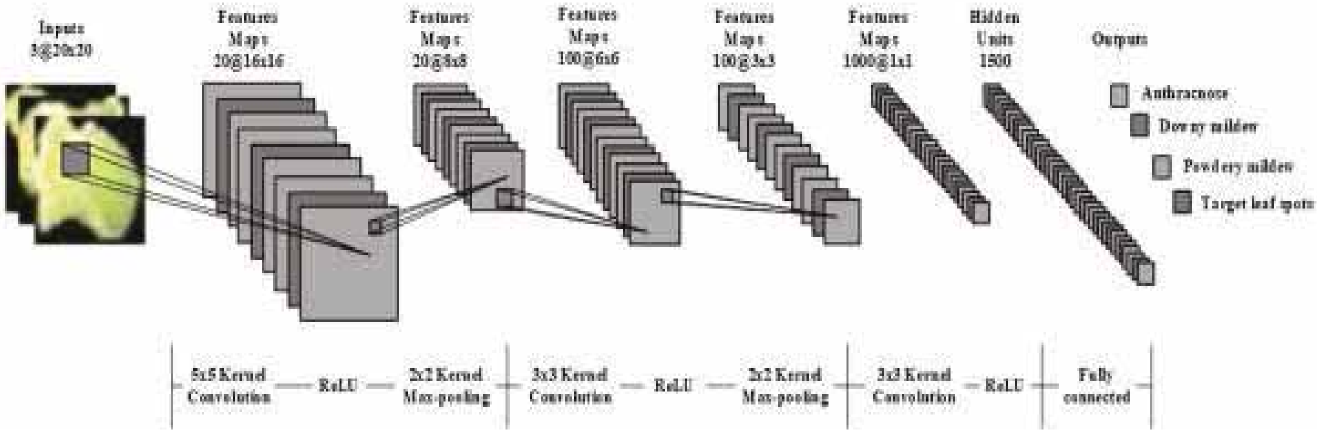


Figure 4. Architecture DCNN model for cucumber leaf disease detection

The first module has *a* convolution layer with 20 filters with size 5x5. Max pooling layer with the filter size of 2x2 stride of 2(preferred down sampling). Module 2 consists of a convolution layer with 100 filters, size of 3x3. Max pooling layer with the filter size of 2x2 stride of 2. Module 3 has convolution layers with 1000 filters, size of 3x3. Module 4 has a fully connected layer with 1500 neurons. The output layer consists of the Softmax function has 4 neurons for each of the classified cucumber images. The accuracy of the confusion matrix given as 93.4%, the best performance was given by the downy mildew, also the AlexNet was used to evaluate the performance to compare with DCNN where the AlexNet outperformed the DCNN with the accuracy of 94.0%, 92.6%. The paper also describes various classifiers used in the field to detect the diseases and compare their performance with DCNN such as SVM was about 81.9 % accurate Random Forest was about 84.8 %. Mildew about 96.7%, powdery mildew as 98.2%, anthracnose 82.0%, and target leaf spots 91.8% using DCNN. The DCNN has given superior results for powdery mildew and downy mildew as there are larger than other classes.

Xihai Zhang et al. "Ref. [6]" has explained the automatic maize leaf disease detection using two improved models known as GoogleNet and Cifar10 models used to train and test the nine types of maize diseases, by regulating the parameters, modifying pooling combinations, appending dropout operation, using Relu function and decreasing the number of classifiers (achieving the accuracy of about 98.9% and 98.8 %). Around 500 images were collected from various online sources such as plantVillage dataset, and other image dataset websites. There are mainly 8 varieties of maize leaf diseases 1 variety of healthy leaves. The comparison procedure(cleaning) was applied to the images by using a python script which erased the redundancy of entities such as image name, size, date later the images were scrutinized by human experts. In the augmentation process the images are further required to expand to recognize the diseases properly by rotating them into 90°

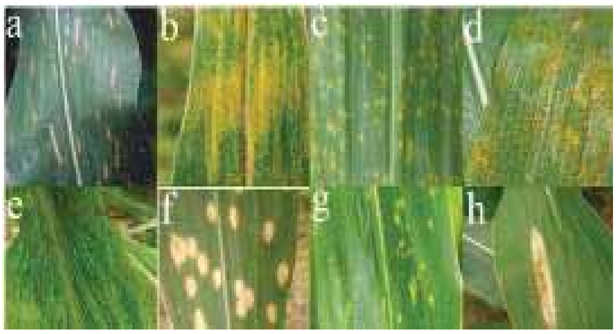


Figure 5.Various Leaf Diseases

E-ISSN 2581 – 7957
P-ISSN 2277 – 3916

DOI: 10.32377/cvrjst2119

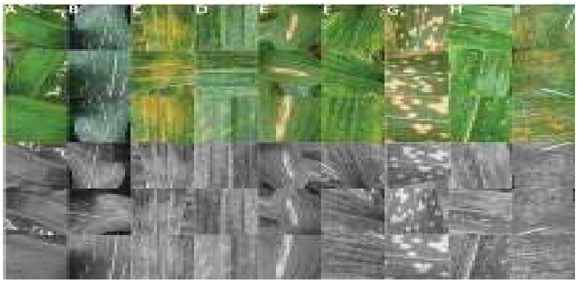


Figure 6. Augmented Leaf Images

a) Curvularia leaf spot
b) Rust
c) Dwarf mosaic
d) Grey leaf spot
e) Round spot
f) Northern leaf blight (refer to figure 5).

180°, 270° and mirroring each image also slitting the middle of the image later converting them into greyscale refer figure 6.A Shows the healthy leaf after rotating slitting and grey level conversion, from B shows the various infected maize leaves. They considered about 3060 images in total and 2248 images as the training set, 612 images as the testing set i.e. 80%(training) and 20% (testing). Images were normalized into 224x224 pixels and 32x32 dots per inch and pre-processed in python using OpenCV framework, for training all the images grouped and labelled by keyword search by agricultural experts which helps for better accuracy and validation also for better classification.

D. Methodology:

Caffe known as Convolutional Architecture for Fast Feature Embedding is a framework based on C++ language used for faster updating, flexibility expansibility in deep learning models such as CNN, RCNN, LSTM, and fully connected networks. GoogLeNet has provided a relatively less error rate by using fewer parameters than AlexNet and

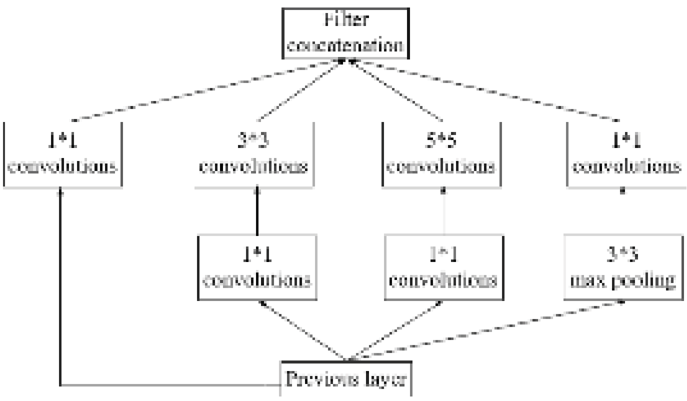


Figure 7. Inception Model

VGG which are mostly used in Network in Network concept applications. Here the GoogleNet uses a pyramid structure that enhances the capacity of width introduces the concept called the “inception model”, refer figure 7. Inception model used to precisely optimize the local sparse structure, here 9 inception models used in GoogLeNet structure.

The 3 classifiers are used to compute top-1, top-5 accuracies, and system loss. In this paper only the first classifier is used for training and testing of all the 9 sample images, further decreasing the number of parameters not affecting the accuracy and the time needed for convergence. To obtain the increase in identification accuracy only the top-1 accuracy is measured in this paper. The Cifar10 model has 3 convolutional layers, 2 fully connected layers, and 1 loss layer, each convolutional layer is followed by a max-pooling layer and ReLu activation function. For training cifar10 modified model is used, Dropout (for reducing overfitting) and ReLu (to learn sparse features) used in between fully connected layers to enhance the recognition accuracy. The hyperparameters are the parameters that affect the performance of the model they include:

1. Solver type
2. Base learning rate
3. Momentum
4. Learning rate policy
5. Weight decay
6. Batch size

Here they discussed the original and modified models of both the GoogleNet and Cifar10 by changing the base learning rate of the Cifar10 model from 0.001 to 0.0002 and the GoogLeNet model from 0.01 to 0.001and batch size for ciafar10 from 100 to 10. Considering the remaining original parameter values same for both Cifar10 and GoogleNet models as Solver type SGD(Stochastic Gradient Descendent), momentum as 0.9, Learning Policy as fixed and step, Weight decay as 0.004, 0.0002 and Gamma as 0.96 for GoogleNet model.

In the original GoogleNet model after 10,0000 iterations the top-1 testing accuracy was given as 98.8%, 98.6%, and 98.2% given by the three classifiers. The top-5 accuracy is 99.6%, 99.6%, 99.6%. The experimental results of the original GoogleNet model are given in Figures 8 and 9

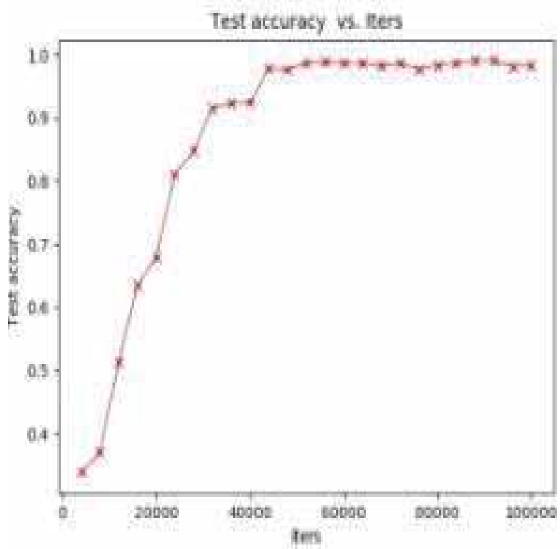
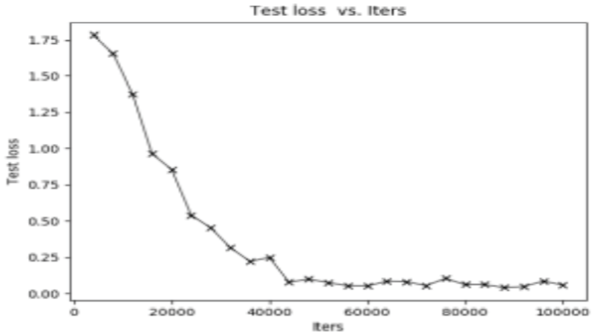


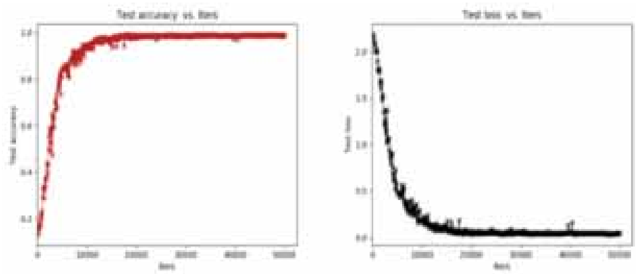
Figure 8. Top-1 Test Accuracy



The original model has a large number of parameters where the recognition accuracy and the system loss converge after 40,000 iterations the training and convergence of the original model also consume a larger time. In the GoogleNet first classifier is used to perform the 50,000 iterations on the maize leaf dataset in this test. After every 100 iterations, the top-1 accuracy and the loss of the model are measured. Figure 10 and shows the modified GoogleNet model, after 10,000 iterations top-1 accuracy tends to 1 and the loss tends to 0, they explain that the average accuracy 98.9% and the loss is 1.6% for the modified GoogleNet model for both training and testing. All the classifications are done by the first classifier of the modified GoogleNet model. The top-1 recognition accuracy of the modified model is more than 0.4% compared to the original model. The system loss is about 14.2% lower than the original model.

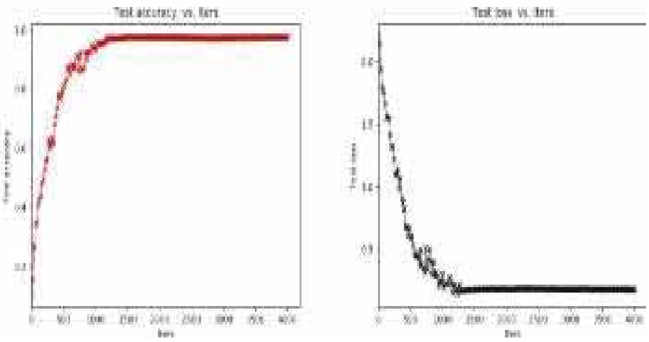
In the modified model the after 10,000 iterations the top-1 testing accuracy approaches to 1 and the loss approaches to 0 both become stable but in the original model, they converge after 40000 iterations which take most of the time and computational resources. So there is an improvement in the modified model than the original model in terms of convergence which in turn enhances the recognition efficiency also.

In the Cifar10 model altering the Dropout operation, the recognition rate and testing accuracy is improved. The correlation between the dropout probability and the recognition rate is given as:
In common the dropout probability rate is taken as 0.5 later increased till 0.75, where the recognition accuracy increased with the increase of the dropout rate. It was found that when the dropout probability was 0.65 the recognition accuracy was about 97.8% this is about the original Cifar10



(a) Top -1 Test Accuracy (b) System Loss
Figure 10. Modified GoogleNet model

model. The Max-Max-Avg pooling combination is chosen on the remaining pooling combinations. In the original Cifar10 model the 4,000 iterations were considered for training the dataset, after 1,200 iterations the testing accuracy and the loss approach to a stable state the average testing accuracy is 97.1% the loss of the system be 17.8% refer to figure 11. When the pooling combination is Max-Max-Avg the training accuracy is 98.8% and the testing accuracy is 97.8% after 20,000 iterations they converge refer to figure 11. Using modified Cifar10 the testing accuracy enhanced by 0.7% and the loss reduced by 10.2%.



(a) Top -1 Test Accuracy (b) System Loss
Figure 11. Original Cifar10 Model

This paper showed the contrast between 2 networks i.e. GoogleNet and the Cifar10 model which have their own advantages and by changing the parameters acquiring the better version of both the individual models. The top-1 identification accuracy given by the GoogLeNet model is 98.5% and the Cifar10 model 97.1% using both original models. By using modified GoogleNet and Cifar10 models the high identification accuracy is given as 98.9% and 98.8%.

Jayme G.A. Barbedo , "Ref. [7]" has mentioned that deep learning has its significance in image classification and recognition. It solves complex problems like image recognition, text classification and also implemented in disease detection within the field of agriculture. This paper describes the parameters that affect the design effectiveness and factors that influence the deep neural networks. The image data were collected from the repository referred to as the digipathos repository which has about 50,000 images freely available. The corn leaf samples are considered during this paper for work. Totally 9 diseases of corn leaf were considered. Anthracnose, Tropical rust, Southern corn rust, Scab, Southern corn leaf light, Pheaosphaeria leaf spot, Diplodia leaf streak, Physoderma brown spot, Northern leaf blight.

E. Methodology:

In this paper, the GoogleNet was used using transfer learning implemented by neural network toolbox a library given by MatLab. The unprocessed images were first trained to three different CNN's where each CNN had its own operation on images. The 80% for training and therefore remaining 20% for validation were used. The training datasets were augmented. As a result, the training set size was increased 12 times and therefore overfitting was decreased. In Cnn1 worked by using actual unprocessed images, later in Cnn2 by using manually removed background in an image, in Cnn3 using subdivided images i.e. the each of the images was subdivided into small images which contain individual symptoms of every disease of every image leaf following some rules for consistency within the subdivision. Finally in Cnn4 was implemented employing a reduced version of trained subdivided dataset images.

The parameters used for training are given as:-

1. Learning rate : 0.001
2. No. of epochs : 5
3. Momentum : 0.9
4. Min batch size : 06

The 10 fold cross-validation approach was used to get the final accuracy. The accuracy achieved in this work done by GoogleNet is given in table III as:

TABLE III.
CORN LEAVES IMAGES ACCURACY USING VARIOUS 3 CNN'S

Dataset	Training Images	Accuracy
Original	1584	76%
Background removed	1584	79%
Subdivided (completely)	100608	87%
Subdivided(reduced)	1584	81%

The accuracy for subdivision of image dataset completely gave more accuracy than all the techniques used in each of the cnn's. The accuracy was about 87% for 100608 images. The high accuracy is due to larger size of the dataset so the model learns a large set of features to detect accurately. The factors for the misclassification of images were identified, they were about 9 factors affecting the classification and overall performance of the CNN. There are extrinsic and intrinsic factors that affect the accuracy of the model for the classification of corn leaf diseases.

A. The Extrinsic Factors:

a. Annotated Datasets:

Annotating the datasets has many disadvantages. Continuous labeling of the images is an expensive, tedious, and a lot time-consuming tasks. If the labels have some uncertainty in them the training process wouldn't be enough which is a serious problem concerning some of the social networks. Mislabeling often occurs especially in labeling large datasets concerned with the plant disease databases with looks impractical.

b. Representation Of Symptoms:

Some datasets do not adequately represent the symptoms which are problematic for the model to classify the diseased class. Symptoms occur due to some of the external factors such as heat, cold, mechanical damage, toxicity, pests many more so that a good model needs to be available to handle the large classes. When the tools for disease recognition handle the real-world data, they have to find the correct class among all often leading to misclassification when they were trained on limited subset diseases. Very rare diseases more often tend to be misclassified.

c. Covariate Shifts:

Covariate shift is a phenomenon where the source domain distribution (training data) is completely different from the target domain distribution (testing data). This says that when a particular model is trained on some plantVillage dataset but when tested with some other trusted online data used i.e. collection site images immediately the accuracy fell to 50%. So, the detecting capability of the model affects it drastically.

d. Image Background:

Learning images with the heterogeneous background is a complex task. Deep neural networks also work in a busy background environment. The experiments conducted with different background produced an accuracy of 76% but for the images with background removed the accuracy was about 79%, this is because the model assumes the elements in the background as part of image symptoms, leaves and learns the background images as well which leads to error. So the leaf segmentation and background removal is a complex task. Selecting the region of interest by the user before the classification process in the touchscreen smartphone tool than placing the panel behind the image.

e. Image Capturing Conditions:

Capturing the images under controlled conditions and later using them is a type of process which includes dealing with images that were captured by various people, environment, intensities, and different angles. Many of them just ignore or treat superficially during analysing the results. Various experiments were carried out when the trained CNN's success rate decreased from99% to 68% when the training was done in field condition images but used the model with laboratory condition images. Some unrelated illumination effects also cause irreversible information loss. Peculiar reflection can be reduced by changing the image capturing angle or changing the position of the leaf.

B. The Intrinsic Factors:

a. Symptom Segmentation:

When the symptoms are localized, and the regions are isolated and segmented which contains the most relevant information. It would be more flexible for the system if the user selects the appropriate individual regions before classification which is more effective by touchscreen technology of smartphones. The model has to deal with multiple diseases with the same characteristics. It is a worth advantage in noticing the regions of interest by focusing on those particular symptoms.

b. Variations in Symptoms:

Each of the diseases have their own symptoms such as they differ in color, texture, shape, size. Variations in the symptoms to the most create difficulty to the image-based diagnosis. If all the various stages of the symptoms (mild to severe) are given in the training the deep learning tool can handle the challenges held along with the diversity of symptom diseases. Practically it is very difficult to give all range of symptoms.

c. Simultaneous Disorders:

When the plant is infected with a particular disease its immune system is weekend which results in the attack of other diseases or pests or insects in turn increases the symptoms in plants or leaves, which is known as multiple simultaneous disorders. If removing or considering the region of interest by the user which is a very tedious task involves noticing every detail of the symptom and submit every one of them to the system. If this would have been done automatically would create many of the errors.

d. Disorders with the same Symptoms:

The occurrence of similar symptoms that can't be properly be identified by the plant pathologists also. although the image is captured with nearly perfect quality where the symptoms are so similar to diagnose. Human experts also consider other issues such as current data, historical data to analyse and draw accurate symptoms, which can be incorporated into systems to improve the classification. Some of the cases can only be solved through laboratory analysis. So, currently too unrealistic to have an automatic disease detection system to have perfect accuracy.

Other few of the factors such as over fitting, and systems that only rely on only one part of the plant, considering one dataset site or dataset downloading sites where all images are made freely available.

IV. CONCLUSIONS

"Ref. [1]" has used MCNN to detect the anthracnose disease in mango leaves the highest accuracy achieved by this model is 97.13%. The model used here can also be improved by involving IoT i.e. remote monitoring of the plants which is a good field where the MCNN can be implemented. Also, the use of some other activation functions that enhances the performance of the model can be used. Using other plant parts such as stem, fruits, flowers can also be used to detect the diseases. Also, by using various ensemble methods which can boost the performance along with the current deep learning models.

"Ref. [2]" has used the AlexNet and SqueezeNet on tomato leaves disease detection where the accuracy of the AlexNet was about 95.65% SqueezeNet accuracy was low as it is 80 times smaller than the AlexNet.The inference time of 150ms for AlexNet and 50ms for SqueezeNet. This model fits well on the field which can be deployed on to a robot that can detect the tomato leaf disease on the field itself.

"Ref. [5]" Among all the techniques which have been used this paper gives almost the best solution in this disease detection domain as it uses DCNN using symptomatic images are considered the accuracy of only 2 classes have large value because there were large image sets in those particular two classes (mildew and powdery mildew). This model can be enhanced by using other plant datasets with more in number to train the model well and achieve a good amount of performance on the remaining classes as well. The less accuracy is mainly due to low number of images used.

"Ref. [6]" This paper has used GoogleNet and Cifar10 models to detect the maize leaf diseases. Both models were trained by using original and improved models by changing the hyperparameters in them resulting from better results than the original models. This idea can be implemented in other domains and technologies to know and experiment on the techniques used which also enhances the scope of domain knowledge and gives the experimental results.

"Ref. [7]" has described the various factors affecting the design and performance of the DCNN models in plant pathology, these are the main factors that reduce the performance without the knowledge of the experimenter by displaying the drastic variation in results and accuracy of the models. These factors can be considered while developing a model, developing the image dataset required for that particular domain, the images also get effected which are also included in this paper they give goo insights on the images which are much important while maintaining a model and working on it. These factors can make or break a model's performance. Few other factors need to ignore while improving on other factors so has to balance the model to have good accuracy and performance with less amount of loss.

This survey paper has discussed various methods useful in detecting the diseases in various leaves which have their technique to implement. Each technique has its uniqueness also each of them have their advantages and disadvantages. This paper mainly focusses on the various convolutional neural network where various researchers have used the AlexNet, GoogleNet, SqueezeNet as their models which are good enough to detect the leaf disease but there is a need for improvement in each of the case like as mentioned as to increase the number of image dataset using ensemble methods along with the CNN's which can boost the performance of the model also by implementing various image processing techniques which give better results than current ones. This also includes best image processing supporting languages such as python, MatLab, Caffe, C++, C# gives better results when used where nowadays C++ is used as they are faster in processing. These Languages are mostly used in advanced computing in various AI, ML, and DL, NLP applications. There are various libraries given such as TensorFlow, OpenCV, Keras, IPSDK for smart segmentation smart classification mostly used in computer vision, and many more for analysing and improving the models performance. Thus for detecting the leaf diseases one can use suitable technique by enhancing the performance of the techniques previously used or develop a new enhanced model.

TABLE IV.
COMPARISION CHART FOR VARIOUS CONVOLUTIONAL NEURAL NETWORKS USED FOR IDENTIFICATION OF LEAF DISEASES

Sno.	Author Name	Type Of CNN Used	Name Of The Leaf	No. Of Leaf Diseases Used	Name Of The Leaf Diseases	Accuracy
1.	Uday Pratap Singh, Siddharth Singh Chouhan, Sukirty Jain, And Sanjeev Jain	Multilayer Convolution Neural Network	Mango	1	Anthracnose	97.13%
2.	Halil Durmuú, Ece Olcay Güneú, Mürvet KÕrcÕ	AlexNet and SqueezeNet	Tomato	10	1. Bacterial spot 2. Early blight 3. Healthy leaf 4. Late blight 5. Leaf mold 6. Septoria leaf spot 7. Spider mites 8. Target spot 9. Mosaic virus 10. Yellow leaf curl virus	AlexNet 95.65% SqueezeNet 94.3%
3.	Juncheng Maa, Keming Dua, Feixiang Zhenga, Lingxian Zhangb, Zhihong Gongc, Zhongfu Sun	DCNN	Cucumber	4	1. Anthracnose 2. Downy mildew 3. Powdery mildew 4. Target-Leaf Spots	Anthracnose (82.0%) Downy mildew (96.7%) Powdery mildew (98.2%) TargetLeaf Spots (91.8%)
4.	Xihai Zhang, Yue Qiao, Fanfeng Meng, Chengguo Fan, Mingming Zhang	DCNN	Maize	8	1. Southernleaf blight 2. Brown spot 3. Curvularia leaf spot 4. Rust 5. Dwarf mosaic 6. Greyleafspot 7. Round spot 8. Northern leaf blight	GoogleNet (98.9 %) Cifar10 (98.8 %)
5.	Jayme G.A. Barbedo	GoogleNet used for training Mainly used 3 types of Cnn's	Corn	9	1. Anthracnose 2. Tropicalrust 3. Southern corn rust 4. Scab 5. Southern corn leaf light 6. Pheaosphaeria leaf spot 7. Diplodia leaf streak 8. Physoderma brown spot 9. Northern leaf blight.	For completely subdivided Images accuracy was 87 %

E-ISSN 2581 – 7957
P-ISSN 2277 – 3916

DOI: 10.32377/cvrjst2119

V. Abbreviations and Acronyms

AI	Artificial Intelligence
CAFFE	Convolutional Architecture for Fast Feature Embedding
CNN	Convolutional Neural Network
DL	Deep Learning
DCNN	Deep Convolutional Neural Network
GAP	Global Average Pooling
GDP	Gross Domestic Product
IoT	Internet of Things
IPSDK	Image Processing Software Development Kit(SDK)
ML	Machine Learning
NLP	Natural Language Processing
NIN	Network in Network
ResNet	Residual Network
VGG Net	Visual Geometry Group

References

[1] Uday Pratap Singh, Siddharth Singh Chouhan, Sukirty Jain, And Sanjeev Jain, “Multilayer convolutional neural network for the classification of mango leaves infected by the anthracnose disease”, in press.

[2] Halil Durmuú, Ece Olcay Güneú, Mürvet KÕrcÕ, “Disease detection on the leaves of the tomato plants by using deep learning”, in Proc. 6th Int. Conf. Agro-Geo-informatics, Fairfax, VA, USA, Aug. 2017, pp. 1–5, in press.

[3] Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, KurtKeutzer, “Squeezenet: alexnet-level accuracy with 50x fewer parameters and < 0.5MB model size” review as a conference paper at ICLR 2017, in press.

[4] Arpita Patel, Mrs. Barkha Joshi, “A survey on the plant leaf disease detection techniques”, Vol. 6, Issue 1, January 2017, in press.

[5] Juncheng Maa, Keming Dua, Feixiang Zhenga, Lingxian Zhangb, Zhihong Gongc, Zhongfu Sun, “Recognition method for cucumber diseases using leaf symptom images based on deep convolution neural netwoks”, August 2018, in press

[6] Xihai Zhang, Yue Qiao, Fanfeng Meng, Chengguo Fan, Mingming Zhang, “Identification of maize leaf disease using improved deep convolutional neural networks”, unpublished.

[7] Jayme G.A. Barbedo, “Factors influencing the use of deep learning for plant disease recognition”, 2018, in press.