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NEURAL NETWORK BASED PLANT LEAF DISEASE DETECTION

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Abstract: Farmers have large range of diversity for selecting various suitable crops and finding the suitable pesticides for plant. Disease on plant leads to the significant reduction in both the quality and quantity of agricultural products. Earlier detection of problems by Adapting to the latest technologies which provide automated processing through machine learning provides a better way for sustainable farming. It is very difficult to monitor the plant diseases manually. It requires tremendous amount of work, expertize in the plant diseases, and also require the excessive processing time. Hence, image processing is used for the detection of plant diseases. The proposed solution improves the system performance and detect damages on leafs accurately. In this paper mainly focuses on three steps, feature extraction, classification and identifying the disease. The experimental result compared and shows better than other methods.

***Index Terms* – Convolutional Neural Networks, Convolution, Pooling, GoogLeNet, Confusion matrix.**

I. INTRODUCTION

In India most of the people depend on Agriculture sector, groundnut is one of the major cultivation field. In the fields of agriculture, the controlled management of farms allows both a yield increasing and an impact reduced negative environmental impact. Mainly groundnut plant leaf diseases are turned to dilemma for formers. Image processing techniques are helpful for detecting the diseases and identification of the disease. Diseases are not able to identify by the cultivator, they have to meet the experts to identify the disease [1]. The monitoring of large fields is very difficult task, so automatic detection of leaf disease and classification is prominent task as it may improve the cultivation of the yield. This involves to better control the appearance of diseases. Imaging techniques can help in the realization of this compromise, intervening especially in the early detection of diseases in plants.

The normal growth of a plant is disturbed when it goes through a period of stress. Thus, it usually presents some visible symptoms (color) but also other symptoms invisible to the naked eye (texture, temperatur). There are several types of stress in plants, water stress, nitrogen stress, pests [2]. Stresses affect the production of chlorophyll, causing loss of chlorophyll and a change in color of the leaf which turns yellow, red and then brown. These colors make image processing more efficient for disease detection.

These colors make image processing more efficient for disease detection. Through against, detecting early is a challenge more relevant. The appearance of the latter, resulting in a change in temperature external, external and internal structures of the sheet, texture and reflectance of the leaf ..., measurement that can be performed at by means of suitable optical systems [3].

Groundnuts are naturally affected by a large number of viral diseases or diseases. In addition, it is one of the most severely infected tropical crops caused by viral diseases. Some of their viruses identified: stunting of groundnuts [4], Cercospora spot disease, frostbite groundnut solée, the rosette of groundnuts. There are also various symptoms that could be attributed to virus diseases, such as rough leaves, leaf curl leaves and bushy stunting, but their aetiology is not known at present.

Figure 1 shows the groundnut stunt virus (Groundnut Clump Virus-PCV) is intermediately between the group of hordeiviruses and that of tobamo- virus. This disease reappears in the same place on crops. Infected plants are stunted with, small dark green leaves [5].

Fig.1. Groundnut Stunt Virus

Figure 2 shows the groundnut Cercospora leaf spot symptoms are characterized by spots dark green in color surrounded by a halo of chlorotic. The yield may be reduced and infected can reach 100 percent [6].

Fig.2. Groundnut Cercospora Leaf Spot

Figure 3 shows the Groundnut Rosette Virus (Groundnut Rosette Virus-GRV) is associated with both a virus that induced symptoms (IBCs) and to a virus that causes no symptoms, but which acts as a pen- before the development of the disease [7].

Fig.3. Groundnut Rosette Virus

Figure 4 shows the Groundnut Curl Virus symptoms of crinkle and speckling are observed on the leaves. The curl is very light, as if the midrib was too short. The number of infected plants often exceeds 50%. 100; the yield is slightly reduced [8].

Fig.4. Groundnut Curl Virus

Some more groundnut diseased images are shown in the table 1 below,

Table 1 Groundnut diseased images

Disease Name	**Leaf Image**
Alternia Leaf Spot	
Bud Necrosis	
Early Leaf Spot	

Late Leaf Spot	
Rust	
Healthy Leaf	

Image processing techniques are considered to be the proficient and versatile to analyse the prominent parts of an image agricultural sectors. Early stage detection of plant disease across a large farming area is a viable solution to predict the problems of plants [9]. This helps to forecast the crop production and initiate necessary remedial actions such as pesticide spraying, soil testing, seasonal crop rotation and maintaining proper water drainage.

This paper proposes an image processing based approach for leaf disease detection and classification in groundnut crops.

II. Literature Survey

of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

Al Bashish et al. [10] used image processing based techniques to implement automatic detection and classification of plant Leaf disease. The k-means clustering means clustering methods are used to identify leaf Disease. The recognition and classification was done by Neural Network based methods. The RGB were effectively segmented with the best results.

Arivazhagan et al. [11] proposed a classification algorithm for detecting plant leaf diseases. It is very efficient plant disease predicting technique. The main advantage if it detects plant diseases with high accuracy and robustness. The big disadvantage is if the input image not provided clearly, it becomes wrong classification.

Akhtar et al. [12] has presented the classification and detection of rose leaf diseases by using Support Vector Machine approach viz., black spot and anthracnose. They used Ostu's segmentation algorithm for segmentation and describe the threshold values In this method, DWT, DCT are used to get the eleven haralick features and texture are extracted and additionally SVM approach used to classify the disease.

Sannakki et al. [13] proposed feed forward back propagation Neural Network based technique for the detection and classification of diseases in grape leaf. K-means clustering technique is used to segment the leaf disease spot and where, anisotropic diffusion is used to eliminate the noise of the image. The final output results were observed by using neural network classification. Considering the confusion matrix with the true positive and false positive parameters are the validations of result.

Dandawate et al. [14] presented the detection and classification of soyabean plants as diseased or healthy species by using Support Vector Machine. The SHIFT is the well-known popular technique that automatically recognizes plant species by their leaf shape. The model accuracy of this method is good to identify the disease.

Ramakrishnan et al. [15] proposed back propagation algorithm for the identification of groundnut leaf diseases. They first transformed RGB color space to HSV, the calculated co-occurrence values of the matrix. By that feature extraction has been done and using the back propagation neural network to achieve the efficient output results.

Singh et al. [16] presented an algorithm for image segmentation method to detect and classify the plant leaf diseases. They proposed genetic algorithm for automatic segmentation detection of leaf diseases on banana, beans, rose and lemon. For classification result Artificial Neural Network algorithm can be used to increasing the recognition rate.

Rajmohan et al. [17] proposed a Sensor based Mobile Application structure for agribusiness. This method provides valuable and accurate data about the paddy fields and its conditions to the agriculturists. For this Deep Neural Network and Support Vector Machine methods are proposed for paddy field classification. In previous K-means and fuzzy logic classifiers were used, which leads very less accuracy.

Santhosh Kumar et al. [18] presented a review on disease detection of various plant leaf using image processing techniques. They debate various plant disease detection techniques used in image processing and machine learning. They address the different plant leaf diseases on maize, tomato, cotton, arcanet, coconut, papaya and brinjal and the diseases such as rust, leaf spot, bacterial wilt, late blight, leaf rot, kole Roga, angular leaf spot and yellow leaf disease. The also discussed, how much important to identify the plant leaf disease and classification.

Sibia et al. [19] proposed Maize leaf disease recognition and classification using CNN technique as computational procedure. This model recognize and identify three different diseases are commonly observed such as rust, gray leaf spot and leaf blight. The authors created and used their own dataset by capturing images from maize field.

Hang et al. [20] tested a proposed method 22on large dataset of different plant leaf diseases. Author used an improved structure of CNN for the identification and classification of plant leaf diseases. To identify different diseases of different plant leaves, this method showed better accuracy and robustness.

Studies shows that classifiers and neural networks can successfully detect and classifies the plant diseases with acceptable accuracy. SVM, KNN, feed forward Back propagation, ANN, etc., are the example of such methods. But the limitations in the existing approaches are lack of accuracy in some cases and detect common plant diseases. There is no unique classification model for groundnut leaf disease detection and classification. Table 2 shows comparison between various existing approaches is proposed by the different authors.

Table 2 Comparison between various existing approaches

Author and Year	Type of the plant and Diseases	Classification technique
Singh and Misra (2017)	Banan, beans, Rose, Lemon	Artificial Neural Networks
Bakshipour and Jafari (2018)	Weed detection	ANN and SVM
Sibia and sumbwanyambe (2019)	Maize	CNN
Ramakrishnan and Sahaya Anselin Nisha (2015)	Groundnut	Back-propagation
Akhtar et al. (2013)	Rose	Support Vector Machine
Rajmohan et al. (2018)	Paddy	Deep Convolutional Neural Networks
Sannakki et al. (2013)	Grape leaf	Feed Forward Back-propagation Neural Networks
Dandawate and Kokare (2015)	Soya bean plants	SHIFT

III. Research Methodology

3.1 Convolutional Neural Networks

Convolutional neural networks are an extension of the classic recurrent neural networks. Such networks are post the sequence of layers consisting of neurons; the first layer is fed input, the last layer is the output, and all in between exact are fully connected each neuron of the inner layer connected by a weighted edge to each neuron of the previous layer. In fact, on the inner layer, the output vector of the previous layer is multiplied is pressed onto some matrix of weights of a fully connected layer, after which some activation function is applied to the obtained values, allowing to introduce nonlinearity of operations.

Convolutional neural networks differ from classical ones in that they may contain not only fully connected layers. The main Layer views also add convolutional and pooling layers.

3.1.1 Convolutional layer

The convolutional layer is analogous to the application of several their filters to the current image, where under the image there is the output of the previous layer is zoomed. For this layer, it is determined its kernel (kernel) of size M×N×C×F. F is the number of channels running image, that is, the number of filters. M×N×C – size of each filter, where M and N are respectively the width and height of the window filter, and C is the number of channels of the input image. In such a way all at once, the result of the convolution itself is formed as follows:

$$conv[a,b,f] = \sum_{i=0}^{M}\sum_{j=0}^{N}\sum_{c=0}^{C} input\left[a-i-{}^{M}/_{2}, b-j-{}^{N}/_{2}, c\right].filter[a,b,c,f] \quad (1)$$

As a result, each channel of the output layer is its own map, showing the presence of a certain feature in the areas values of the previous layer.

After the convolution, the addition of some offset is a constant that is the same for all values of the obtained matrices. However, with the normalization described below, the offset is sometimes goes down.

The last step in the convolution is to apply the asset function to all values of the resulting matrix. When working with an image as an activation function instead of tanh almost always the function ReLu (x) = max (0; x) is applied. The main reason for choosing of this function is that when training deep networks there is no problem of an extremely small gradient at large x, in the difference from the tanh (x) function, the gradient of which tends to 0 as the identification x. Also by cutting off negative ReLu values increases the sparseness of values in the inner layers of the network, which well provides non-linearity and is also useful with computational points of view.

As a result, convolution is equivalent to applying the formula:

$$output = activation(input * filter + bias) \quad (2)$$

Where, input is the input layer, filter is the convolution kernel, bias is the offset and output is the result.

3.2.1 Pooling

The pooling layer is used to reduce the size of the matrix. The layer helps to maintain the invariance of the network to scale, and also allows you to search for more global features in the image. The main pooling method used is max-pooling. The input layer is divided into cells of a given size and from each cells, the maximum value is taken (sometimes the average value is taken cage). Thus, for a window size M×N, the image decreases by M×N times.

3.1.3. Normalization

This work uses two methods of normalization: local response normalization and batch normalization. Both normalizations are used to prevent a slowdown in the learning rate of network parameters.

Local response normalization is an independent layer of the network. This operation normalizes each value of the input matrix by channel, that is, the following formula applies:

$$output[a,b,c] = \frac{input[a,b,c]}{k+\alpha\left(\sum_{i=-n/2}^{n/2} input[a,b,c+i]^2\right)^{\beta}} \quad (3)$$

Where, n is the width of the normalization window, k, and are other customizable options.

Batch-normalization, first introduced in [4], applies the standard normalization to the obtained values, and then linearly transforms:

$$y = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}}.\gamma + \beta \quad (4)$$

Here, γ and β are configurable parameters; μ and σ are average the value and variance depend on what stage is now networked. If the network is being trained, then these values are taken from the messages received only at the moment. During testing network values are taken from all collected statistics.

Batch normalization is applied immediately after the operation is applied convolution and before applying the nonlinearity operation (activation function).

3.1.4 Fully Connected Layer:

After several layers of convergence and concentration, CNN usually ends with several fully connected layers. The multidimensional arrays (tensor) that have at the output of these layers are converted to vector and then add several layers of perceptron.

3.2 GoogLeNet Architecture

GoogLeNet is a Convolutional Neutron Network that not only shows high accuracy, but also has a relatively small the number of calculations. This neural network is selected for the task determining abnormalities, as it is not only the winner of the ImageNet Recognition Challenge, but also this network has shown itself well in the task of recognizing of images showing it efficiency when working with classification.

The GoogLeNet neural network is a 22-layer convolutional network with an error rate of 6, 7%. Due to the large number of filters and layers, the implementation of this model requires large computing resources, and also increases the likelihood of retraining.

There are elements in the network, computational operations on which can be performed in parallel. The network module that contains parallel chunks is called Inception. In this architecture uses Inception blocks.

The network starting from the 60 epoch, the loss function practically reduced to zero, and the other criteria for the quality of network training are practically equal to one. This means that the recognizability of the class is practically equal to 100%. Figure 5 shows the interception block below,

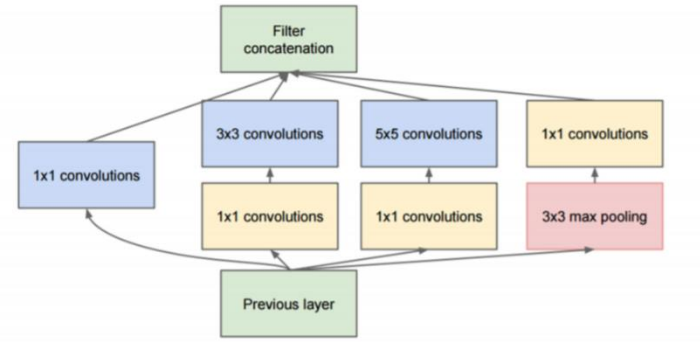

Fig.5 Inception block

It is important to note that such a network increases not only in depth, but also in width, by using convolutions of different scales in parallel. In each block have convolution layers with kernels of different sizes, so that recognize signs of various scales. Also in this model 1×1 convolutions are actively used to reduce the dimension of tensors, which will be fed to the input of the next layer. In order not to lose information obtained in the previous layer also applies sub-sampling layer. Convolutional is also applied after it for layer with a 1×1 convolution kernel, in this case in order to align the dimension of the tensors at the output after each parallel layer. Then there is a concatenation of feature maps obtained on each parallel layer. In a complete network, nine are used in succession.

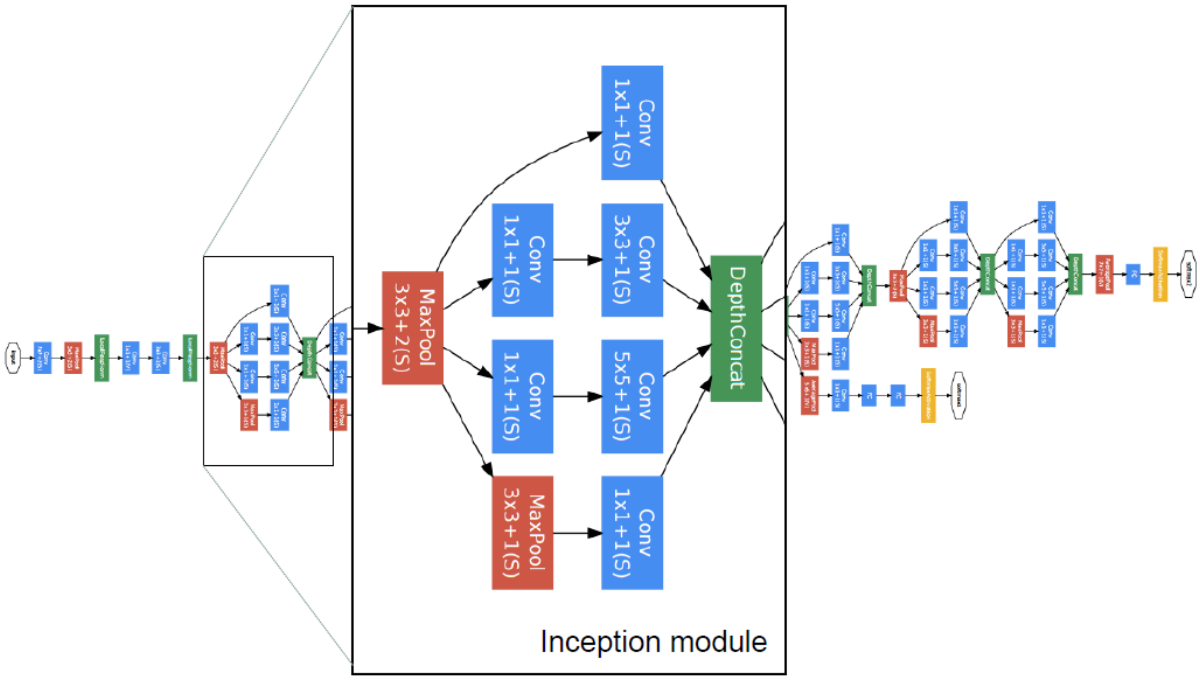

Fig.6. Inception block in the GoogLeNet neural network

Prior to bringing the investigation of the GoogLeNet architecture to a nearby, there's one more segment that was executed by the makers of the network to regularize and forestall overfitting. This additional part is known as an Auxilary Classifier.

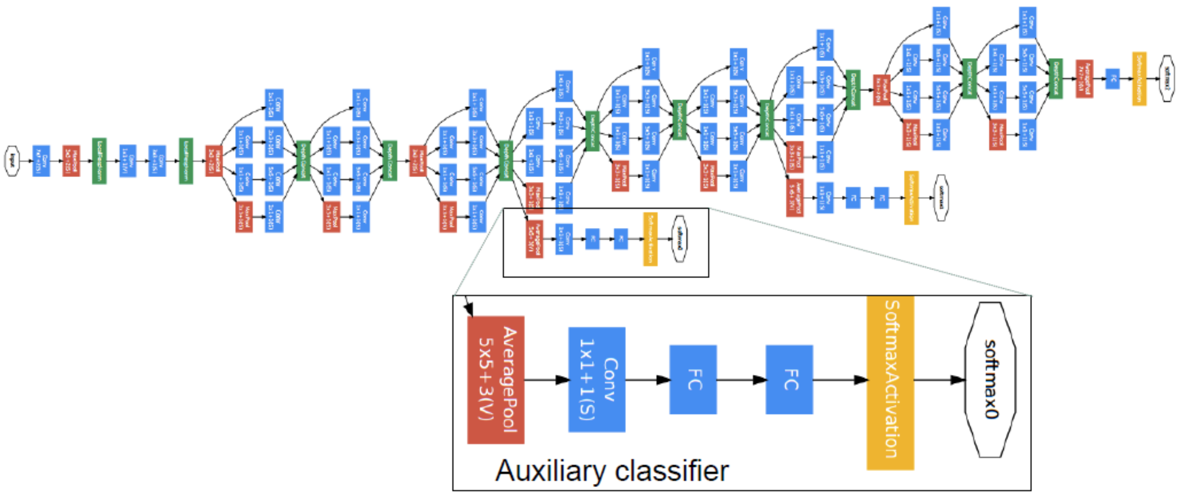

Fig.7. Auxiliary classifier block in the GoogLeNet neural network

Regularize preparing with clump standardization, diminishing significance of Auxiliary classifiers. More variations of origin modules with forceful factorization of channels are significant. Increment the quantity of highlight maps while diminishing spatial goal (pooling).

IV. RESULTS AND DISCUSSION

4.1 Convolutional Neural Networks

In CNN, a distinction can be made between three methods for optimizing the training process and adapting the model during the training process become:

- Stochastic Gradient Descent
- Batch Gradient Descent
- Mini-Batch Gradient Descent

The course of the training process is particularly important for optimizing the training parameters. Since after each epoch of training a sample of the classification based on the validation dataset is carried out for validation, these results can be obtained be evaluated as an intermediate result of the training. The CNN Framework was designed in such a way that, in addition to the log outputs in the console display, there is also a graphic display of the Training history created. For this purpose, the intermediate results of the classification accuracy and the training loss are used as a function of the training epochs recorded. The diagram created is shown in Figure 8.

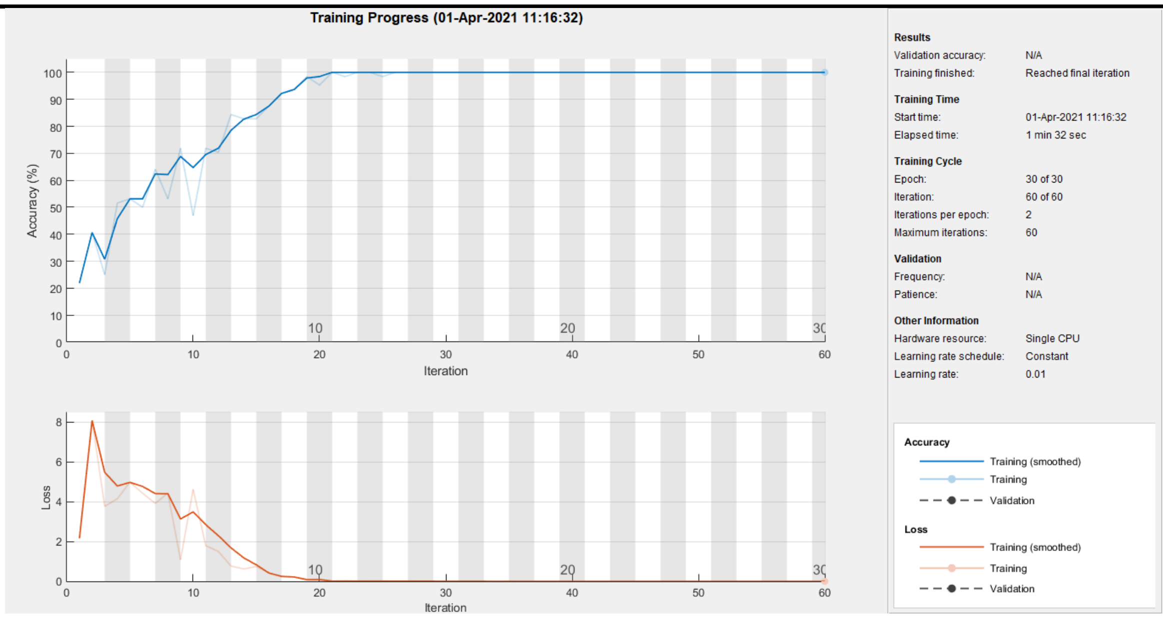

Fig.8. Training process of CNN

The figure 9 shows the validation training accuracy of CNN. The total validation accuracy of the GoogleNet is 91.3%.

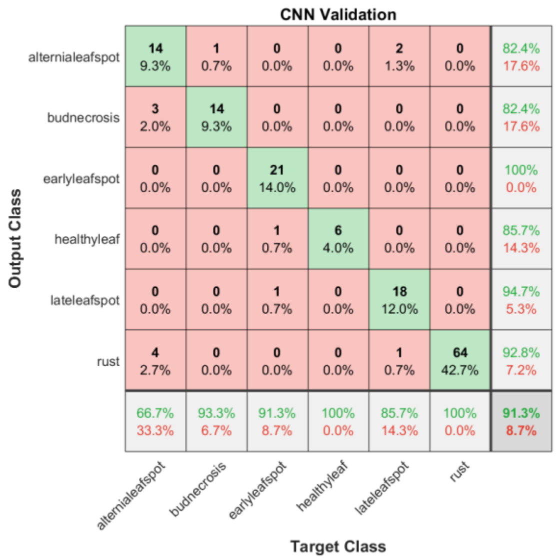

Fig.9. Validation Accuracy of CNN

The table 3 shows the calculated parameter results for CNN. The parameters included in the table are True Positive, False Positive, False Negative, True Negative, Precision, Sensitivity, Specificity and model Accuracy.

Table 3 Model parameters of CNN

Parameters	**Alternatia Leaf Spot**	**Bud Necrosis**	**Early Leaf Spot**	**Healthy Leaf**	**Late Leaf Spot**	**Rust**
True Positive	14	14	21	6	18	64
False Positive	3	3	0	1	1	5
False Negative	7	1	2	0	3	0
True Negative	130	136	128	145	129	86
Precision	0.82	0.82	1	0.86	0.95	0.93
Sensitivity	0.67	0.93	0.91	1	0.86	1
Specificity	0.98	0.98	1	0.99	0.99	0.94
Model Accuracy is						91.3%

4.2 GoogLeNet:

4.2.1 Preparing data for training:

For research work, two different set of images: artificially generated and from the real world. It was assumed that the first experiments would be run on a synthetic set, and if successful, it will work on more complex data.

All datasets were divided into training and test samples. Although due to the rather large amount of data, as well as due to training method (the network does not maximize functionality on all data immediately, but on small subsamples) the results of the work described yes- More algorithms are the same for test and training data.

4.2.2 GoogLeNet training process:

When training a network, several images are fed to the input at once. The average value of the calculated values is taken as the objective function values for each image from the subset.

Initially, training took place on the training dataset. On such data, the network is almost instantly trained to an accuracy> 90%. This is logical - since the arrows were on black background, then all nonzero values of the image are "important" for the neural networks and the gradient of the objective function immediately changes the parameters of the network in desired direction.

The figure 10 shows the training process of the GoogLeNet. The training process has Accuracy and loss graphs.

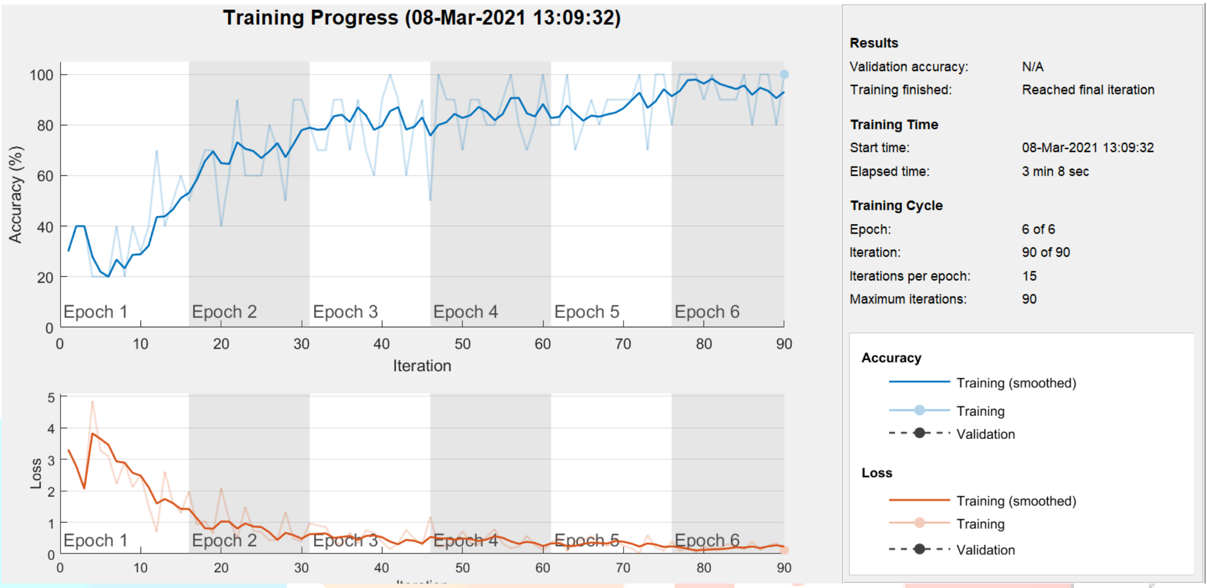

Fig.10. Training process of the GoogLeNet

The figure 11 shows the validation accuracy of the GoogLeNet. There are 6 different groundnut disease images are applied for the training, those are Alternatia Leaf Spot, Bud Necrosis, Early Leaf Spot, Late Leaf Spot, Rust, and Healthy Leaf. The total validation accuracy of the GoogLeNet is 99.3%.

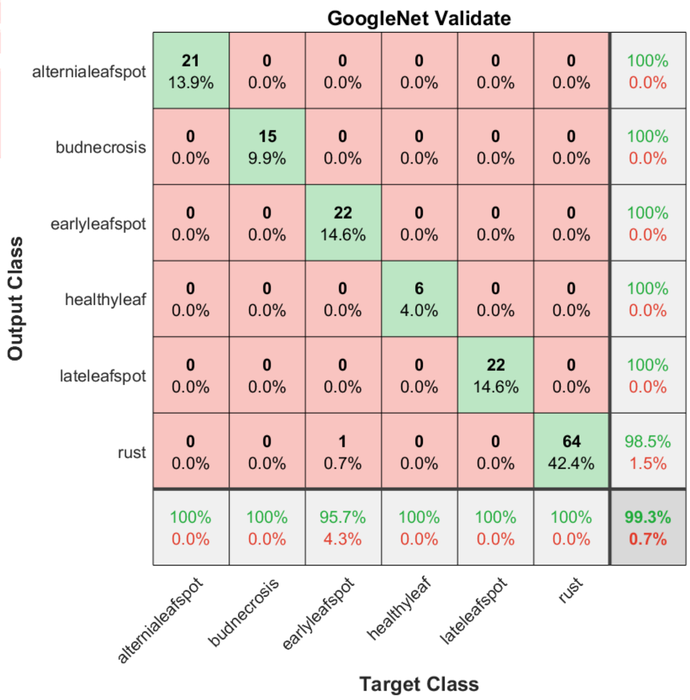

Fig.11. Validation accuracy of GoogleNet

The table 4 shows the calculated parameter results for GoogLeNet. The parameters included in the table are True Positive, False Positive, False Negative, True Negative, Precision, Sensitivity, Specificity and model Accuracy.

Table 4 Model parameters for GoogLeNet

Parameters	Alternatia Leaf Spot	Bud Necrosis	Early Leaf Spot	Healthy Leaf	Late Leaf Spot	Rust
True Positive	21	15	22	6	22	64
False Positive	0	0	0	0	0	1
False Negative	0	0	1	0	0	0
True Negative	130	136	128	145	129	86
Precision	1	1	1	1	1	0.98
Sensitivity	1	1	0.96	1	1	1
Specificity	1	1	1	1	1	0.99
Model Accuracy is						99.3%

4.3 Testing:

The table 5 represents the predicted results for different diseases using GoogLeNet. The 6 classes are predicted successfully.

Table 5 Predicted Results for different diseases

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<tr><th>Input Image</th><th>Predicted Image</th><th>Predicted Result</th></tr>
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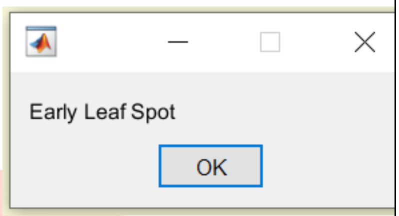
</td><td>
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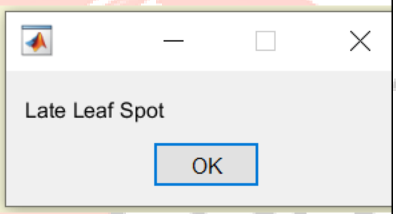
</td><td>
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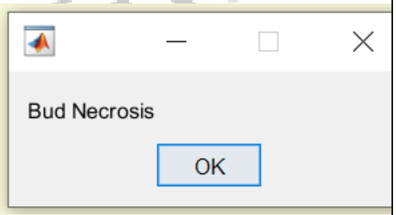
</td><td>
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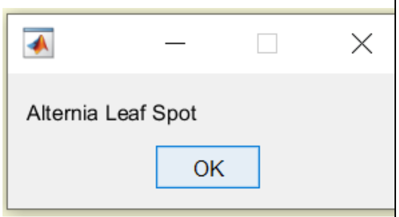
</td><td>
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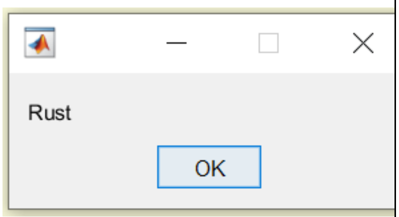
</td><td>
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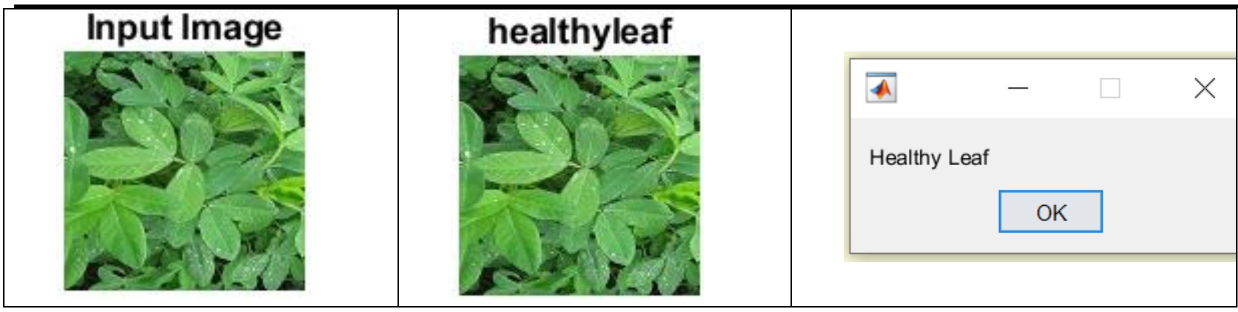

IV. Conclusion and Future Scope

The proposed GoogLeNet method and basic convolution neural network based methods are designed and verified with an accuracy of 99% and 91% respectively thereby showing that the GoogLeNet based model provides us with better results and accuracy and finally the groundnut leaf disease is obtained. The experimental results indicate that the proposed approach is a valuable approach, which can significantly support an accurate detection of leaf diseases in a little computational effort.

An extension of this work will focus identify the other plant disease using various attributes and it will perform better results using GoogLeNet model.

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