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# Detection and classification of Groundnut Leaf Disease using Convolutional Neural Network

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## Abstract

Groundnut is a major oilseed crop and food crop. In groundnut plant major diseases are occurs on the leaf part. The diseases of the leaf will greatly impact the quality and the production of the groundnut is also reduced. In order to reduce the diseases occurring and the problem happens due to the diseases, this paper uses Artificial Intelligence to identify the disease of groundnut leaves. This proposed model identifies the leaf diseases such as leaf spot, rust, groundnut bud necrosis, root rot and web blotch. In this model image processing and CNN are used along with the Artificial Intelligence. This proposed model was trained with large number of leaf diseased data sets collected from farms. The collected datasets are tested using CNN and the results of the dataset were evaluated. In this experiment than the traditional method Artificial Intelligence had a higher efficiency and accuracy. The accuracy of this model was as high as 96.50%. This research study can come up with an instance for the leaf disease identification of groundnut. The provided solution is a anecdote, scalable and accessible tool for the identification of disease and the management of diverse agricultural plants.

## Keywords

Groundnut leaf disease, Artificial intelligence, Convolutional neural network ,image processing.

## 1. Introduction

In India, the foundation for all the human needs is agriculture and the Indian economy is also raised from this agriculture by means of foreign trade. India is suitable for many cultivatable crops, and groundnut is one among them. Groundnut is a leguminous crop which belong to the Leguminosae family. Groundnut or peanut is commonly known as the poor man's nut. Today, it is an important oil seed crop. It is the sixth important oil seed in the world. The rank of India in the production of groundnut is second. In India, the availability of groundnut is throughout the year because it has two crop cycles harvested in March & October. Yet agriculture is the backbone of India, there is no development and advanced technologies in the area of leaf disease detection so far. Due to the non-development of advanced technologies the problems in the production and the quality of the food crops are high caused by different diseases. Nowadays because of the emerging techniques many researchers are emerging towards the field of leaf disease detection and providing a sophisticated result. Diseases of groundnut leaves will reduce the quality and yield of groundnuts by destroying the chlorophyll and the green tissues in the leaves.

Identification of groundnut-leaf diseases needs a competent knowledge, and it is too easy to camouflaged them only by the observation of artificial visual. Anyway using this method, groundnut diseases in leaves cannot be properly analysed and manage in time. The best solution to control groundnut disease is quickly and accurately diagnosing the type of the disease and taking corresponding measures within time. In traditional method, experts will determine and identify the plant leaf diseases on baredeyes. But the baredeyed disease detection will give a low

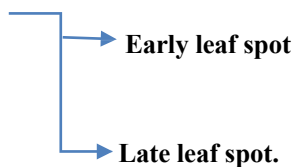
accuracy on the identification of the disease. So this technique to identify the disease is a loss. Mostly 85% of the diseases occurs on the plants leaf rather than the other parts. It is noticed that in India efficacy of a fiscal destruction. It occurs due to plant syndromes and it is about 15%,if it not controlled it may lead to the loss of 40% to 60%.In current years,artificial intelligencemethodsisanoptimisticmethodandmademanyinnovationinthefieldsofobject detection, speech recognition etc., By using the advantages of the CNN we can greatly reduce the parameters and the storage requirements and thereby increasing the network efficiency. Artificial Intelligence had made more advancement in the plant leaf disease detection.

This research study is mainly fascinated on the identification of single and mixed diseases on each leaf of the groundnut. The types of leaf identification include healthy leaves and other diseases like rust, root rot, leaf-spot, budnecrosis,webblotchandcombinationofthesediseasesatthesametime.Intraditionandexistingmethod,thereisno better combination of artificial intelligence and deep learning so in this study deep learning is used as a base model and prediction is based on the artificial intelligence.

## 2. ProblemStatement

Cercospora leaf spot is a major disease caused by fungi on leaves of groundnut crop. Although it is a major problem traditional farmers in Sierra Leone consider these spots on the groundnut leaves as sign of maturityofthecrop.Themostissuesofthefarmersisthatthereisadifficultyinthedifferentiationofearly leaf spot and late leaf spot. The major leaf disease occur in groundnut are listed below:

### 1. LEAFSPOT



### 2. RUST

### 3. ROOTROT

### 4. GROUNDNUTBUDNECROSIS

### 5. WEBBLOTCH

## 2.1 Leaf Spot

### i) Early Leaf Spot

Caused by-*Cercospora arachidicola* –

(fungi)Symptoms:

Earlyleafspotsymptomsontheupperleafsurfacearedarkcircularbrownspotswhicharesurroundedby a yellow halo as shown in fig 1.1. Lower leaf early leaf spots are smooth and brown in color as shown in fig 1.3.InOklahomamostcommonlyoccurringfoliardiseaseisEarlyleafspot.

The fungal pathogens attack any portion of the plant above the ground.

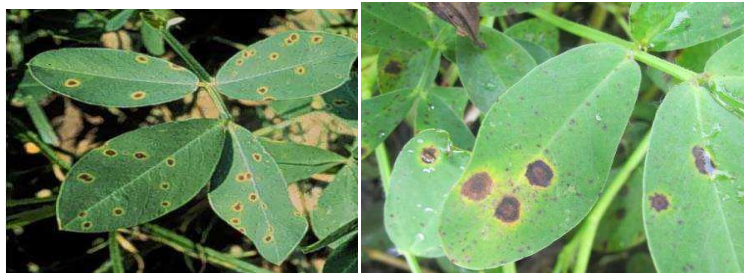


Fig1.1

Fig1.2

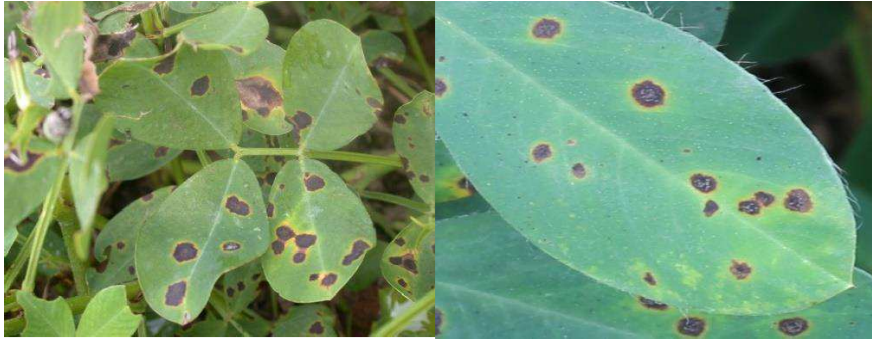


Fig1.3

Fig1.4



Fig1.5

**Fig1-TheImagesofEarlyLeafSpotDisease****ii) LateLeafSpot**

**Causedby:** *Cercosporidiumpersonatum-(fungi)*

**Symptoms:**

Late leaf spot symptoms on the upper leaf surface are dark circular brown to black spots which is surrounded by affiant yellow halo or without a halo as shown in fig 2.1 and 2.2. The symptoms for late leaf spots on the lower leaf surface are black in color and be rough.



Fig2.1



Fig2.2



Fig 2.3

Fig2TheImagesOfLateLeafSpotDisease

**2.2.RUST**

**Causedby:** *Pucciniaarachidis-(fungi)*

**Symptoms:**

All the aerial part of the plant is affected. The symptoms can be identified in all the aerial parts of the plant. The symptoms will appear on the lower leaves which looks like small brown dusty pustules (uredosori) as shown in fig3.1. On the leaf's upper surface small brown spots will appear. The rust spots can be seen on the stem and petioles. The symptoms like brown teliosori as dark spots will appear on the late season. Small shriveled seeds will be produced by the plant on the severe infection.



Fig3.1



Fig3.2



Fig3.3



Fig3.4

**FIG3-TheImagesOfRustLeafDisease**



### 2. 3.RootRot

Caused by: *Macrophomina phaseolina-*

(fungi)Symptoms:

Over head the soiled dish brown lesions are identified as the symptoms as shown in fig4.1.Drooping is seen in the leaves which cause the death of the plant as in thefig4.2.



Fig4.1



Fig 4.2



Fig4.3

**Fig4-ImagesofRootRotDisease**

### 2.4GroundnutBudNecrosis:

Caused by: *Groundnut budnecrosisvirus(GBNV-Tospovirus)*

Symptoms:

The first seen symptom is rings potin2-6 weeks as showninfig5.1and5.3.The newly appearing leaves is identified with small ring spots with leaf inched inwards assign fig5.4.

The other symptoms noticed are necrotic spots and the lesions are develop din irregular shapes on the leaves of the plant. Stem and petioles exhibits necrotic spots.

Damage: This disease leads the plant to grows taunted with short in ternodesand auxiliary shoots.



Fig5.1



Fig 5.2



Fig5.3



Fig5.4

**Fig5-**The Images of Groundnut Bud Necrosis Leaf Disease

### 2.5.WEBBlotch

**Caused by:** *Phoma arachidicola* –

**(fungi)Symptoms:**

The web blotch is identified as large and it is irregularly shaped with dark brown blotches with irregularly light brown margins as shown in fig 6.1 and 6.2. It appears 1st on the upper leaf surface. Affected leaves will dry and become brittle and fall from the plant.

The disease is most severe on Spanish and Virginia



Fig 6.1



Fig6.2



Fig6.3

**Fig6-**The Images of Web Blotch Leaf Disease

Identification of above these diseases through bare eyes is not possible and it is not that much accurate compared to modern techniques for identification. Even the expert cannot accurately say the results of the disease identification. If there is not proper detection of these diseases, then the percentage of wastage of groundnut crops will increase. If the disease is identified incorrectly and according to the misidentification if the farmer uses pesticides, then that will affect the groundnut crop badly. If the groundnut crops are affected, then that leads to decreased production of groundnut and that further affects the economy of the farmer as well as nation. So in order for the accurate identification of the leaf diseases this model is proposed.

AI has been nowadays a successful application and it is in corporate image processing which is a path for finding many solutions. Now AI has set foot in to the field of agriculture. Currently, several computers based vision applications in Artificial Intelligence such as DBM (deep Boltzmann Machine), CNN (convolutional neural network), DBN, RNN has higher performing accuracy. For this proposed method the most prominent application is CNN. These days, to detect and execute the analysis of different objects and its automatic drawings CNN is used. In CNN K-fold cross-validation technique is recently suggested for the splitting of the datasets and generalization in boosting for the CNN model. Generally, this research is highly-developed as an abrade rather than modifying the existing model.

### 3. Literature Review

A crop prediction model [1] was developed using ANN by using smart phones by the researchers Ravichandran and Koteswari (2016). This model has three layers and efficiency is based on hidden layers. First, this model is trained by algorithms like as Rprop, Almeida's and Silva algorithms, Delta-bar-delta. By training this model by these algorithms a most favourable configurations are found. This model is based on the efficiency so a rather way is required to examine the no of hidden layers. To examine the correct hidden layer's trial and error method was executed. Finally, it was predicted that more the no of hidden layers in ANN the more the accuracy of the model.

The study [2] says that datasets are used in CNN model for the classification and identification of rice plant diseases. Here for training the model 500 different infected images were collected and given for the processing from the rice field.

In [3], the researches uses deep learning to the problem. They tried this method in mango plant. The researchers selected five different diseases of mango leaf and collected the samples from different varieties of mango plant. From these collections they have addressed about 1200 datasets. Here CNN structure was used to evaluate the disease affected leaves. CNN model is trained with 80% of images and left 20% is used for testing the datasets from the 600 images of 1200 datasets. The left other 600 images, which were used to find the mango leaf disease and the accuracy of the model which shown the practicability of it in real world application. If more images are provided, then by fine tuning the CNN parameters the accuracy of the classification can be increased.



A prediction model is developed by Robinson and Mort (1997) [10] where the primary data like precipitation, humidity, cloud cover, temperature is fed using neural networks. These data are then converted into binary data and divided into two groups such as input string and output string for the neural network. This model was trained with 10 trial sets. Finally, most efficient values were predicted from the above mentioned parameters.

According to [4] different graph formats are formed for the CNN for the process of data of uniform encephalography which is used to predict the four classes of motor imaginaries. This data is used to disclose with the electro encephalography electrode. The data is conveyed by them with 2D to 3D transformation. Through these dimensions the structure was processed.

In order to make use of the deep learning a short term voltage stability is proposed [14]. They maintained a clustering algorithm to increase their liability.

In study [5] a aim taken using image processing for the detection of cotton leaves. Here, for the segmentation of the datasets K-means algorithms were used.

In [6] Research is based on the identification of leaf disease in banana plant. In this study for training the images used is 3700. In each class the data set is not balanced. Different experiments were carried out, for example the model is trained by using the datasets obtained from the coloured and grayscale images. Best accuracy is obtained at 98.6% by them in coloured images they acquired the accuracy of 98.6% in colour images.

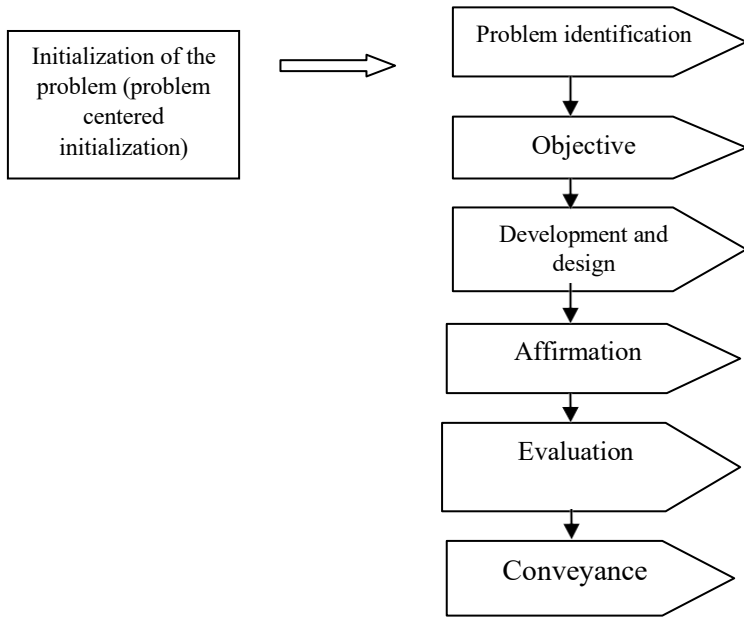
The researcher Li et al. (2010) proposed a neural network with the mixture of back-propagation for the identification of cotton leaf disease. Initially the areas like stem and leaves disease are identified using the images with phone window application.

The researcher Wan et al. (2019) proposed a methodology by the recommendation of famous convolutional neural network (CNN) which is a highly robust technique to extract the features manually. Here the CNN is converted into low space dimensional and the network structured information is protected. This proposed methodology is very effective and suitable for the detection of leaves disease.

#### **4. Methodology of The Research:**

This study is used to create different innovations and ideas to design a product using qualitative or quantitative data. In this model DSRM model is used which is an ideal datasets representation. The below figure represents the processing model for this research. Here “problem-centered initiation” is used for this model. For solving the problem only, the problem-centered initiation can be used. Here the problem is observed by the research experts so it is applicable for this model and it deals with the domain of groundnut leaf disease identification. The below shown figure depicts the DSRM method proposed by the researchers which is accommodated to this research.

#### **Processes Model of DSRM**



## 5. Proposed Methodology

### 5.1. Dataset Collection and Sampling Technique

The data used for this model are both primary and secondary data. Here primary is nothing but the images which are taken freshly with infection. Secondary data is nothing but analyzing the data collected by another researcher for the first time for another purpose (i.e. referring from other authors, institutions or other persons). In this model the researcher has used judgmental model for that they have selecting 5 different infected sample and one healthy sample from a non probabilistic population. For this model, about 3600 images were collected and distributed into leaf spot, rust, root rot, groundnut necrosis, web blotch and healthy. These 6 classes were used provided with the balanced data set to train the model.

### 5.2 Groundnut images sample digitization

In this model data acquisition system is used to create a clear impartial and clarified digital images for the database of groundnut plant leaf. The aim of this is to provide the computerized system with balanced or uniform illumination and lightning. The captured images from smart phones and digital camera are then transferred to the computer and stored in hard disk in PNG format.

### 5.3 Image Pre-Processing

The first and the foremost basic task is to insert the pre-processed images into a network. The commonly used image processing techniques in all image processing applications are image augmentation, vectorization, image resizing, normalization. In this proposed method all these processes were carried out before going into deep learning using Raspberry pi.

### 5.4 Feature Extraction

Different shortcomings of Artificial Intelligence is solved by Deep learning, extracting the features manually by using CNN model. In CNN model there are different layers. Those layers will grasp the knowledge. By using the mechanism of filtering the values are extracted by matching the Data.

### 5.5 Dataset Partitioning and Model Selection Methodology

K-fold cross validation dataset partitioning is used in this model. Here the data are partitioned into  $k$  values.  $K+1$  value should be obtained for future divisions. The  $k$  value is assigned as 10 as it is there commended value for Artificial Intelligence. Now the values of  $K$  are 10, therefore it is 10-fold cross validation where the datasets are divided by 10.  $D=3600/10=360$ . So for each fold 360 data were used. 80% of images is used for the training from this continuous activity (2880 images) which provides the most significant performance and 20% remaining (720) images are used for the testing; therefore, the validation of the experimental model is done.

### 5.6 Tool Selection

For the collection of the Groundnut leaf diseased images to train this model, two devices are taken in use to capture the images, one is smart phone and another one is digital camera. This proposed evolution model was trained on the Raspberry pi and the training and the testing was carried out on CPU.

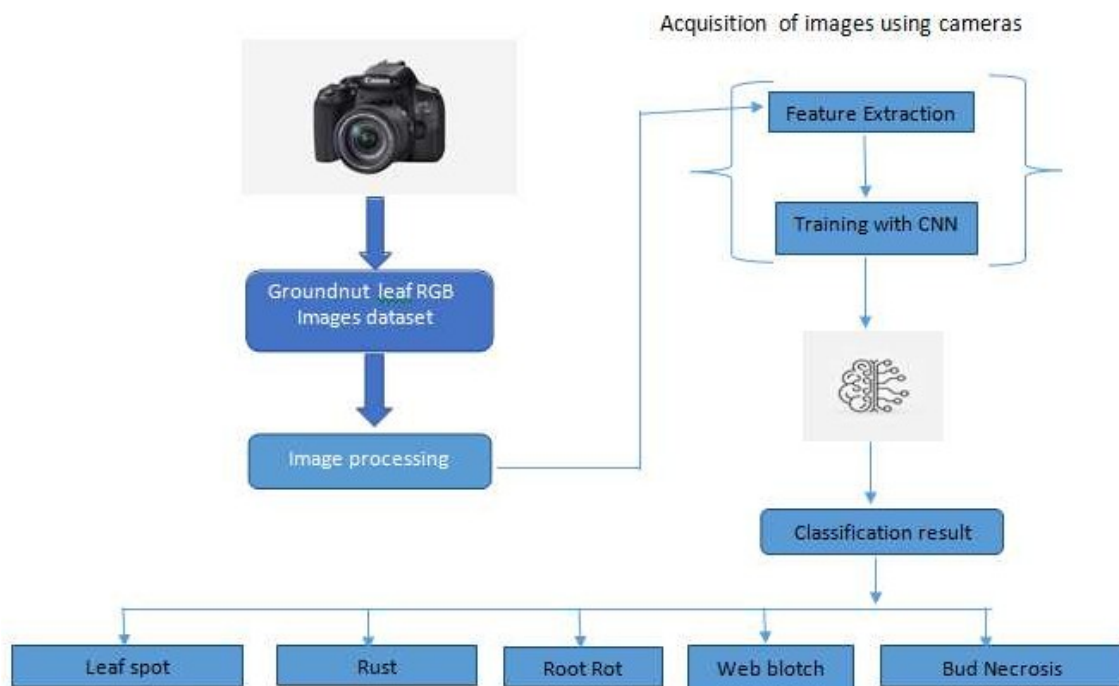
### 5.7. Technique for Evaluation

Routine structure of the models is evaluated by researchers using different techniques at different time periods like in the starting (developmental) stage and at end. The researcher have 1<sup>st</sup> evaluated the procurement of the prototype by using the confusion matrix and four evaluation metrics for the confusion

matrix on the testing dataset. The four evaluation metrics are F1-score, Recall, Precision and Accuracy. For the subjective evaluation a questionnaire is used by the experts to estimate the performance of the prototype. The result of this evaluation finally says the practical applicability of the model.

## 6. Designation of Groundnut Leaf Disease Detection Model

For the designation of the model the 1<sup>st</sup> step made is the image acquisition of the images collected through the digital camera and smart phone from the fields. After this step for the further analysis, techniques of image pre-processing were applied to get the acquired images. Next to this step, all the pre-processed images along with the neural network were fed in the CNN algorithm. By using image analysis an image is extracted for the representation of best-suited extraction. Depends on the best-suited eradicated features, the testing and the training data used for the identification are extracted. At-last, a new image is classified by the trained knowledge into its class of syndrome. The steps and methods taken for training the model and result of training the model are shown in the below flow diagram. By understanding the flow diagram, the whole process undergone through this model can be clearly known. The trained model here is depicted the result by classifying the different leaf disease.



**Fig.7.**Groundnut leaf diseases detection model.

## 7. The Architecture Proposed for the CNN of the Model

The architecture for this proposed CNN model has two sections namely classification and feature learning section. Normally, it starts from images feeding through input layer and stops with output layer. Between the input layer and the output layer there are many hidden layers consisting of different layers. Here, the output layer name will both epoch name of a groundnut images which is also the label of groundnut leaves disease. Generally, for in this proposed CNN architecture, every groundnut leaf images are added with the neurons and after that those images



where augmented with equivalent weights. The processed augmentation output for the fore coming layers are prepared and it is then replicated to the upcoming layers. The layers of output show the predictions task for calculating the neurons for this model.

### **CONVOLUTIONAL LAYER:**

Similarly, the technique of impartial community with inside the convolutional layer is the maximum famous and effective concept (Lin et al. 2013). Hence, the layer of convolution is small; with inside the case of multilayer perceptron incorporates absolutely linked of a couple of layers. Employing the activation characteristic is nonlinear, and the nonlinear neural community with linear clear out out is altered. The convolution system for photo category is depicted , with its deserves and layers mentioned in the subsequent section:

- The function maps reduce the numerical illustration of parameters for the duration of the system of weight sharing.
- The correlation of neighborhood learns connectivity surrounded through the closer pixel.
- The items can show off invariance to the location.

### **POOLING LAYER:**

Consequently, the derived data from the feature maps with its spatial measurement is decreased via way of means of method of pooling. common pooling, max pooling, and L2-norm pooling are the distinct varieties of pooling manner; in particular max pooling is a greater powerful and effective manner as it has an more advantageous convergence speed (Scherer et al. 2010).

### **ReLU LAYER:**

The Rectified Linear Unit Layer (ReLU) with the neurons is uncovered to the functional loss or nonlinearity saturation is given in below Eq

$$F(x) = 0; x < 0$$

$$F(x) = x; x > 0$$

The complete community does now no longer have an impact on the convolution later of the receptive area, and it grants the decision feature with the nonlinear property. There is a low range of nonlinear saturated feature, so we upload the feature of tanh and logistic in given below eqn. In ReLU, the training method turned into repeated several times, however there's no different dissimilarity insignificant for accuracy simplification

$$F(x) = \tanh(x)$$

$$F(x) = \frac{1}{(1 + e^{-x})}$$

### **FULLY CONNECTED LAYER:**

The final layer of the convolution is fully connected layer. In this layer the input is fed and the inputs are the number of vector. This layer is named as fully connected as every input is coupled with every output. Finally from the last layer N- dimensional input and output are collected and the length of predefined vector with a feed-forward network.

### **LOSS LAYER:**

The version output and goal characteristic overall performance are calculated in taking the area of layer loss. The inputs of forwarding and backward goal traits are used. Based at the enter and goal values, the loss cost is calculated (forward). In backward, the gradient loss characteristic related to the elements is calculated. Thus, the weight in DCNN with its gradient loss characteristic is envisioned by the usage of the back propagation algorithm. Therefore, the stochastic gradient descent is utilized in weight updation of back propagation and it's far mentioned as follows

#### **Start:**

Parameter of initial value and learning rate  $\beta$  should be selected

#### **Repeat:**

Repeat the procedure till the minimum approximation is received.

Generate randomly shuffle examples in a training set

**For**  $j=1,2,3,\dots,n$  do:

$$F = f - \beta \nabla Q_j(f)$$

**End For**

**End Repeat**

**End**

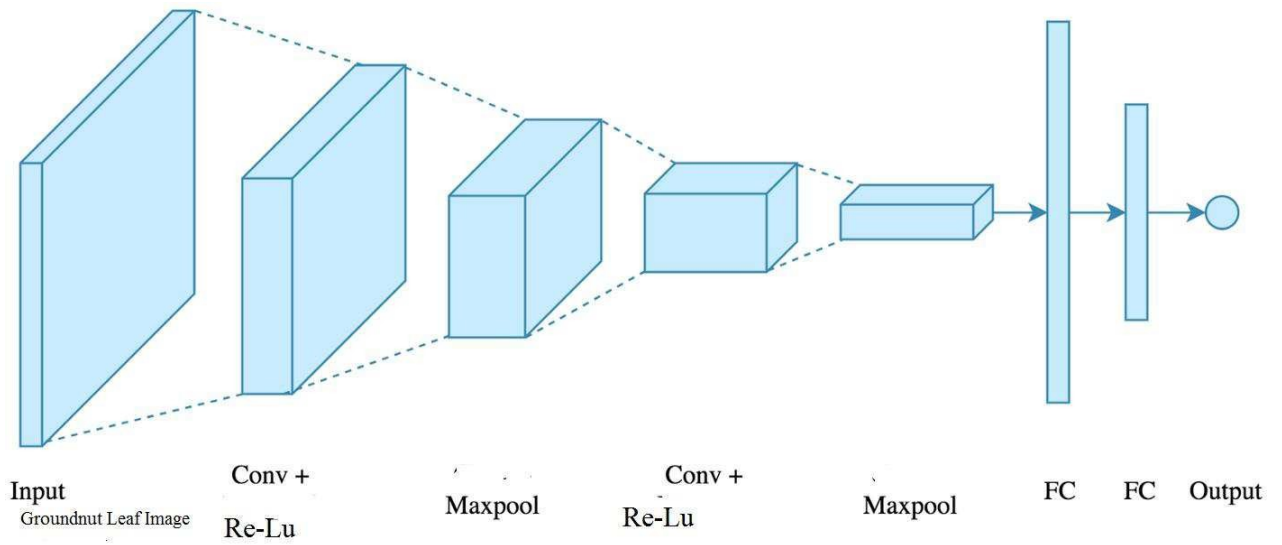
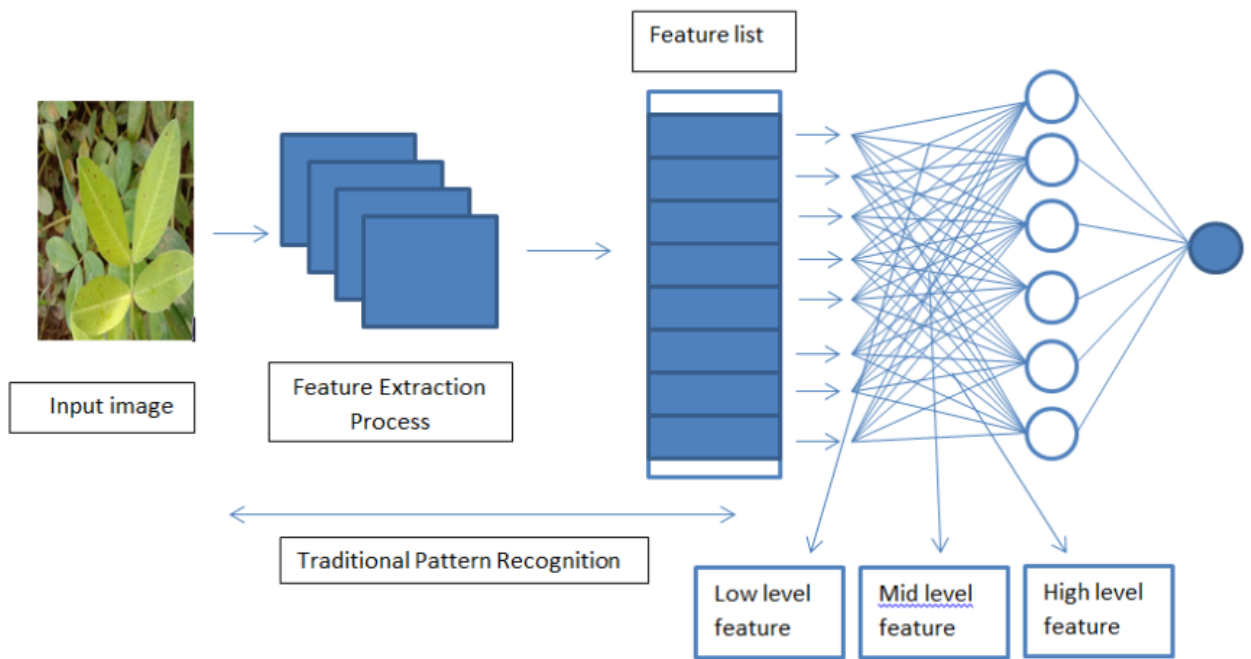


Fig.8.Thearchitectureof Basic Proposed Network



Architecture of proposed method.

Table1.1LayerDescription

Layer	Description
Layer-1	128*128*3
Layer-2	128*128*3
Layer-2	120*120*3
Layer-2	88*88*5
Layer-3	35*35*25
Layer-3	30*30*25

OutputLayer-Classification	<ul style="list-style-type: none"> <li>• Rust</li> <li>• Webblotch</li> <li>• Leafspot</li> <li>• Root rot</li> <li>• healthy</li> <li>• Budnecrosis</li> </ul>
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### 8. Experimental Results

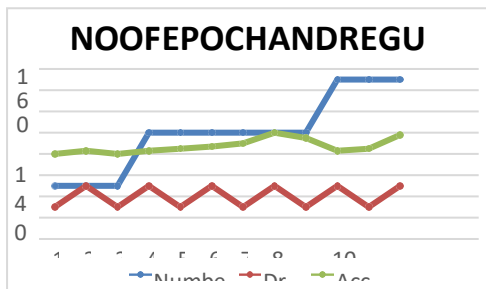


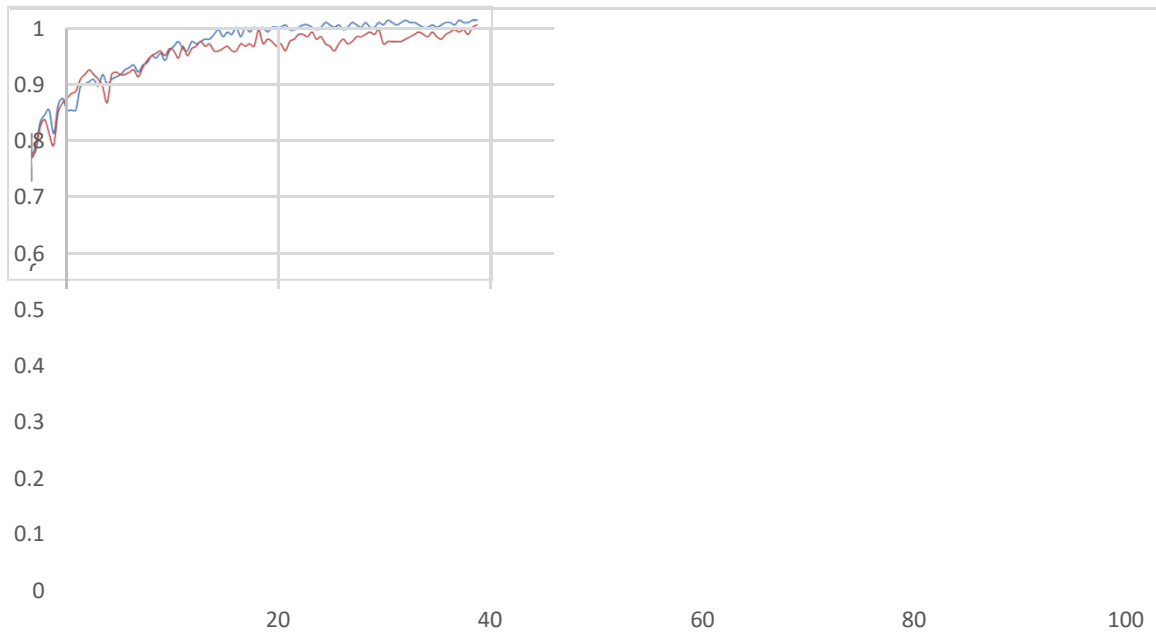
Fig.9. ThenumberofEpochandRegularisationmethodsduringExperiment

TABLE1:

The data that were collected during the experiment for the accuracy and the dropout for the model in different no of epochs.

	Number of epoch	Dropout	Accuracy
1	50	30	80
2	50	50	83
3	50	30	80
4	100	50	83
5	100	30	85
6	100	50	87
7	100	30	90
8	100	50	100
9	100	30	95
10	150	50	83
11	150	30	85
12	150	50	98

### TRAIN ACCURACY Vs VALIDATION ACCURACY



**Fig.9.**The Training Accuracy Vs Validation accuracy

#### TABLE2:

The values used while training the model and the accuracy obtained at the values while validating it are listed below.

X-Values	Train	validation	81	0.97	0.89
0	0.3	0.4	82	0.96	0.89
0	0.35	0.5	83	0.97	0.89
0	0.4	0.4	84	0.98	0.9
1	0.45	0.43	85	0.97	0.91
2	0.55	0.53	86	0.97	0.92
3	0.58	0.56	87	0.96	0.93
4	0.6	0.5	88	0.95	0.92
5	0.5	0.45	89	0.95	0.91
6	0.62	0.59	90	0.96	0.93
7	0.65	0.63	91	0.95	0.91
8	0.6	0.65	92	0.96	0.9
9	0.6	0.67	93	0.97	0.92
10	0.6	0.68	94	0.97	0.93
11	0.7	0.73	95	0.96	0.94
12	0.71	0.75	96	0.98	0.93
13	0.72	0.77	97	0.97	0.94
14	0.73	0.75	98	0.97	0.92
15	0.7	0.73	99	0.98	0.95
16	0.75	0.7	100	0.98	0.96



To get an efficient model we undergone different experiments by customizing various parameters. The parameters dataset color, number of epoch, augmentation, optimizer and dropout. In this project the model is trained by 3 different no of epochs 50,100,150. The model gave the best performance in in 100 epochs. A dropout is added to the CNN to give additional performance (2.75%). So during the experimental process 0.25 and 0.5 dropout percentage is used and the best performance is seen in the 0.5 dropout. In regularization method a most important experiment is carried out, that the usage of optimization algorithm will reduce the loss by updating the iterations according to the gradient. From the above graph the regularization method and the no of epoch are observed is identified. For this study, Adam and RMS Prop which are most recently used optimization algorithms. 2.5% of loss is reduced by Adam optimization algorithm as shown in graph. Highest validation accuracy is observed at the 100<sup>th</sup> epoch as 0.960 for the corresponding training accuracy by these researchers.

As per the Training at 100th epoch we have observed the highest accuracy as 0.98. The above graphs show all the success rate of validation and training data sets achieved during the experimenting graph 1 and graph 2.

## 9. Results and Discussion

The final analyze of this experimental model is done using the K-fold cross validation. The above method produced 20% of best performance. 15% of performance is being provided by RGB image dataset with augmentation. As color is an important factor in the identification of leaf disease, training the model by coloured dataset will take a longer time to train and to increase the performance even in the complex layer. The CNN model and grayscale dataset achieved the accuracy of 97.5%. The Adam optimization method and the no of epoch gave 15% and 5.2% model performance. At last different pre-processing techniques were used by the researchers to remove the noise. The overall performance of the model is 95.8% accuracy for the detection of the leaf diseases in groundnut crops plants.

## 10. Conclusion

This Artificial Intelligence based model was implemented in Raspberry pi. We have obtained an efficient model using different parameters and methods. The overall performance of the groundnut leaf disease detection was 70% satisfied by the evaluator and 15% extremely satisfied and remaining 10% is somehow satisfied. From this it shows that problem solving ability of this model is high and helps the farmers to identify the groundnut leaf diseases. Also this model reduces the time taken for identification plant leaf disease and the complexity in it.

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