Detection of Early Leaf spot of groundnut using Neural Network techniques

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Abstract - *India ranks second in groundnut and its oil production after China followed by USA and Nigeria (Tiwari et al., 2018). In Konkan region groundnut is grown on 20,000 ha area with a productivity of 1800 kg ha^{-1} [1]. The area under groundnut crop has increased enormously in Konkan region. The major biotic factors affecting groundnut yield and quality are foliar diseases, viz. early (Cercospora arachidicola Hori.) and late leaf spots (Phaeoisariopsis personata Berk. And Curt.). The combined losses due to both these leaf spots are more than 50% depending on the time of occurrence and congenial weather. The disease damage the plant by reducing the leaf area available for photosynthesis and stimulating the leaflet abscission leading to heavy defoliation [2]. In order to improve the recognition rate of disease diagnosis, researchers have studied many techniques using machine learning and pattern recognition such as Convolutional Neural Network, Artificial Neural Network, Back Propagation Neural Network, Support Vector Machine and other image processing methods. Due to higher performance capability in terms of computation and accuracy, Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) models are most widely used for detection of plant diseases in agriculture [3]. With this view, the present investigation is planned to develop disease detection model with the help of Convolutional neural network and Artificial neural network for early leaf spot of groundnut caused by Cercospora arachidicola.*

Key Words: **Convolutional Neural network, Artificial Neural network, Teachable machines, Mobiroller, Multilayer Perceptron, Conjugate Descent gradient, Levenberg Marquardt.**

1.INTRODUCTION

India ranks second in groundnut and its oil production after China followed by USA and Nigeria [4]. It contains 48-50% oil and 26-28% protein, and a rich source of nutrients. In Konkan region groundnut is grown on 20,000 ha area with a productivity of 1800 kg ha^{-1} [1]. Optimum temperature and humidity with potash rich porous soil favors higher pod yield in groundnut in this region as compared to rest of the Maharashtra.

The major biotic factors affecting groundnut yield and quality are foliar diseases, *viz.* early (*Cercospora arachidicola* Hori.) and late leaf spots (*Phaeoisariopsis personata* Berk. And Curt.). These are the most widely distributed and economically important foliar disease of groundnut causing sever reduction in oil content. The combined losses due to both these leaf spots are more than 50% depending on the time of occurrence and congenial weather. The disease damage the plant by reducing the leaf area available for photosynthesis and stimulating the leaflet abscission leading to heavy defoliation [2].

In order to improve the recognition rate of disease diagnosis, researchers have studied many techniques using machine learning and pattern recognition such as Convolutional Neural Network, Artificial Neural Network, Back Propagation Neural Network, Support Vector Machine etc. Due to higher performance capability in terms of computation and accuracy, Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) models are most widely used for detection of plant diseases in agriculture [3]. With this view, the present investigation is planned to develop disease detection model with the help of Convolutional neural network and Artificial neural network for early leaf spot of groundnut caused by *Cercospora arachidicola.*

2. LITERATURE SURVEY

Kumar and Sowrirajan [5] proposed an image-processing based approach to automatically classify the normal or diseased leaves (Early leaf spot, Late leaf spot, Alternaria leaf spot). The RGB image samples of leaves of groundnut, mango, brinjal, tomato and maize were collected using high resolution camera. During pre-processing stage, the resizing of image to 256x256 pixels, color space conversion and region of interest selection was performed. Color, texture and geometric features of the image were extracted by the HSV conversion, GLCM and Lloyd's clustering respectively. BPN-FF classifier was used for classification based on learning with the training samples and thereby provided the information on the disease (Early leaf spot, Late leaf spot and Alternaria leaf spot) as well as the respective control measures.

Gowrishankar and Prabha [6] applied threshold-based color segmentation technique for image segmentation along with Artificial neural network classifier to analyze Leaf spot of groundnut. The groundnut leaf images for study were collected from a groundnut farm using high resolution camera, from which 6 set of color images were selected. A number of color image segmentation tests were performed on the selected set of images to obtain the different threshold values for complex, real and low intensity images. The ANN was trained using these threshold values. At the 37th epoch ANN reached the goal with the best performance of training iterations. The classified images by the Artificial Neural Network gave result as 51.98% of leaves were affected by leaf spot disease.

Patil and Nagpure [7] developed a Northern Leaf blight of Corn detection model using Teachable machine platform. The uploaded dataset contained 1090 healthy leaf images and 1762 northern leaf blight infected leaf images of corn plants collected on field manually with smartphone camera. the image project model selected for disease detection was trained at 50 epochs, 16 batch and with 0.001 learning rate. The developed model achieved 98% accuracy for detection of northern leaf blight and 99% accuracy for healthy leaves. The developed model was deployed using Web App.

3. MATERIAL AND METHODS

3.1 Crop sowing and Maintenance details

Groundnut is an annual legume crop and the incidence of leaf spot can be found in all seasons damaging the plant by reducing the leaf area available for photosynthesis and causing defoliation. Sowing of groundnut seeds c.v Konkan Trombay Tapora was done in first week of June i.e., 8th June 2022 at 20 × 15 cm spacing. The field soil was lateritic with soil pH 4.41 and electric conductivity 0.038 dS m^{-1}.

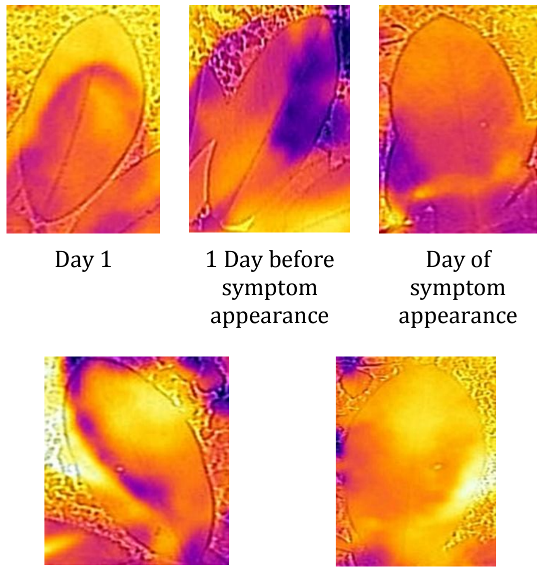
3.2 Technology used

Thermal images of groundnut leaves were collected using FLIROne MSX® thermal camera with the ability to detect temperature differences as small as 0.18° F (0.1° C). The RGB images were collected using Vivo S1 smartphone with 32MP front camera and 16MP+8MP+2MP rear camera which captures images with 1080 × 2340 pixels resolution. To develop CNN based neural network and mobile application platform Teachable machine (https://teachablemachine.withgoogle.com/) and Mobiroller (https://www.mobiroller.com/en/) websites were used. Artificial neural network model was developed using Neurosolution's Artificial Neural Network Software.

3.3 Image collection techniques

Thermal image collection using FlirOne Thermal imaging camera

Healthy groundnut leaves (100) were selected and tagged for observations. The leaves were tagged before development of infection and observed daily. Tagging of leaves and image collection was started on the same day. The FlirOne thermal camera was carefully mounted on the smartphone and held at a distance of approximately 0.5 meter to capture the image. The image collection was continued at 2-day intervals till full visual symptom development of leaf spot of groundnut (Fig.1). Thermal image collection was done in morning during 09:00 am to 10:30 am regularly.



Day 1 | 1 Day before symptom appearance | Day of symptom appearance

3rd day of symptom appearance | 5th day of symptom appearance

Fig.1 Thermal image dataset of groundnut leaves in sequence

RGB image collection using Smartphone Camera

RGB images of healthy groundnut leaves and leaves infected with leaf spot disease were taken at random. All collected images were in RGB format and collected using smart phone camera. The smart phone was vertically oriented at a distance of 0.5 meter from the plant sample while capturing the images. Images were taken separately for infected and healthy leaves. Images were collected in the morning during 10:00 AM – 12:00 PM. The collected images contained the disease symptoms of the respective disease only and were free from other insect pest attack and pathogen infection. Total RGB image dataset contained 700 images each of diseased and healthy leaves (Fig.2) out of which, 500 images were used to train the CNN model and 200 images were used for validation.

Healthy leaf of groundnut   Leaf spot infected leaf of groundnut

Fig. 2 RGB image dataset of Groundnut leaves

3.4 Image processing

Thermal Image processing

Data grouping and rename

Collected thermal images were segregated and grouped on the basis of No. of observation/tag and observation day. Thermal images were renamed as per date and tag no. and were arranged in sequence.

Temperature difference data extraction

Each image of a single tag was viewed in FlirOne thermal camera image view application. The FlirOne application provided information regarding reflectance temperature of plant surface, IR resolution, time and date on which the image was taken and emissivity. Temperature difference in healthy and diseased leaf area for each tag from day one on which data collection was started, one day prior to symptom appearance, day of symptom appearance 3rd day of symptom appearance and 5th day of symptom appearance were calculated. For day one and the day before symptom appearance two temperature values from the healthy areas were taken. After symptom appearance the temperature value of diseased and healthy leaf area was taken.

Table -1: Statistics of Groundnut leaf spot thermal data of healthy and diseased leaf area.

	Healthy leaf	1 day before symptom appearance	Day of symptom appearance	3rd day of symptom appearance	5th day of symptom appearance
Min. temp (^{0} c)	0.10	0.10	0.10	0.10	0.60
Max. temp (^{0} c)	0.80	0.80	0.50	0.60	2.50
Avg. temp (^{0} c)	0.24	0.28	0.24	0.29	1.06
St. Dev.	0.16	0.17	0.13	0.12	0.47
'p' value	Non-significant	Non-significant	Extremely significant	Extremely significant	Extremely significant

The temperature values of healthy and diseased leave areas were compared using paired 't' test. Here, both the temperature values were dependent on each other therefore, paired 't' test was selected. The 't' test proved that there was no significant difference between temperature values of day one and the day prior to symptom development. The 't' test was found significant for the temperature difference of the first day of symptom development, 3rd and 5th day of symptom development (Table 1).

The observations of these three days were classified into temperature difference grade based on minimum and maximum temperature difference and were used to develop artificial neural network model (Table 2).

Table -2: Temperature difference-based Grade scale for Leaf spot of Groundnut

Temp. difference in ^{0}C between diseased and healthy leaf area	Grade
0.1 - 0.5	1
0.6 - 1	2
1.1 - 1.5	3
1.6 - 2	4
2.1 - 2.5	5

RGB Image processing

The randomly collected RGB images of leaf spot of groundnut using smartphone camera were transferred to the laptop and saved into a single folder. RGB images which clearly showed leaf spot disease symptoms without any other disease symptoms were selected. The image contrast and saturation were adjusted to highlight the infected area. The RGB image dataset of groundnut leaf spot disease was renamed as Leaf spot (Image No.) and grouped into a single folder.

3.5 Artificial neural networking model development using thermal dataset

ANN consisted of three layers, an input layer, a hidden layer and an output layer. Input layer usually receives the input signal values. Neurons in output layer produce the output signal. For present study, Multilayer perceptron back propagation feed forward neural networking model was used [8]. The general procedure required to develop ANN disease detection model was as follows (Fig.3).

Normalization of Data

Data normalization was essential to limit the data range within 0 to 1 interval before analyzing the data using ANN. Data normalization ensured that the data series had normalized value closer to 0.5 and within 0 to 1 range. The following equation was used for normalizing the dataset.

$$X_{norm} = \frac{Xi}{Xmax}$$

Where,
X_{norm} = normalized value,
x_i = original value,
x_{max} = maximum value

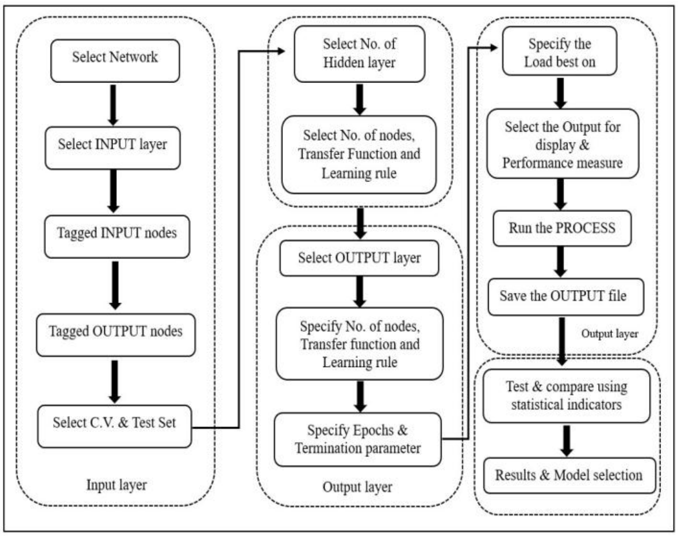


Fig.3 Execution of Artificial Neural Network

ANN architecture development

ANN architecture development involved creation of network topology and network training under various combinations of nodes in hidden layers, number of hidden layers, training cycles and parameters of training function (Table 3). The performance of each combination was evaluated on the basis of statistical indicators. The simple architecture with less nodes i.e., less numerical load in training gave best results during testing.

Table -3: Specifications for Implementation of Artificial Neural Network

Parameters	Selected type
Neural network model	Multilayer Perceptron BP Feed Forward neural network
Input layer	1
Input layer nodes	2
Hidden layer	1
Number of nodes in Hidden layers	2, 4, 6 (2n+2)
Output layer	1
Output layer node	1
training: validation ratio	70:30
Learning Algorithms	Levenberg Marquardt (LM) Conjugate Descent Gradient (CDG)
Transfer function	Sigmoid Axon
Epochs	200, 400, 600, 800, 1000
Model termination	Min. MSE (Mean Square Error)

Number of Nodes in Input layer

The number of nodes in input layer depended on number of parameters under study. In present study, two input parameters, namely, temperature difference in healthy and diseased area and grade assigned to the temperature difference were used as nodes in input layers for analysis.

Number of Nodes in Hidden layer

Three different combinations of hidden layer nodes were performed 2, 4 and 6 to avoid the under-fitting and over-fitting estimate while model training (Table 4).

Table -4: No. of Nodes in different layers of ANN model architecture

Sr. No.	Input layer nodes	Hidden layer nodes	Output layer nodes	ANN model
1	2	2	1	2-2-1
2	2	4	1	2-4-1
3	2	6	1	2-6-1

Number of Hidden layers

The number of hidden layers in the network architecture depends on the non-linearity of function to be learned. One hidden layer was enough to create the model architecture and train the model [9].

Transfer Function

The Sigmoid Axon transfer function was utilized for limiting the amplitude of output to some finite values [8].

Number of Nodes in Output layer

The number of nodes in the output layer depended on number of target variables. In present study, the output layer had a single node corresponding to the Grade in which the temperature difference belongs.

Number of Training Cycles (Epochs)

All ANN architectures were trained at 200, 400, 600, 800 and 1000 epochs and with goal of mean squared error of 0.01 during both training and validation.

Learning Algorithm

Learning algorithm optimized error function in order to modify the link weight. Two types of learning algorithms i.e., Levenberg-Marquardt learning algorithm (LM) [10] and Conjugate gradient decent learning algorithm (CDG) were employed in ANN architecture development for detection of Leaf spot of Groundnut.

Performance Evaluation of ANN model

The performance evaluation of ANN models was done using statistical analysis. The selected statistical indicators were as follows.

Root Mean Square Error (RMSE)

The root mean square error measured the average difference. Smaller the RMSE values, better the model performance. The optimum value for RMSE should be zero $\leq$ RMSE. The RMSE represented by

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2\right]^{0.5}$$

Where,
P_i = Predicted reference temperature difference grade for i^{th} observation
O_i = Targeted reference temperature difference grade for i^{th} observation
N = Number of Observations

Mean Bias Error (MBE)

The mean bias error was used to measure model bias. It provided general biasness but not average error that could be expected. The positive MBE value indicated overestimation and negative value indicated underestimation. The absolute value was indicator of model performance. With the optimal value of zero the biasness lies between -∞ to +∞ ($-\infty < \text{bias} \leq +\infty$). The MBE given by

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)$$

Index of Agreement (I.A)

Index of agreement provides a relative measure of error allowing cross comparison of the model. The model performance was good, when value of degree of index of agreement d $\geq$ 0.95 with optimal value one. The index of agreement expressed as

$$d = 1 - \left[\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}((P'_i| - |O'_i)^2)}\right]$$

Where,
N = number of Observations
$P'_i = P_i - \bar{O}$
$O'_i = O_i - \bar{O}$

Coefficient of correlation (r)

The value of correlation coefficient, if greater than 0.9 showed high level of correlation and 0.5 showed low correlation and between 0.5-0.9 represented moderate correlation. The correlation coefficient (r) measured strength of linear relationships between two variables. The correlation coefficient was calculated using equation

$$r = \frac{\sum PO - \frac{\sum P \sum O}{N}}{\sqrt{\left(\sum P^2 - \frac{(\sum P)^2}{N}\right)\left(\sum O^2 - \frac{(\sum O)^2}{N}\right)}}$$

3.6 Convolutional Neural Network model development on Teachable machine website

In teachable machine, three projects were available, Image project, Audio project and Pose project. Out of three projects image project was selected to create the image-based detection model for leaf spot of groundnut. In the model, two classes were created as class 1 infected leaf and class 2 as healthy leaf. 500 RGB images of infected leaf class and healthy leaf class from the groundnut image dataset were uploaded manually using drag-drop method. Three training parameters were needed to train the disease detection models. Batch size i.e., number of samples processed before model updated was set to 16, number of epochs at which the model was run for training was set to 50 and 0.001 learning rate was set. The process of model training was completed within 5 to 7 minutes. Firstly, the model was uploaded online to convert it into "TensorFlow lite" format to download. After which the model link was created and download option arrived [11].

Developed Teachable Machine model link – "https://teachablemachine.withgoogle.com/models/X6J8sBZJk/"

The equations used to calculate Accuracy, Recall, Precision and F1 Score using Confusion matrix of teachable machine groundnut leaf spot detection model are given below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where
TP = True Positive
TN = True Negative

FP = False Positive
FN = False Negative

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1\ score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

3.7 Android application development using Mobiroller website

A free trial account was created on Mobiroller website with one-month free trail programme using email-id and new application project was selected. In the main control panel, there were more the fifteen options available to add as application content. Three application content options were selected *viz.*, website link, standard application content and contact information. The website link content was selected in which the teachable machine model links of Groundnut disease detection model was uploaded. In standard content option the detailed information about Groundnut leaf spot disease was uploaded along with causal organism, symptoms and control measure and required contact information was mentioned in the contact content. general application settings were updated with text font, size, and background image etc. Android Package Kit (APK) file format was used to generate the application and publication on Google Play. Location, Storage, Microphone and Camera permissions were granted while generating the application. After application generation the link was forwarded to registered email-id for download.

4. EXPERIMENTAL RESULTS

4.1 Artificial Neural Network Model based on Thermal images of groundnut leaf spot

The ANN architecture 2-2-1 with LM algorithm trained with 1000 epochs performed well with r= 0.96, I.A.= 0.97, MBE= -0.0090 and RMSE= 0.05 for training and r= 0.97, I.A.=0.97, MBE= -0.0080 and RMSE=0.04 for cross validation sets. The correlation coefficient was more than 0.9 for both training and cross validation sets with highest close agreement (i.e., 0.97 and 0.97) between the training and cross validation datasets. The MBE (MBE= -0.0090 & -0.0080) and RMSE (RMSE = 0.05 and 0.04) showed very fever error in prediction of leaf spot of groundnut for training and cross validation sets.

The ANN architecture 2-4-1 with LM algorithm trained at 1000 epochs performed with r= 0.95, I.A.= 0.96, MBE= -0.0118 and RMSE = 0.06 for training set and r= 0.97, I.A.= 0.98, MBE= -0.0097 and RMSE= 0.03 for cross validation set. The correlation coefficient for training and cross validation set was more than 0.95. The I.A. indicated close agreement between training (0.96) and cross validation (0.98) sets. The MBE of -0.0118; -0.0097 and RMSE of 0.06 and 0.03 indicated very error in prediction of leaf spot of groundnut for both training and cross validation sets.

The ANN architecture 2-6-1, with LM algorithm was developed for five different epochs i.e., 200, 400, 600, 800 and 1000. The statistical indicators of 2-6-1 architecture with LM algorithm trained at 1000 epochs were r= 0.94, I.A.= 0.96, MBE= -0.0073 and RMSE =0.06 for training set and r = 0.96, I.A.=0.97, MBE= -0.0086, RMSE= 0.04 for cross validation set. These statistical indicators showed that 2-6-1 architecture with LM algorithm trained at 1000 epochs performed better than other developed models with different range of epochs.

The ANN architecture development for groundnut leaf spot detection also tested for Conjugate descent gradient learning algorithm. The different architectures i.e., 2-2-1, 2-4-1 and 2-6-1 at 200, 400, 600, 800 and 1000 epochs were tested.

The 2-2-1 ANN architecture with CDG learning algorithm was trained at different epochs and tested with statistical indicators. The statistical indicators showed that, the ANN architecture 2-2-1 with CDG algorithm trained at 1000 epochs performed well in terms of r= 0.93, IA.=0.96, MBE= -0.0158, RMSE=0.06 for training set and r= 0.96, I.A.=0.97, MBE= -.0164 and RMSE= 0.04 for cross validation set. The correlation coefficient was more than 0.9 for both training (0.93) and cross validation (0.96) with high Index of Agreement (I.A.) between both training (0.96) and cross validation (0.97) sets. The MBE and RMSE indicated less error in prediction of leaf spot of groundnut for both training (MBE= -0.0158 and RMSE= 0.06) and cross validation (MBE= -0.0164 and RMSE= 0.04) sets.

The 2-4-1 architectures with CDG learning algorithm trained at different epochs (i.e., 200, 400, 600, 800 and 100) the 2-4-1 architecture with CDG trained at 1000 epochs was suitable based on statistical indicators. The training dataset showed correlation coefficient of 0.76, I.A.= 0.79, MBE= -0.0178 and RMSE= 0.11. the correlation coefficient for cross validation set was 0.79 with 0.84 I.A., MBE= -0.00057 and RMSE= 0.08. The statistical indicators for both training and cross validation showed close agreement with less error in prediction of leaf spot of groundnut with field observations.

The ANN 2-6-1 architecture with CDG algorithm at 200 epochs performed well with r= 0.79, I.A.= 0.80, MBE= -0.0117 and RMSE= 0.11 for training set and r=0.81, I.A.=0.84, MBE= 0.0013 and RMSE=0.08 for cross validation set. The statistical indicators for 2-6-1 architecture with CDG trained at 200 epochs were at par with the same architecture at 400 epochs. The correlation coefficient and I.A. values of 2-6-1 architecture with CDG algorithm trained at 400 epochs were increased to 0.83 and 0.82 for training and decreased to 0.31

and 0.54 for cross validation sets. Increase in error was observed for both training and cross validation sets for 2-6-1 architecture with CDG algorithm trained at 400 epochs.

The statistical analysis results of selected best 2-2-1, 2-4-1 and 2-6-1 ANN architectures trained with two learning algorithms and five different combinations of epochs for groundnut leaf spot detection presented in Table 5.

Table -5: Best ANN architecture observed from the performed ANN architecture combinations for groundnut leaf spot disease detection

Algorithm	ANN arch	Epoch	Statistical Indicators							
			Training				C.V.			
			r	I.A.	MBE	RMSE	r	I.A.	MBE	RMSE
CDG	2-2-1	1000	0.93	0.96	-0.0158	0.06	0.96	0.97	-0.0164	0.04
	2-4-1	1000	0.76	0.79	-0.0178	0.11	0.79	0.84	-0.0057	0.08
	2-6-1	200	0.79	0.80	-0.0117	0.11	0.81	0.84	0.0013	0.08
		400	0.83	0.82	-0.0209	0.10	0.31	0.54	-0.0123	0.13
LM	2-2-1	1000	0.96	0.97	-0.0090	0.05	0.97	0.97	-0.0080	0.04
	2-4-1	1000	0.95	0.96	-0.0118	0.06	0.97	0.98	-0.0097	0.03
	2-6-1	1000	0.94	0.96	-0.0073	0.06	0.96	0.97	-0.0086	0.04

4.2 Teachable machine model and android application for detection of leaf spot of groundnut

Gowrishankar and Prabha [6] developed ANN model using GLCM technique to analyze leaf spot of groundnut. The accuracy of the ANN system was 98% superior similar to the results achieved using proposed ANN model with two learning algorithms.

Teachable machine disease detection model results were calculated using confusion matrix to record accuracy, precision, specificity and F1 score of Groundnut leaf spot detection model. Confusion matrix was used to describe model performance. Each row of the matrix represented the instants in actual class and each column represented instances in predicted class.

Basic terminology was used in confusion matrix were true positive, true negative, false positive and false negative. When the disease class was predicted correctly it was considered true positive, if the model predicted no disease i.e., healthy and there was no disease on leaf then it was true negative, when the model predicted disease class and if there was no disease then it was false positive, similarly if the model predicted no disease i.e., healthy then it was considered at false negative. Fig. 4 represents the confusion matrix of Groundnut leaf spot detection model.

Groundnut disease detection model performed well with 98% accuracy with 98% recall and 97% precision i.e., out of all diseased and healthy leaf samples tested 98% samples were classified correctly with 97% precision. F1 Score for groundnut disease detection model was 97% which considered both precision and recall and accounted for both false positive and false negative values. In calculation of accuracy only true positive and true negative values were considered. Patil and Nagpure [7] found similar results for teachable machine model developed for detection of northern corn leaf blight 98% accuracy at 50 epochs.

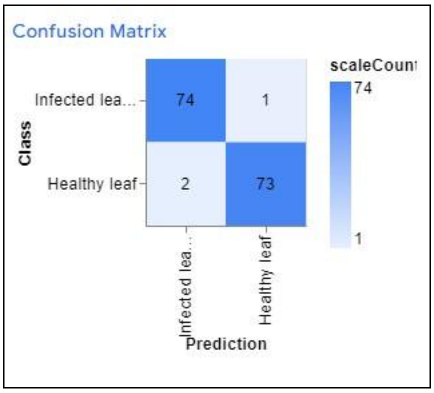


Fig. 4 Confusion Matrix of groundnut leaf spot detection model

The gap between training and testing accuracy in accuracy curve was very low (Fig.5), so there were no issues of model over fitting and concluded as the model learned correctly. Loss was calculated at each epoch showed in Fig.6 The loss at training was low in beginning and decreased as the number of epochs increased.

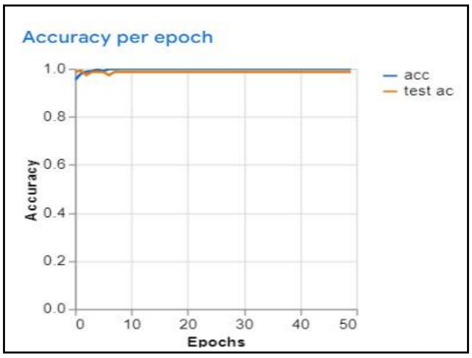


Fig. 5 Accuracy curve of teachable machine model

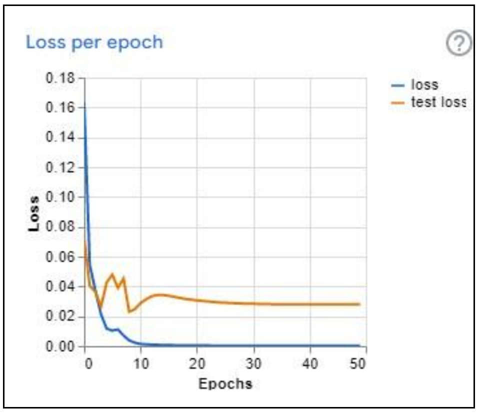


Fig.6 Loss curve of teachable machine model

4. CONCLUSIONS

In the proposed work, the developed ANN and CNN models for groundnut leaf spot disease detection performed very well as compared to the existing plant disease detection techniques developed using machine learning. This will help in early detection of groundnut leaf spot disease. Therefore, the disease management practices can be effectively forewarned to the farmers thereby reducing the losses due to groundnut leaf spot disease in economical and ecofriendly manner.

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