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Classification of Mango Leaf Disease by MCNN

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Abstract: Parasitic (fungal) illnesses not just impact the financial significance of the plants and its items yet in addition decrease their biological conspicuousness. Mango tree, explicitly the fruits and leaves are exceptionally influenced by the parasitic illness named as Anthracnose. The primary point of this undertaking is to build up a proper and compelling strategy for conclusion of the malady and its side effects, along these lines upholding an appropriate framework for an early and financially savvy arrangement of this issue. In the course of the most recent couple of years, because of their better ability as far as calculation and exactness, PC vision, and profound learning procedures have picked up ubiquity in assorted fungal diseases classification. Subsequently, in this venture, a multilayer convolutional neural system (MCNN) is proposed for the grouping of the Mango leaves contaminated by the Anthracnose contagious ailment. The dataset contains both solid and tainted leaf pictures. The outcomes conceive the higher order exactness of the proposed MCNN model when contrasted with the other best in class draws near.

Keywords: Parasitic Illness, Anthracnose and MCNN.

I. INTRODUCTION

Fungal diseases are very common in plant leaves. The diseases in the plants are cause for dropping the quality and the quantity of the agriculture production [1]. The plant diseases affect the quality of the leaves, fruits, stem, vegetables, and their products. This heavily impacts on the productivity and thus reflects on the cost. Report of Food and Agricultural Organization (FAO) estimated that the world population will reach to 9.1 billion by 2050, thus requiring about 70% growth in the food production for a steady supply [2]. The key factors that affect the plants and its products are classified into two category 1. Diseases 2. Disorder. The diseases are the biotic factors that are either caused by the fungi, bacteria or algae whereas, the disorders are the abiotic factors caused by the temperature, rainfall, nutrient deficiency, moisture etc. [3].

The conventional means of disease management implicate farmers and the plant pathologists. The diagnosis and use of the pesticide are more often done in the fields. This process is time-consuming, challenging, and most of the time results in incorrect diagnosis with unsuitable exercise of the pesticides [4]. With the advent of Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) technologies, progress have been achieved in developing automated models empowering, accurate and timely identification of the plant leaves disease. In the last decade, AI and ML technologies have attained a prodigious interest with the availability of a number of high-performance computing processors and devices. Over the last few years, it has been recognized that Deep Learning (DL) has been predominately used in agriculture [5]. This concept is important in making efforts for developing, controlling, maintaining, and enhancing agricultural production. It is to the core of smart farming methodology that is known for the adaptation of new technologies, algorithms, and devices in the agriculture [5], [6].

DL is a special class of ML algorithms which have multiple layers for transforming the raw data into information. Eventually, it has been applied to solve several complex tasks like image classification, pattern analysis, feature extraction, and transformation [6], [7]. Authors have used this concept in various studies like, Chen et al. in [8] have proposed a novel method using deep learning for counting the apples and oranges from the real-time images. An automated method based on Convolutional Neural Network (CNN) has been proposed by Dias et al. in [9] for the semantic segmentation of apple flowers. The author has validated the performance of the proposed work compared with other plants, proving the supremacy of the proposed method for counting the number of flowers from the plants. Ubbens et al. in [10] have presented a novel framework for the image based plant phenotyping, for this purpose, authors have used CNN to count the leaves of a plant. The dependency of having a large dataset to work with deep learning has been overcome by using high-quality 3D synthetic plants. In [11] Lottes et al. have used Fully Convolutional Neural Network (FCNN) with sequential information for the detection and classification of robust crop and weed from the field. Suh et al. in [12] have presented three variants of AlexNet for the classification of weeds from the crop images. For this purpose, the sugar beet and volunteer potato images have been considered and the result shows the effectiveness of the work.

A. Problem Statement

The economic importance of the mango trees and its products are influenced by the fungal diseases like anthracnose which also affects the ecological prominence. The key problem is that we don't have any appropriate and effective method for diagnosis of the disease and its symptoms in early stage. Our challenge is to develop higher performance system in terms of computation and accuracy, computer vision, and deep learning methodologies for fungal diseases classification.

B. Objectives

1) To develop an effective system this carried automatic and an early diagnosis of a disease and its severity so that timely treatment can be taken in advance.
2) To assist in identifying the nature and life cycle of the disease, thus helping to learn vulnerability among them.
3) To propose a deep learning model named as MCNN for the classification of leaves infected by the Anthracnose disease.
4) To evaluate the proposed system on the collected and standard database when compared with the other state-of-the-art approaches.
5) To develop an automatic, computationally efficient, and cost-effective system that can help in sustaining the importance of the Mango tree and its yields both ecologically and economically.

C. Existing System

CNN is inspired by the biological nervous and vision system. It is an unsupervised deep learning classification model having high classification and recognition accuracy. This model possesses a complex structure as it constitutes large number of information processing layers. This multiplayer architecture differs it from the conventional Artificial Neural Networks (ANN's). They are having the capabilities of learning features from the training dataset. CNN models require very few neurons when compared with the traditional ANN but, they require a very large number of data for their training.

D. Proposed System

This project proposes a Multilayer Convolutional Neural Network (MCNN) for the classification of Mango leaves infected by the fungal disease named as Anthracnose. The performance of the model is validated on the images acquired in the real condition. The images are preprocessed with the help of histogram of equalization that balance the invariability among images captured in real conditions. These images are resized to a standard size image using the central square crop method. Then, the MCNN based ternary classification model is trained and tested.

II. LITERATURE REVIEW

Iqbal et al. in [1] have presented the number of studies for the identification and classification of the citrus plant leaves diseases. In this review work, the authors have discussed almost all the methodologies associated with detecting the disease, including concepts of image processing, techniques, challenges, advantages, and disadvantages etc.

Golhani et al. in [2] has present various studies of neural network approaches used for the identification and classification of the disease from the leave images of the plant. This work introduces various models, types, mechanisms, and classifiers used and the further they have presented the various concepts of imaging with respect to hyperspectral images.

Ma et al. in [4] all the images are acquired in the real-time and has been classified using the Deep Convolutional Neural Network (DCNN).

Ferentinos in [5] has proposed a VGG convolutional neural network for the identification and classification of the plant leaves. The proposed method classifies the given images between healthy and diseased. The result was validated on a large dataset shows the accuracy of the deep learning approach.

Too et al. in [6] have used four different deep convolutional network architectures including VGG 16, Inception V4, ResNet and DenseNets for the classification of disease from an image. The images were taken from the plantVillage dataset consists of 38 diseased classes and 14 healthy classes. The DenseNets network achieves higher classification accuracy and lesser computational time when compared with other architectures.

Barbedo. in[7] have presented a study of the deep learning in the plant pathology. The author in this work has presented various issues and parameters that affect the efficiency of the network. Finally, the results verified the performance of the convolutional neural network on the images taken from the Digipathos repository.

Kamilaris and Prenafeta-Boldu in [8] have introduced various studies of the deep learning that were adopted in agriculture. This study compromises the different methods, imaging and computer vision theories, related problems, applications, and evaluation metrics etc. The size and variety of the images in the database are an important aspect when working with the concepts of deep learning.

Barbedo in [9] have present various issues and challenges in the classification of plant diseases. The author has investigated this work with twelve different plants having different attributes and with different diseases.

Kaur et al. in [10] have presented a study of the computer vision concepts and methods adopted for the detection and classification of the plant leaves. The advantages and disadvantages of the several studies have been discussed separately.

Picon et al. in [11] have used DCNN for the classification of three fungal diseases found in the wheat plant. The images in the proposed work were collected in the real-time environment at two locations for about three consecutive years.

Zhang et al. in [12] GoogLeNet and Cifar10 network have been presented for the classification of diseases from the maize leaf images. The proposed models achieve higher accuracy when compared with other networks like VGG and AlexNet for classifying nine different types of maize leaves.

Lu et al. in [13] have proposed a DCNN for the classification of ten different types of rice leave disease from the repository of about five hundred images containing both the healthy and infected images. Authors have adopted the 10-fold cross validation strategy for achieving higher classification results.

Gandhi et al. [14] have worked with Generative Adversarial Networks (GANs) and CNN for the identification of diseases from the plant leaf images using a mobile application.

Durmus et al. in [15] AlexNet and then SqueezeNet deep learning network has been usedfor the classification of plant leaf diseases. The images are taken from the plantVillage database for the tomato plant leaf images in ten different classes.

Jain et al. in [16] CNNs have been proposed for the real-time classification of the disease from the plant leave images. The proposed method is built on a cloud-based environment for performing this task. The images of the plant leaves are collected in the real-time for classification.

III. REQUIREMENTS SPECIFICATION

A. Functional Requirements

Functional requirements are the software capabilities which are to be present in order for the user to get the service from the system.

1) *Image Acquisition*: Action of retrieving an image from some source, it is the first step in the workflow sequence because, without an image no processing is possible. The image that is acquired is completely unprocessed.
2) *Preprocessing (Contrast Enhancement)*: Is a process by which image the pixel intensity of the image is changed to utilize the maximum possible bins. It minimizes the ambiguity arises between different regions in an image.
3) *Preprocessing (Resizing):* Image interpolation occurs when you resize or distort an image from one pixel grid to another. Image resizing is necessary when increasing or decreasing the total number of pixels, whereas remapping can occur when correcting for lens distortion or rotating an image.
4) *Class Labeling*: To count the object in an image.
5) *Training Dataset*: Classify pixels in order to segment different objects.
6) *Testing dataset*: Testing it to check its working.

B. Non-Functional Requirements

Non-Functional Requirements provides criteria that are used to decide the operations of the system. The following are the non-functional requirement:

1) *Scalability:* The proposed system can extended to any number of farms.
2) *Reliability:* Our proposed system is reliable. There will be no false data and lesser loss of information as it ensures increased data utility.
3) *Flexibility:* The proposed system is more flexible to the user as it uses simple techniques and also less complexity so that everyone can understand easily.
4) *Performance:* Our proposed system accurately classifies the diseases than the legacy system.
5) *Cost:* Lesser cost compare to existing technique.

C. Hardware And Software Requirements

1) Minimal Hardware Requirements

a) Processor : Corei5 or higher.
b) Hard disk : 256GB.
c) RAM : Minimum 4GB.

2) Software Requirements

Minimal Software Requirements

a) Operating System: Ubuntu 18 or higher.
b) Tools used : Pycharm.
c) Database : dbSQlite.
d) Framework : Django.

IV. SYSTEM DESIGN

System design thought as the application of theory of the systems for the development of the project. System design defines the architecture, data flow, use case, class, sequence and activity diagrams of the project development.

A. System architecture

This architecture diagram illustrates how the system is built and is the basic construction of the software method. Creations of such structures and documentation of these structures is the main responsible of software architecture.

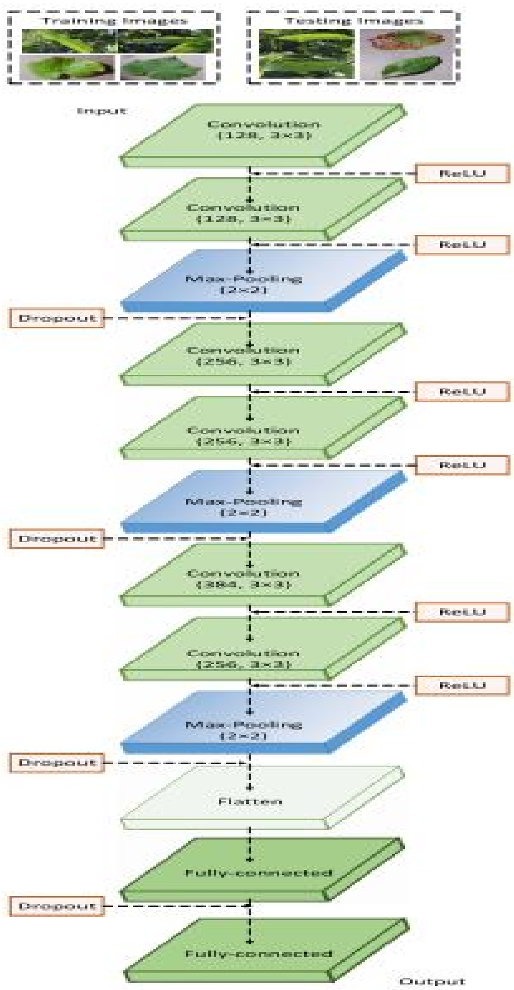

Fig. 1: Architecture Diagram.

B. Sequence Diagram

A sequence diagram it is a type of communicative diagram which demonstrates how the techniques or processes work with each other and also gives the information about in which order they are working. Sequence diagram, its develop communication arrangement graph. These figures some time named occurrence figures, occasion situations, What's more scheduling figures.

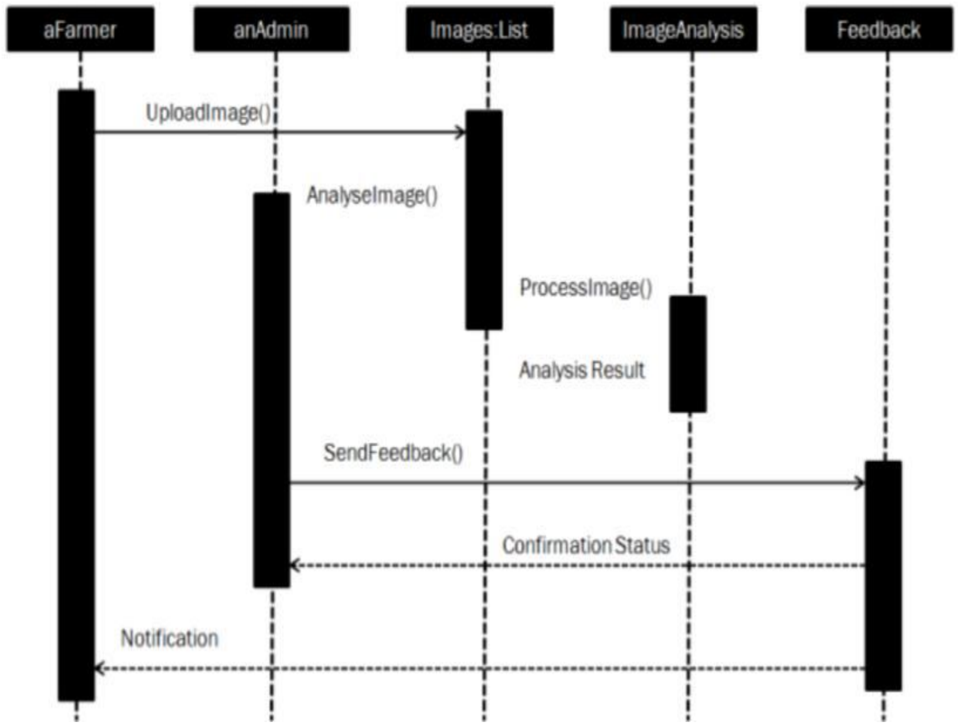

Fig. 2: Sequence Diagram.

C. Data Flow Diagram

Data flow diagram also referred as bubble graph. This diagram is useful for representing the system for all degree of constructions. The figure is differentiated into parts which show maximizing data path & practical aspect.

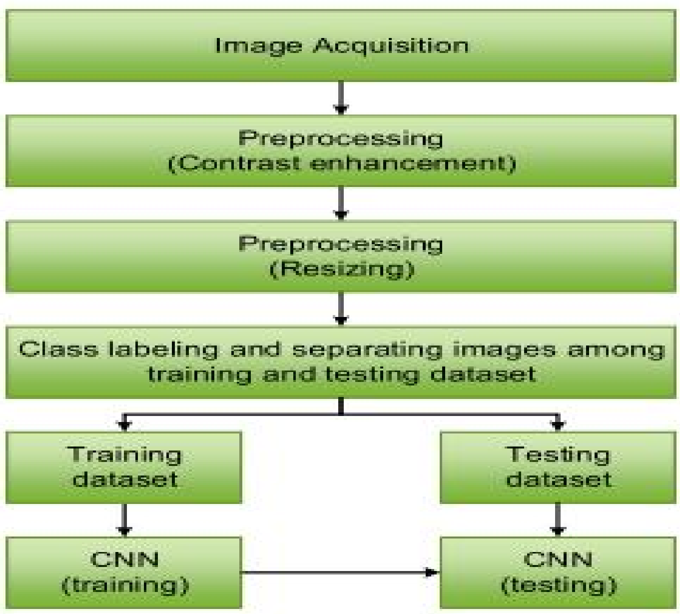

Fig. 3: Data Flow Diagram

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V. IMPLEMENTATION

A. Algorithm

1) *Step 1:* Acquire the real time images of the mango tree containing both diseased and non-diseased leaves and also images from plant village data set.
2) *Step 2:* Preprocess all the images for contrast enhancement using histogram equalization method and rescaling using central scaling crop method.
3) *Step 3:* Assign the class labels to the images.
4) *Step 4:* Categorize the images among training and testing dataset selecting from all the class labels.
5) *Step 5:* Train the images with the help of training images.
6) *Step 6:* Test the images with the help of testing images.
7) *Step 7:* Validate the performance of the proposed model and compare the results with the other state-of-the-art approaches.

B. Methodology

1) *Dataset:* In the proposed work, mango leaf database repository have been used, which contains the real-time Mango leaves dataset. A total of 435 images are used in this. These images categorized among two classes namely Mango leave images with the disease. Based on the category these images are labeled to their respective classes. Fig. 4 and 5 shows the sample dataset consists of two Mango leaf images taken in the real condition. Table. 1 shows the details of the images.

Fig 4 : Sample of healthy images.

Figure 5: Sample of Diseased image

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Table 1: Details of image categories.

Image Type	Class Label	No. of images
Healthy leaf	C_0	170
Diseased leaf	C_1	265

2) *Preprocessing of Images:* At first, the training and testing images were preprocessed for contrast enhancement and rescaling them to a 128×128 pixel size. Two different methods namely histogram equalization method for contrast enhancement and central square crop method are used for this purpose for the entire set of database. The contrast of the images is improved by assigning a uniform intensity value to the pixel using the histogram of an image with the help of histogram equalization method given by eq. (1) [26]. Further, the images are rescaled using the central square crop method given by eq. (2)

$$H\left(P_{(x,y)}\right) = round\left(\frac{f_{cdf}\left(p_{(x,y)}\right) - f_{cdf_{min}}}{(R \times C) - f_{cdf}} \times L - 1\right) \quad (1)$$

Where, fcdf = cumulative frequency of the gray level, fcdf min = minimum value of cumulative distribution function, fcdf P(x,y) = intensity of the current pixel, R and C = product of number of pixels in rows and columns and L = number of intensities.

$$def\ centeredCrop(img, new\_height, new\_width) \quad (2)$$

2) *Convolutional Neural Network:* With the advancement in computationally efficient devices like Graphics Processing Unit (GPU), deep learning related applications have attained exponential development. The concept of deep learning is motivated by the conventional artificial neural network. The deep learning model is stacked with the number of preprocessing layers in which the information is extracted from the raw input to the final task-specific output. DL models have tremendously emerged after the image classification accuracy of CNN over ILSVRC dataset in 2012 proposed by Krizhevsky et al. [23]. Since then applications of deep learning have been found in the number of applications for image classification, pattern recognition, voice recognition, object detection, etc. [24], [25].

A convolutional neural network is the deep learning model used for solving complex pattern recognition and classifications problems with a large amount of databases. The model majorly comprises of four different layers namely convolution, max-pooling, fully-connected, and output layer stacked over one another. The novelty of the architecture lies in its flexibility to its configuration depending on the task related results. There are many different CNN models available like AlexNet, VGG, GoogLeNet, ResNet etc. These models differ based on their depth, configurations, the nonlinear function, and the number of units. There are various adjustable parameters like the dropout rate, the learning rate used in complex processing for solving classification and pattern recognition problems [24], [25]. The architecture of the proposed CNN have used for the classification of the infected Mango leaves. This model is inspired by the AlexNet architecture, which consists of six convolutional layers each followed by a Rectified Linear Unit (ReLU), three max-pooling layers, and two dense or fully-connected layers last layer acting as an output layer with a Softmax activation function. A flatten acting as a hidden layer is used to convert the images in a 1D array, thus enhancing the performance and making it simpler to handle the data. The size of each convolutional layer is 3×3 and each max-pooling is 2×2, whereas the size of the input images and feature maps varies shown in the figure. Stochastic gradient descent (SGD) or Backpropagation algorithm (BPA) is used for the training of the CNN.

The input volume is convolve with weights volume. Depending on the padding and out striding the input layer is expanded or shrinked. In the convolution process the spatial width and height is reduced, but increasing the depth. Non-linear activation function is added to each layer for modelling the more complex target function varying in a non-linear way with the given input. ReLU reduces the probability of a vanishing gradient. This also introduces sparsity to the model. Pooling helps in reducing computational requirement and spatial size of the activation function. Max pooling due to higher convergence and better performance is more commonly used. The images are down sampled using max-pooling layer. It also reduces the likelihood of overfitting. Dense or fully connected layer is the final layer responsible for predicting the class of an image. Further details of the proposed multilayer convolutional neural network are given as:

a) This model is a sequential model having a series of layers to convert the standard size image into a feature set for further processing.
b) The first two layers of this model M are the convolutional layer with 128 filters and ReLU as the activation function.
c) The third layer is the max pooling layer that will reduce the size of the convoluted image by (2, 2).

d) It again adds two more convolutional layers will 256 filters and ReLU as the activation function.
e) The sixth layer is the max pooling layer with a pool size of (2, 2).
f) A convolutional layer with 384 filters and ReLU activation function is added to the model.
g) The next layer is again a convolutional layer with 256 filters and ReLU activation function. 8 Then it has a max pooling layer followed by dropout rate 0.2.
h) Then this model has added one more layer to flatten the output of the above designed convolutional neural network model.
i) This flattening process will give the feature set for every image in the form of output.
j) Now, this model has two fully connected layers that will be used for the classification of images based on the generated feature set.
k) This dense layer act as the hidden layer of the artificial neural network having 512 hidden neurons and the activation function is ReLU. This model is designed in such a way that every input neuron is connected to every other hidden neuron forming a fully connected layer.
l) It has one more fully connected layer which acts as the output layer of the artificial neural network having 3 output neurons. The number of output neurons is always dependent on the classes. It uses SoftMax as the activation function.
m) The output of this layer is the predicted class label which is used to evaluate the overall accuracy of the proposed model. The various parameters and configuration details of the proposed CNN is given in table below.

Table 2: Configuration details of the proposed CNN.

Convolutional layers	6 (each with 3×3 filters)
Max-pooling	3 (each with 2×2 filter)
Dropout	0.2 - 0.5
Learning rate	0.01
Momentum	0.09
Weight decay	1e-6
Activation function	ReLU
Batch size	15
Epochs	100
Training algorithm	BPA / SGD

3) *Training And Testing:* Initially, the entire dataset is divided into two parts, the training and the testing dataset. This is done by randomly splitting dataset into training set comprises about 80% of the images and the testing set constitutes about 20% of the images. This ratio distribution is predominately used in the neural network applications. Therefore, for the training of the CNN 348 images are used and 87 remaining images are kept for testing the performance of the model.

Training a CNN is the practice of running training examples through the model from the input layer to the output layer simultaneously making a prediction and figuring out the results or errors. If the prediction is wrong then this is back propagated in reverse order i.e. from last layer to first layer. For this work, we use backpropagation algorithm for adjusting the weights of the network slightly aiming for the better result. This complete process is known to be one epoch. The weights in this work are optimized by using stochastic gradient descent algorithm. The proposed model does not includes the object segmentation process. This step can be excluded when working with deep neural network as they have the tendency of extracting the essential features for the given image while eliminating the excessive ones [5]. This incapacitates the overhead of handling the real-time complex images and thus improves the efficiency.

Proposed Multilayer Convolutional Neural Network based ternary classification model is then trained for the detection and classification of Mango leaves. This ternary model includes two cases i.e. (i) the image is a non-diseased Mango leaf image, and (iii) the image is a diseased Mango leaf image. The training images were taken from each of the class labels C_0 and C_1 respectively maintaining the ratio of 80% images. All the other remaining 20% images were untouched during the complete process. Each image from the normalized training dataset is given as an input to the Multilayer Convolution Neural network model to extract the features. This model is trained to predict the class label for every training image.

VI. TRAINING AND TESTING

A. Overview

The proposed model consisting of training and testing process were implemented using an open source software framework known to be Tensor Flow with Python programming language. The learning rate is set to 0.01, dropout rate varies from 0.2 to 0.5, and the momentum was chosen to be 0.09, with weight decay of 1e-6 respectively. Training was accomplished in about 7 days and testing was completed in a few minutes. The training process was implemented on the GPU of an NVIDIA GTX1080 card, using the CUDA platform. In the experiments for testing the proposed algorithm is implemented on a desktop computer with Intel (R) core (TM): 7-7700 CPU (3.60 GHz), Windows 10 Pro (64 bit) operating system, 16.0 RAM, GPU (Integrated 2 GB NVIDIA GeForce GT 710), and 1TB hard disk.

The proposed CNN is validated on the real mango leaf set of images database, the first self-acquired database encompasses of Mango leaves both healthy and infected from the Anthracnose.

The images were divided among the training and the testing database upholding the ratio i.e. 80% images for training and 20% images for testing. Before the training process, the images are normalized for histogram enhancement and rescaling. The results are compared with the other state-of-the-art approaches named as Confusion matrix which includes precession and recall. This approach including proposed network is verified with the three cross-fold validation strategy. These results show the accuracy, missing report rate, and false report rate of all the proposed method selected for the classification of disease Mango leaves.

The accuracy is computed by the eq. (1).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots\ldots\ldots 1$$

Recall can be defined as the ratio of the total number of correctly classified positive examples divide to the total number of positive examples. High Recall indicates the class is correctly recognized (a small number of FN).

$$\textit{Recall} = \frac{TP}{TP + FN} \quad \ldots\ldots\ldots\ldots 2$$

To get the value of precision we divide the total number of correctly classified positive examples by the total number of predicted positive examples. High Precision indicates an example labelled as positive is indeed positive (a small number of FP).

$$\textit{Precision} = \frac{TP}{TP + FP} \quad \ldots\ldots\ldots\ldots 3$$

The accuracy of the proposed method was computed to be 80% which is higher than other classification methods. The proposed model also reports a missing report rate of about 2.87% with 0.70% false report rate. This missing rate is due to the vulnerabilities present in the real-time database.

Images taken in real condition majorly suffers from the problem of:

1) Variation in Temperature
2) Shadowing,
3) Overlapping of leaves
4) Presence of multiple objects.

Handling these issues we can improve the performance of the proposed approaches.

VII. RESULTS AND OUTPUT SCREENSHOTS

A. Results

The results of presented methodology focus on:

1) Primary task is to classify the given image is Mango leaf or not. Then, the secondary task is to identify the leaf is a non-diseased Mango leaf, and third is to identify and classify that the leaf is a diseased Mango leaf or not.
2) Measuring the accuracy for both the training process and the testing process of the proposed network.
3) To report corresponding missing report rate, and false report rate.

B. Output Screenshots

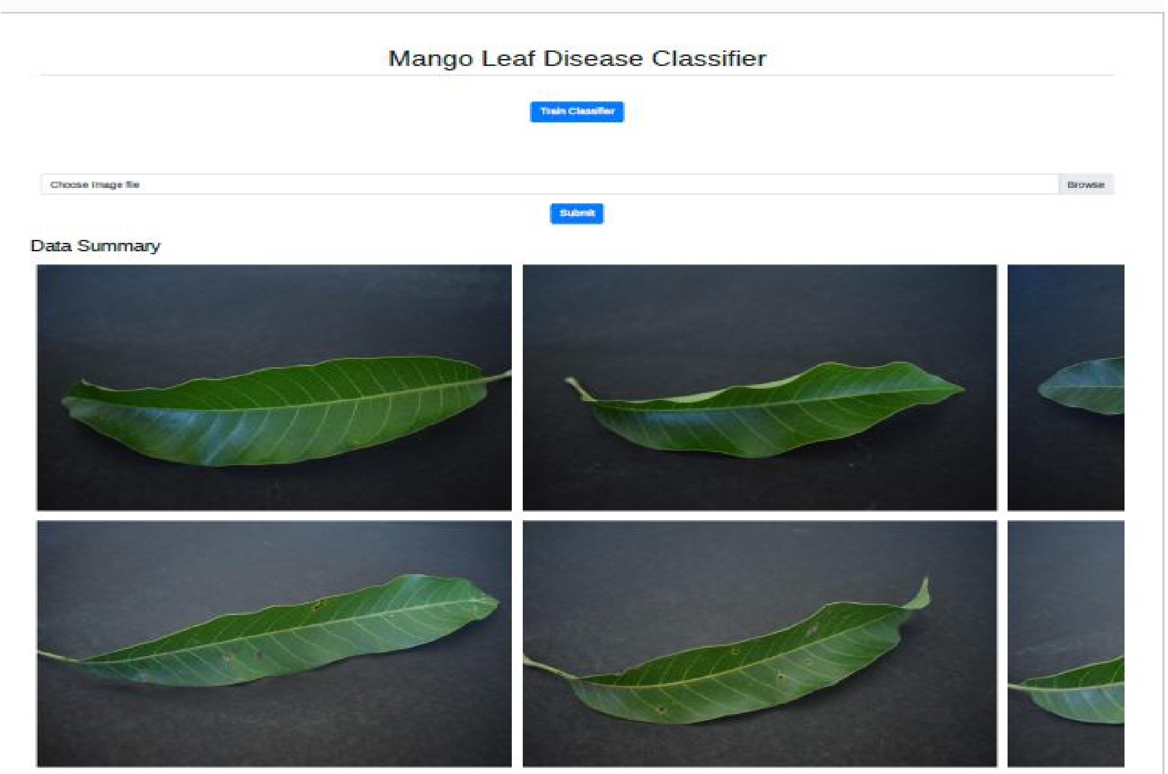

Fig. 6: Front end for our proposed system

The figure 6 above shows the front end GUI of the proposed system. It contains the interface for uploading the test dataset images. It also displays the dataset images used for training and testing. We have given train classifier button to train the newly available dataset images. When we upload image for testing, results is displayed in the new pop-up window as shown in figure 7 and 8.

Figure 7: Results of Diseased Test image

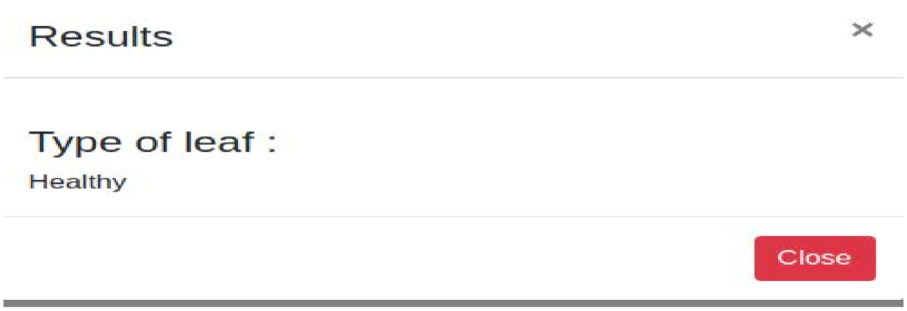

Figure 8: Results of Healthy test image

Figure 9: Model Training and testing accuracy (%)

From the plot of accuracy we can see that the model could probably be trained a little more as the trend for accuracy on both datasets is still rising for the last few epochs. We can also see that the model has not yet over-learned the training dataset, showing comparable skill on both datasets. The figure 9 shows the model training and testing accuracy graph.

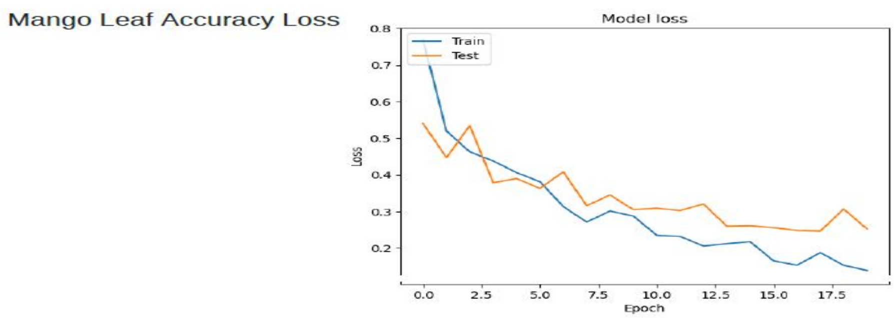

Figure 10: Model loss

From the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labeled test). If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch.

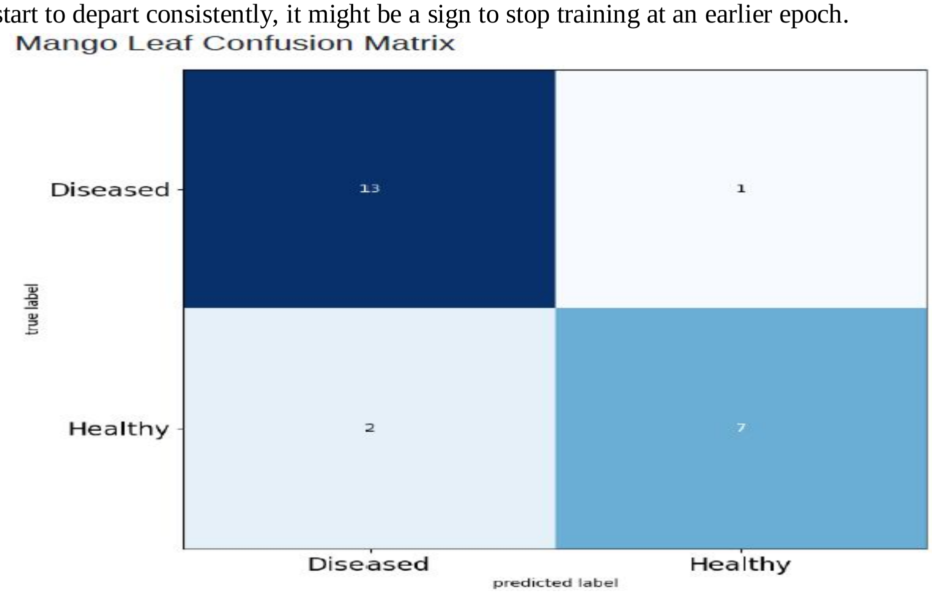

Fig 11: Confusion matrix for validation

The above figure 11 is the confusion matrix for validating the proposed system. It will change based on the dataset. The results show the accuracy, missing report rate, and false report rate of all the methods selected for the classification of disease Mango leaves.

VIII. CONCLUSION

A. Conclusion

By controlling the biotic factors causing severe losses in the crop yield, we can enhance the productivity and quality of the plants and its products. Computer vision with machine learning methodologies has outperformed in solving a number of plant leaves disease problems including pattern recognition, classification, object extraction etc. Therefore in this work, we propose an innovative model named as MCNN for the classification of Mango leaves infected from the fungal disease named as Anthracnose. The higher performance of the proposed work is confirmed with accuracy of 97.13% when compared with other state-of-the-art approaches for its accuracy. The presented model is also computationally efficient and simple.

B. Future Work

1) The use of some other function instead of Softmax activation function can enhance the performance of the CNN making it compatible for classifying multiple diseases.
2) Counter measuring the inconsistencies encountered working with real-time dataset.
3) Working with other plants with economic importance and calculating the severity of the disease considering other parts of the plants as well.

To build a Web/Internet of Things (IoT) enabled real-time disease monitoring system

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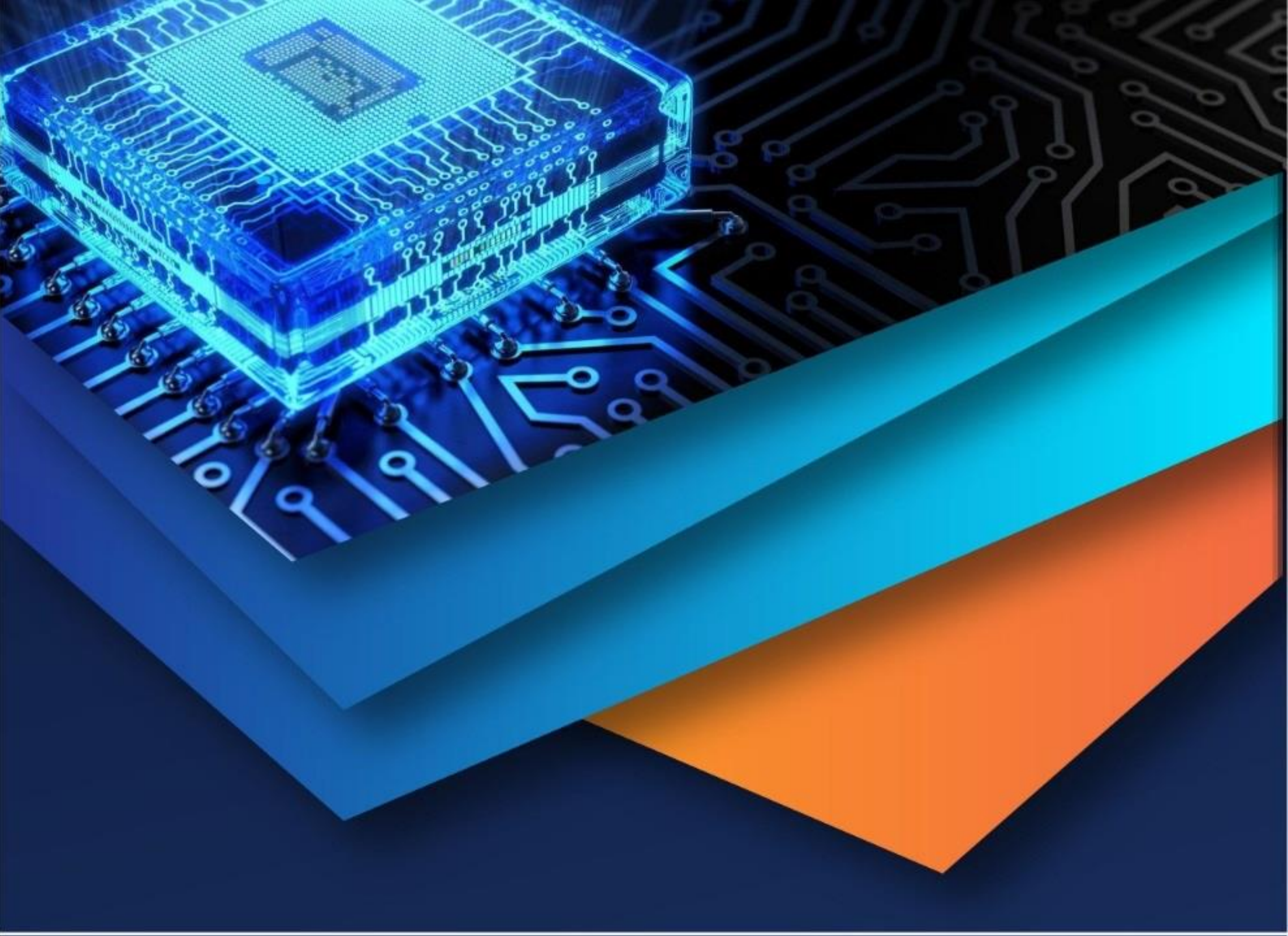

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