Mangifera Indica Leaf Disease Detection and Severity Analysis Using Deep Learning Techniques

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Abstract -With the advent of medicine, human evolution has reached an unpredictable level. The human race begins to exploit natural resources in order to live a sophisticated lifestyle. In this situation, it is mandatory to protect our plants' environment, which provides invaluable oxygen supply, nutritional value, and medicinal benefits to society. This encourages efforts to employ novel artificial intelligence methods, including deep learning, to safeguard the Mangifera Indica (mango) species from illness. The following are some of the benefits of mango plants: It has numerous benefits, including anti-cancer, anti-inflammatory, and curing respiratory and kidney diseases, among others. So, this plant species is considered the king of all species.The most common mango plant diseases are identified, and a severity analysis of the diseases is also done using the convolutional neural network (CNN) technique. The proposed disease detection system will be more beneficial to agricultural workers because remedies for corresponding diseases will be given based on severity levels. The disease detection technique and knowledge about most of the affected diseases' causes, symptoms, and management are also illustrated. The entire disease identification was done by using 8 categories with 4000 mango plant leaf images. The CNN-based system model is trained, validated, and tested with the help of MATLAB software as well as GitHubdatasets. The results of the analysis, comparison, and accuracy levels are illustrated clearly.
Keywords - *Mangifera Indica (Mango); Leaf Disease Detection; Deep Learning Techniques; Convolutional Neural Network (CNN).*

I. INTRODUCTION

The second-largest producer of agricultural products in the world is India. There is no hesitation that agriculture is the backbone of India. Almost two-thirds of the population is involved in agricultural activities. Recently, many young people have been keen attention in cultivating crops with the help of technological advancements. This proposed research presents a deep learning technique for mango leaf disease identification and severity analysis. Mangifera Indica is a botanical name for this plant species.The research is driven by the peculiar characteristics of the plant species in an effort to save them from extinction. Nowadays, it is rare to find mangoes during their prime season. Every part of the mango species, including the seeds, flowers, bark, trunk, leaves, and fruits (raw and ripe), are extremely useful to humans and is also used as medication to cure complicated disorders [1].

According to a list of Mangifera indica's nutritional advantages, (i) it can guard against muscular degeneration, (ii) maintain blood pressure and heart rate, (iii) prevent cardiac illnesses, (iv) assist people overcome weakness, (v) boost their resistance to free radicals, and (vi) prevent ulcers. Similarly, pharmacological advantages include those related to (i) gastro-intestinal infections, (ii) diabetes, (iii) anti-cancer, (iv) anti-bacterial, (v) anti-inflammatory, and (vi) anti-oxidant properties. Mango leaves have the following medicinal benefits [2]. They are: (i) Anti-oxidant as free radical scavengers, (ii) Antiviral activity, anthelmintic,(iii) Anti-allergenic activity, (iv) Anti-inflammatory, (v) Diabetes medication properties, (vi) Improves digestion, (vii) Boosts memory and amnesia properties, (viii) Cures respiratory complicated diseases, (ix) Lowers blood pressure as hypotensive agent, (x) Heals wounds/burns and gut, (xi) Treating kidney diseases, keeps cholesterol in check, (xii) Fights cancerous cells, and aphrodisiac properties.

Mango production and exports from India rise every year as a result of the several benefits outlined above. Unfortunately, these peculiar species have been difficult to find on the market for several years. Even though it is available, it is not enough to bring all of the people to the area where it is grown. It's because 50% of the product will be shipped out to other countries for usage in food and medicine. The remaining goods were contaminated with the illnesses and useless for any purpose. The important illness or diseases of mango and their management are presented in [3]. They are as follows: Sooty mould, powdery mildew, gall midge, die back, cutting weevil, bacterial canker and anthracnose.These illnesses are initially seen on the surfaces of their leaves. Both mango production and fruit ripening will be affected. As a result, earlier prediction of plant disease and pest detection is required to protect the plant and increase yield. Traditionally, experienced farmers detected and prevented it. The human eye can sometimes miss identifying a disease; even if it is correctly identified, taking the appropriate remedy can be difficult. These are the problems identified while dealing with plant disease detection. The proposed work attempts to address the aforementioned flaws.

The paperwork is organized as follows: The related studies are presented as a literature review in Part IIto analyse and determine the best disease detection techniques and software to employ. In PartIII, the classifications, root causes, and recommended preventative methods for illnesses affecting mango leaves are discussed. Part IV describes the proposed CNN-based Deep Learning (DL) methodologies, architecture, and process flow. The suggested Matlab system implementation, together with its results and comments, is covered in Part V. Lastly, Part VI presents the work's conclusion.

II. RELATED LITERATURE REVIEW

The works are associated to the proposed methodology are as follows: Conventional machine vision-based illness diagnosis techniques, like classic image processing algorithms to manually create the features and a classifier, are frequently utilised in addition to sophisticated human-eye detection [4].For this traditional technique to provide consistent illumination, a suitable light source with a suitable shooting angle is required. The setup of the system has the disadvantage of raising application costs and making input challenging. In natural light conditions, the impacted area in the leaf contrast fluctuations and noise render standard algorithms ineffective in achieving superior identification results [5].In [6] and [7], image processing techniques are used to analyse two mango leaf diseases, such as anthracnose and leaf spot, using a few input images. It is possible to reduce the likelihood that disease outbreaks would ruin a maize crop by using machine learning techniques[8].The diseases mango leaf anthracnose and red rust are detected in paper [9] using proposed machine vision approaches such as support vector machines (SVM) and minimum distance classifiers. From the comparison of results, the accuracy obtained was 79.16% and 83.34%, respectively. For mango leaf disease pattern recognition, a K-Nearest Neighbour (KNN) clustering-based artificial neural network (ANN) is used, with an average accuracy of 80% in [10].

In [11], the segmentation-based deep learning algorithm was proposed, with a 73% accuracy. To improve efficiency by up to 95.5%, a novel segmentation method incorporating a vein pattern-based SVM classifier method [12] was proposed. Due to the successful application of a convolutional neural network (CNN)-based deep learning model, the approach has recently been applied in several disciplines such as scenario text identification [13], medical picture recognition [14], face recognition [15], and expression recognition [16]. A review study was used to compare image analysis along with deep learning methods in terms of process flow, surroundings, and valid cases.[17], which is presented in Table 1. According to the comparison study, CNN-based deep learning algorithms outperform other machine learning techniques. The infected mango leafclassification using multi-layer CNN was proposed in [18]. It has been demonstrated to outperform other approaches. The open source platformsfor deep learning are as follows: Theano [19], Caffe [20], Tensorflow [21] and PyTorch [22].Table 2 lists the characteristics that were considered in order to select the leading platform.

Table 1. Comparative study between deep learning approach with image processing

Techniques	Image Processing	Deep Learning
Process Flow	Manual design features + Classifiers (Rules).	CNN that automatically learns features from a lot of data.
Image Segmentation	Laplace & Kirsh Edge Detection; Threshold and Region Segmentation.	
Extraction of Features	Methods for extracting shape, colour, and texture features include SIFT, HOG, and LBP.	

Classification	BP, SVM, Bayesian.	
Required Environments	The strong contrast between the lesion and non-lesion areas; minimum noise are requirements for an exceptionally difficult imaging environment.	High-performance computing machines and enough learning data.
Valid situations	In order to improve recognition performance in challenging natural contexts, it is frequently necessary to tweak the threshold or the algorithm when the classification of a plant disease or pest changes.	It has the capacity to adapt to specific, complicated changes in the natural environment.

Table 2. Characteristics analysis of different platform of deep learning

Product Tools	**Supporting Hardware**	**Publisher**	**Programming Platform**	**Benefits**
Theano	CPU, GPU	MILA	Python	Flexibility and perfection
Tensorflow	CPU, GPU, Mobile	Google	C, Python	Strong performance, design portability, and assistance with distributed applications.
Caffe	CPU, GPU	BAIR	Python, Matlab	Good readability, simple expansion, quick speed, a vast user group, and a large community
PyTorch	CPU, GPU, FPGA	Facebook	C, Python, Lua	Simple to grow, lot of useful features, enable dynamic neural networks, and easy to debug and create

According to the aforementioned review, other approaches using a CNN-based deep learning model produced outstanding results. The suitable product tools and platform are Tensorflow by Google Publisher, which uses a user-friendly Matlab language. The research is completed using the aforementioned combinations. The nature of the diseases must be studied in order to evaluate the proposed system's performance. As a result, Part III provides a thorough understanding of disease aetiology, manifestations, and therapeutic approaches.

III. MANGO LEAF DISEASES: CLASSIFICATION & MANAGEMENT

The most affected diseases are examined, and management studies are conducted based on the available literature[23], [24],&[25]. They are as follows:

3.1. Anthracnose

Causes **-**A fungus infestation has occurred. The widespread fungus Colletotrichum gloeosporioides is the causative agent of anthracnose infections on mango leaves.

Symptoms **-** Tan to dark brown patches can be seen along the margins of infected leaves which is shown in Fig.1. Semi-circular lesions can be seen on immature bronze and light green leaves. Eventually, the lesions fall off the leaves. Old leaves develop stains that resemble charcoal, and the leaves curl.

Management **-**

(a) Spraying 1.0 percent Bordeaux mixture or 0.1 percent carbendazim (50 WP) every 14 to 20 days will control foliar anthracnose.
(b) From the time when panicles initially show until the growth of fruits, above-ground fungicides should be applied four to five times.
(c) Branches that are infected should be cut down and burned.

Vol 12 Issue 02 2023
ISSN NO: 2230-5807

Fig. 1. **Mango Leaf Anthracnose disease**

3.2. Bacterial Canker

Causes **-** A bacterial infestation has occurred. The Xanthomonas campestris is the causative agent of bacterial canker infections on mango leaves.

Symptoms **-** The illness causes water-soaked sores that subsequently develop into typical canker and is seen on twigs,leaves, stems,leaf stalks, fruits, and branches. On leaves, angular elevated lesions with a diameter of 1-4 mm are generated by water-soaked irregular satellites.

Fig. 2. **Bacterial Canker on Mango Leaves**

These lesions are originally bright yellow in colour with a yellow halo, but as they degenerate or group together, they take on an irregular shape and turn a dark brown colour which is shown in Fig. 2. The leaves drop off and turn yellow after severe illnesses.

Management **-**

(a) Using sterile planting and grafting supplies and approved seedlings
(b) Fruit infection is reduced by two sprays of streptomycin (200-300 ppm) spaced 20 days apart. It works to dip the fruits in an agrimycin-100 solution with a 200-ppm concentration.

3.3. Cutting Weevil

Causes **-** It is an insect infection and caused by Curculionidae - coleoptera [26].

Symptoms **-**Young leaves that have been clipped and have fallen to the ground are the most visible sign of a D. marginatus attack which is shown in Fig. 3. The infected plant has plainly visible stripped shoots. Young leaves develop "windowpanes" from adult eating.

Fig. 3. Cutting Weevil on Mango Leaves

Management -

(a) Egg-filled cut leaves can be gathered, dried, or burned. The pupae may perish if the soil beneath the host plants' crowns is ploughed.
(b) When immature leaves are 3 cm wide, insecticide is administered. The young shoots can be effectively shielded from D. marginatus attack with just two or three applications spaced out over a week.
(c) D. marginatus can be controlled with the help of insecticides like trichlorphon, deltamelthrin, and fenvalerate.

3.4. Die-Back

Causes - It is a fungal infection on Mango species and caused by fungi Botryosphaeriaceaein [27].

Symptoms - Twig tip dieback, depicted in Fig. 4, is one of the signs of this disease that develops into old wood and causes branches to dry out and die as well as branches and leaves to burn and fall off, ultimately killing plants.

Fig. 4. Die-Back Disease on Mango Leaves

Management -

(a) Trees that have the disease can be treated by spraying infected trees with Copper Oxychloride (0.3%) and cutting diseased twigs 2 to 3 inches below the affected area.
(b) About 0.3% of Copper Oxychloride is pasted on the clipped twigs’ cut ends [28].

3.5. Gall Midge

Causes - Thecommon mango midges Keiffer and Cecconi, which are responsible for Procontarinia matteiana infection, also cause gall formation.

Symptoms - Mango midges primarily harm newly emerging leaves. Adult midges lay their eggs on the underside of mango leaves in the months of March, July, and October. The larvae produce raised, smooth to rough, blister- or wart-like galls on the upper surface of mango leaves. Depending on the type of midge, various gall types may develop on the same leaves.

Fig. 5. Gall Midge on Mango Leaves

Several hundred of these galls can grow on a single leaf during a severe infestation. Gall formation and larvae feeding on the phloem sap inside the leaves both decrease the photosynthetic area and hence the yield. The gall formation on mango leaves is shown in the Fig. 5.

Management -

(a) If the insect population is small, hand-pick it.
(b) Seasonally prune the infected branch.
(c) To catch the fly, use a yellow sticky trap.
(d) Mist insecticides such as monocrotophos, bifenthrin, and methyldemeton 25 EC at 2 and 7 millilitres per litre, respectively. Dimethoate 30 EC is also effective.

3.6. Powdery Mildew

Causes - It is a fungal infection disease. It is caused by the fungus Oidium mangiferae.

Symptoms - Oidium mangiferae preys on the developing tissue of all inflorescence components, including the leaves and fruits. Small patches of white powdery mycelium that are the first signs of infection may subsequently merge to cover considerable areas which is shown in Fig. 6. As the white growth deteriorates, diseased tissue on older leaves and fruits takes on a purplish-brown colour.

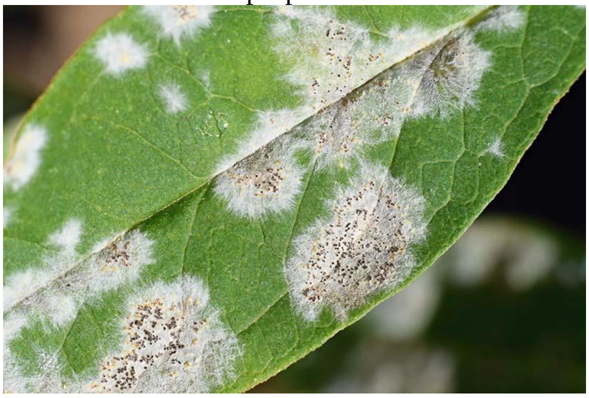


Fig. 6. Powdery Mildew on Mango Leaf

Management -

(a) Applying fine sulphur (250–300 mesh) at a rate of 0.5 kg per tree to the damaged plants.
(b) The first application, which can be done soon after blooming, and the second application, which can be made 15 days later, may both be made with a spray containing Wettable Sulphur (0.2%), Carbendazim (0.1%), Tridemorph (0.1%), or Karathane (0.1%).

3.7. Sooty Mould

Causes - It is a fungal infection disease. Sooty mould on mango leaves is shown in Fig. 7.

Symptoms - The surface of the leaf has a black velvet covering. The symptoms may at first just be seen as flakes on the leaf, or they may eventually cover the entire leaf surface. In extreme circumstances, the entire tree turns entirely black as a result of the mould that covers every inch of the twigs and leaves. Such impacted leaves curl and shrivel during dry spells.

Fig. 7. **Sooty Mould on Mango Leaves**

Management -

(a) The disease cannot spread if damaged branches are promptly pruned and destroyed.
(b) Using Wettable Sulphur (0.2%) or Mancozeb (0.2%) Plus Clorpyriphos (2 ml/l) at intervals of 10-15 days is quite effective.

IV. PROPOSED CNN-BASED DEEP LEARNING TECHNIQUES

4.1. CNN Architecture

A Convolutional Neutral Network (CNN) has an input layer, an output layer, and further hidden layers. The key elements of the hidden layers are the convolution layer, pooling layer, parametric rectified linear unit (PReLU), dropout layer, and normalisation layer. When categorising photos, an image serves as the input and the output, often referred to as a label, and appears to be the class name.

There are numerous pre-trained convolutional neural network designs, such as Alexnet, VGG-16, and VGG-19, served as inspiration for the design of the deep CNN architecture suggested in this work, which contains three hidden layers.The organisation of the structure of each individual layer is not defined by a specific rule. Fig. 8 illustrates the intended CNN architecture based on Mangifera Indica leaf disease recognition.

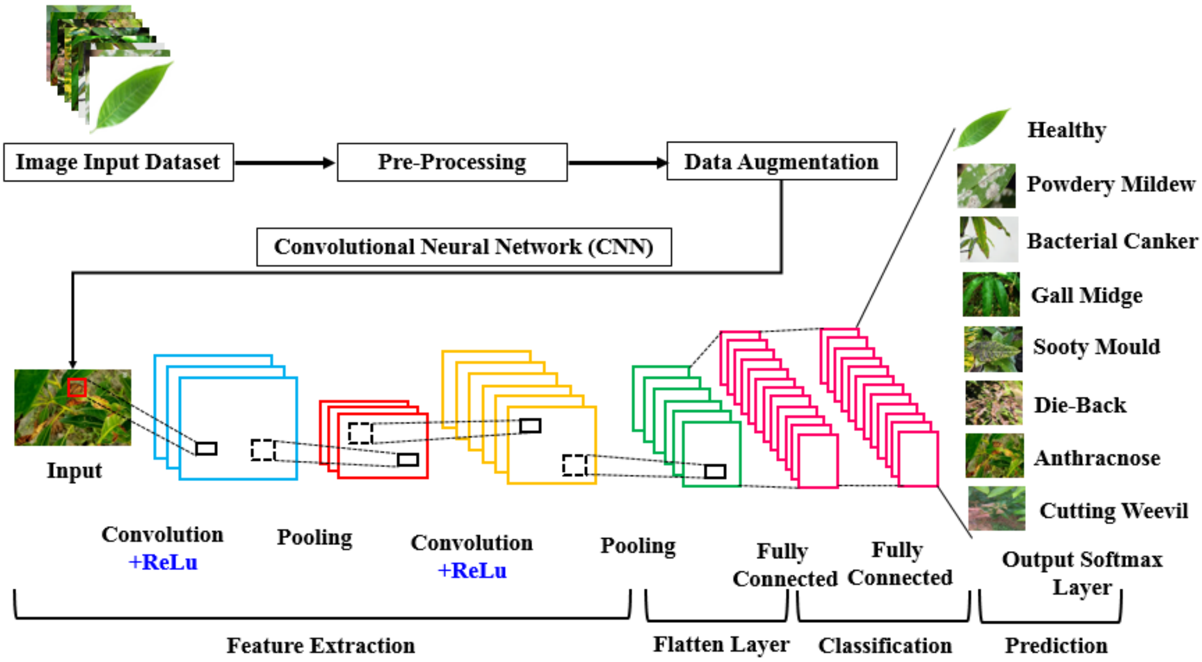


Fig. 8. **Flow Diagram of the Proposed CNN-based Identification Process**

4.2. Input Layer

The CNN model can be connected directly to the image as input. The image size is specified as 256, 256, 3, which denotes the height, width, and RGB colour of the image. For feature extraction purposes, the input image is converted into grayscale, which is denoted by the number 1. Before sending the images to the CNN model, data augmentation can be performed.

Due to the huge data requirements of neural networks and deep learning models, the dataset is expanded by creating artificial data and adding it to the initial dataset. While maintaining the image's name, various changes are applied to the photographs to enhance them. These transformations include rotating, zooming, cropping, transposing, and skewing.

4.3. Convolutional Layer

The convolution operation is the CNN's main process.The first network layer of a CNN is always a convolutional layer, and the input for the second network layer is either a feature map from the layer before or an image for the first network layer. The input and the filters, or kernels, are convolved to produce the output feature maps. The output of convolution process can be represented as,

$$x_j^l=f\left(\sum_{i\in M_j} x_i^{l-1} * k_{ij}^l+b_j^l\right) \quad (1)$$

Where, x_j is the collection of output feature maps; M_j is the collection of input maps; k_{ij} is the convolution kernels; b_j denotes the bias process. The output feature map's size is determined by the equation (2).

$$O = \frac{W-K+2P}{S} + 1 \quad (2)$$

Where, O is the feature map's output; W is the input width, K is the size of filter; P denotes Padding and S denotes the Stride. In order to keep the output's size constant, the input's edges can be padded with zeros. By using the filter size, it is possible to determine the padding amount, P, which is represented in the equation (3).

$$P = \frac{K-1}{2} \quad (3)$$

4.4. Parametric Rectified Linear Unit (PReLu) Layer

Rectified Linear Unit (ReLU) use to address the gradient disappearing problem is the primary characteristic of the pre-trained CNN model [24]. The learning cycle is significantly shortened and speed and efficiency are both increased when the ReLU function is used in the network. ReLU's disadvantage is that they are unable to learn from cases for which they have zero activation. ReLU is often placed on the hidden layers and the neural network is initialised with a value of 0.

To shorten the issue, a type of activation function based on a Rectified Linear Unit (ReLU) is known as a Leaky Rectified Linear Unit (Leaky ReLU), which has a small slope for negative values as opposed to a flat slope. Even though it has same issues produced while using ReLU function. By combining both ReLU and Leaky ReLU function, Parametric ReLU (PReLU) is used here, and its mathematical formula in equation (4).

$$y_i = \max(0, x_i) + a_i \times \min(0, x_i) \quad (4)$$

A learnable parameter among them is a_i. Leaky ReLU is the result when a_i is a fixed lower non-zero value. When it is 0, PReLU and ReLU are identical.

4.5. Max-Pooling Layer

In this layer, the input is divided into several, non-overlapping blocks, and the most significant information from each block is output to produce a smaller output. It has the ability to manage the overfitting issue as well. In this layer, there is no learning process.

4.6. Drop-Out Layer

The fundamental principle behind the dropout layer is that input items with a specific probability are either silenced or dropped out, enabling individual neurons to learn properties that are less reliant on their environment. The training period is the only time this process takes place.

4.7. Batch Normalization Layer

Occasionally the convolution and PReLu layers are placed before the batch normalization layer. It improves training speed while decreasing network initialization sensitivity. In this layer, the activations of each channel are normalised by dividing by the mini-batch standard deviation and removing the mini-batch mean. This is followed by an offset shift, β and a factor scaling of the input, γ.

The training method involves changing these two variables. The normalized batch output, y_i is expressed in equation (5).

$$y_i=BN_{\gamma,\beta}(x_i)\equiv\gamma\widehat{x}_i+B \quad (5)$$

Where, $\widehat{x}_i$ is the normalization of activation layer, x_i and it is expressed in equation (6).

$\widehat{x}_i=\frac{x_i+\mu_B}{\sqrt{\sigma_B^2+\varepsilon}}$ (6)

Where, ε - Constant; μ_B and σ_B^2 are the mini-batch mean and variance respectively. It can be given in the equations (7) and (8).

$\mu_B=\frac{1}{m}\sum_{i=1}^{m} x_i$ (7)

$\sigma_B^2=\frac{1}{m}\sum_{i=1}^{m} (x_i-\mu_B)^2$ (8)

Where, m denotes the size of the mini-batch. In this method, the optimization issue can be simplified and network training accelerated.

4.8. Fully Connected layer

The completely connected layer integrates all of the features that the previous layer had learnt to facilitate categorization. All of the neurons in the fully connected layer are coupled to every neuron in the preceding layer.The output of this layer is an N-dimensional vector, where N is the number of classes.

4.9. Output Layer

The output layer's initial layer is the classification layer, which is followed by the Softmax layer. Using the probability distribution that the Softmax layer generates, the network model classifies an instance as belonging to the class with the highest probability value. The Softmax function, also called the Normalised Exponential, is described by equation (9).

$P(C_r|x,\theta)=\frac{P(x,\theta|C_r)P(C_r)}{\sum_{j=1}^{k} P(x,\theta|C_j)P(C_j)}$ (9)

Where, $P(x,\theta|C_r)$ is the conditional probability at an instance given class r. The equation (9) can be re-written as,

$P(C_r|x,\theta)=\frac{\exp(a_r(x,\theta))}{\sum_{j=1}^{k}\exp(a_j(x,\theta))}$ (10)

Where, $a_r = \ln(P(x,\theta|C_r)P(C_r))$.

V. PROCESS IMPLEMENTATION, RESULTS AND DISCUSSIONS

5.1. Process Implementation

The total dataset comprises of 4000 pictures of both healthy and diseased mango leaves. It is categorized into two groups: testing and training. Of the images, 75% are randomly selected for training. The majority of neural network applications employ this ratio distribution. In order to train CNN, 3200 photos are used, while the remaining 800 images are saved for performance evaluation, as seen in Fig. 9.

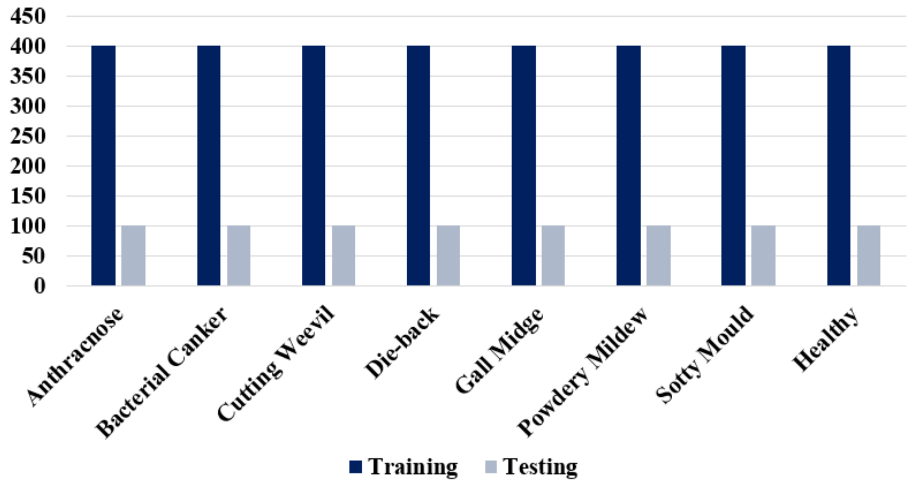


Fig. 9.Dataset distribution for training and testing

Running training examples through a CNN from the input layer to the output layer while making a prediction and analysing the outcomes or errors is known as training a CNN. The open-source programming language Matlab is used to implement the proposed CNN-based deep learning system for mango leaf disease detection, and Fig. 10 demonstrates a flowchart for the system's process.

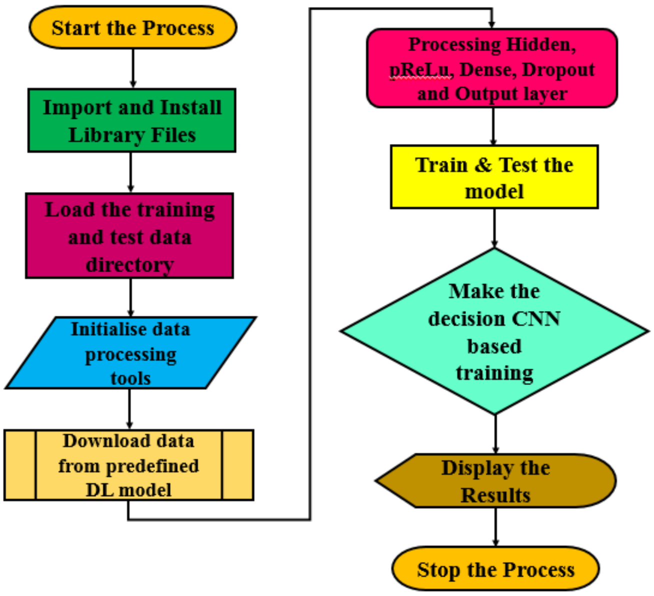


Fig. 10.Flowchart for process implementation

5.2. Results and Discussions

The identification and analysis of several kinds of mango leaf diseases are carried out using MATLAB 2019 simulation software in accordance with the methods detailed in Section IV and the recommended architecture illustrated in Fig. 8.

The multiple image datasets provided in [29] are used in the simulation-based proposed technique.Using the well-known CNN models, the simulations were initially ran on normalised and improved datasets. The well-known CNN model studied is the PReLU activation function. The trained picture dataset contains 75% of its saved data in Mat format. This phase is expected to be significantly faster to perform than the ReLU function. The testing results obtained during the identification phase are shown in Fig. 11.

Fig. 11. Simulation results through identification phase

The effectiveness of various machine learning algorithms can be evaluated using a wide range of indicators. The success of the suggested technique is evaluated using the seven most popular measures, including accuracy, loss function, recall,precision, F1 score,specificity andconfusion matrix[30]. The equation (11) for mean average precision (MAP), which assesses the precision of recognition.

$$\text{MAP} = \frac{\text{No.of True Detection}}{\text{No.of True Detection+No.of False Detections}} \quad (11)$$

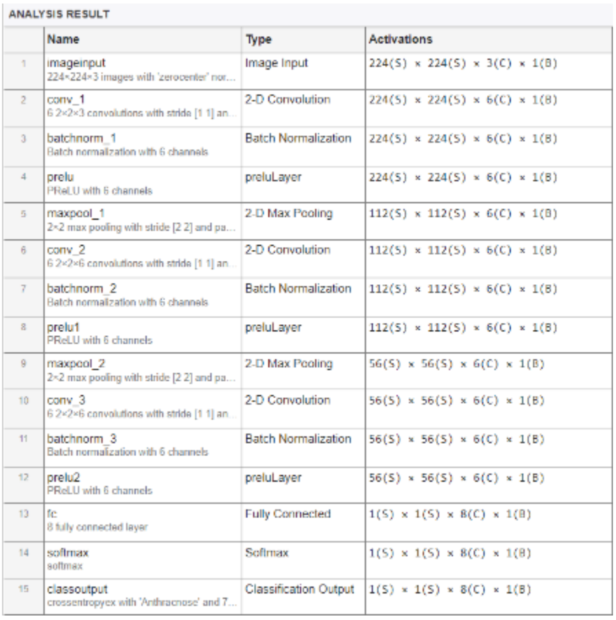
The performance of CNN is also evaluated using the loss function, which makes predictions from a small collection of outcomes known as classes.Equation (12) represents accuracy as the measure of the proportion of accurate classifications to all classifications.

$$\text{Accuracy} = \frac{T_P+T_N}{T_P+T_N+F_P} \quad (12)$$

The accuracy and loss obtained from the proposed system simulation are listed in Table. 3.Figs. 12 and 13show the proposed CNN procedure with PReLU function analysis, as well as the confusion matrix.The accuracy obtained by this system is 96.12%.

Table 3. Accuracy and loss analysis of proposed system

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:01:01	3.91%	27.82%	3.0688	1.8459	0.0003
3	50	00:05:52	89.84%	87.75%	0.3900	0.3871	0.0003
5	100	00:11:00	94.53%	93.34%	0.2396	0.2476	0.0001
7	150	00:15:49	96.09%	95.97%	0.2002	0.1946	4.8000e-05
9	200	00:20:39	95.31%	96.22%	0.1583	0.1780	4.8000e-05
10	240	00:24:31	96.88%	96.75%	0.1667	0.1698	1.9200e-05



ANALYSIS RESULT

	Name	Type	Activations
1	imageinput 224×224×3 images with 'zerocenter' nor...	Image Input	224(S) × 224(S) × 3(C) × 1(B)
2	conv_1 6 2×2×3 convolutions with stride [1 1] an...	2-D Convolution	224(S) × 224(S) × 6(C) × 1(B)
3	batchnorm_1 Batch normalization with 6 channels	Batch Normalization	224(S) × 224(S) × 6(C) × 1(B)
4	prelu PReLU with 6 channels	preluLayer	224(S) × 224(S) × 6(C) × 1(B)
5	maxpool_1 2×2 max pooling with stride [2 2] and pa...	2-D Max Pooling	112(S) × 112(S) × 6(C) × 1(B)
6	conv_2 6 2×2×6 convolutions with stride [1 1] an...	2-D Convolution	112(S) × 112(S) × 6(C) × 1(B)
7	batchnorm_2 Batch normalization with 6 channels	Batch Normalization	112(S) × 112(S) × 6(C) × 1(B)
8	prelu1 PReLU with 6 channels	preluLayer	112(S) × 112(S) × 6(C) × 1(B)
9	maxpool_2 2×2 max pooling with stride [2 2] and pa...	2-D Max Pooling	56(S) × 56(S) × 6(C) × 1(B)
10	conv_3 6 2×2×6 convolutions with stride [1 1] an...	2-D Convolution	56(S) × 56(S) × 6(C) × 1(B)
11	batchnorm_3 Batch normalization with 6 channels	Batch Normalization	56(S) × 56(S) × 6(C) × 1(B)
12	prelu2 PReLU with 6 channels	preluLayer	56(S) × 56(S) × 6(C) × 1(B)
13	fc 8 fully connected layer	Fully Connected	1(S) × 1(S) × 8(C) × 1(B)
14	softmax softmax	Softmax	1(S) × 1(S) × 8(C) × 1(B)
15	classoutput crossentropyex with 'Anthracnose' and 7...	Classification Output	1(S) × 1(S) × 8(C) × 1(B)

Fig. 12. Process flow Analysis

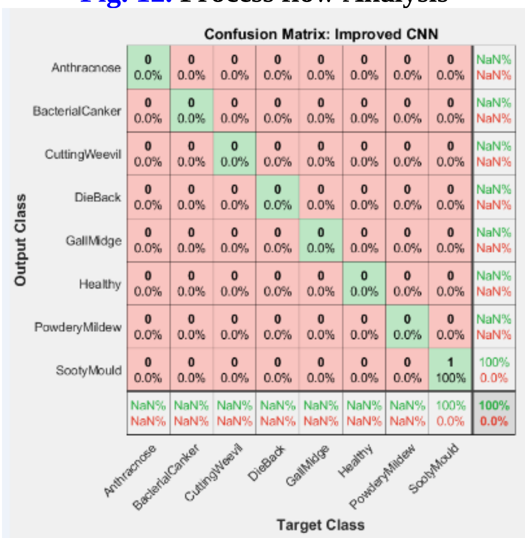


Fig. 13. Confusion Matrix

VI. CONCLUSION

A CNN model pre-trained with the PReLU activation function was used to analyse eight different forms of diseases affecting Mangifera Indica (mango) plants. The following are the advantages of the suggested methodology over others: Less convolutional layers are used when using the PReLU function, boosting accuracy; reducing resource requirements due to fewer layers; reducing system complexity; and enhancing accuracy over others.The proposed CNN with PReLU activation-based identification and analysis has demonstrated its uniqueness, it is determined.Other agriculturally focused disease analysis will be conducted using the same methodologies to forecast the proper diseases at the proper time for the welfare of the farmers as well as the nature and scope of the future work.

References

[1] Fizza Mubarik, San a Noreen, Fatima Farooq, Ayesha Siddiqa & Mudassir Khan, "A Review on Pharmacological and Nutritional Benefits of Mango (Mangifera Indica Linn): A Remedy for Cancer, Diabetes and Gastrointestinal Infections", Abasyn Journal of Life Sciences, vol. 3, no. 2, pp. 82 - 92, 2020. http://dx.doi.org/10.34091/AJLS.3.2.8

[2] Ali, Abdullahi Attah Alfa, Kokori Bajeh Tijani, Egbeja Tsobaza Idris, Umar Sabdat Unoyiza Junaidu, "Nutritional Health Benefits and Bioactive Compounds of Mangifera indica L ıves Methanolic Extracts", Asaian Plant Research Journal, vol. 6, no. 2, pp. 41 -51, 2020. g/10.9734/aprj/2020/v6i230126

[3] OM. Prakash and A. Misra, "Important diseases of mango and their effect on production", Biological Memoirs, vol. 18, pp. 39 - 55, 1992.

[4] Sotirios A Tsaftaris, Massimo Minervini, Hanno Scharr "Machine Learning for Plant Phenotyping Needs Image Processing", Trends in Plant Science, vol. 21, no. 12, pp. 989 - 991, 2016. http://dx.doi.org/10.1016/j.tplants.2016.10.002

[5] Fuentes A, Yoon S, Park DS. Deep learning-based techniques for plant diseases recognition in real-field scenarios. In: Advanced concepts for intelligent vision systems. Cham: Springer; 2020.

[6] Shripad S.Veling, Rohit S. Kalelkar, Likhita V. Ajgaonkar, Nivedita V. Mestry, Nilesh N. Gawade, "Mango disease detection using Image Processing", International Journal for Research in Applied Science & Engineering Technology (IJIRASET), vol. 7, no. 4, pp. 3717 - 3726, 2019. https://doi.org/10.22214/ijraset.2019.4624

[7] S. Sujatha, N. Saravanan and R. Sona, "Disease Identification in Mango Leaf using Image Processing", Advances in Natural and Applied Sciences, vol. 11, no. 6, pp. 1 - 7, 2017.

[8] Budiarianto Suryo Kusumo, Ana Heryana, Oka Mahendra and Hilman F. Pardede, "Machine Learning-based for Automatic Detection of Corn-Plant Diseases using Image Processing", International Conference on Computer Control, Informatics and its Applications (IC^{3}INA), 2018. https://doi.org/10.1109/IC3INA.2018.8629507

[9] Shriroop C. Madiwalar and Medha V. Wyawahare, "Plant Disease Identification: A Comparative Study", International Conference on Data Management, Analytics and Innovation (ICDMAI), Pune, 2017. https://doi.org/10.1109/ICDMAI.2017.8073478

[10] Md Rasel Mia, Sujit Roy, Subrata Kumar Das & Md. Atikur Rahman, "Mango Leaf Disease Recognition using Neural Network and Support Vector Machine", Iran Journal of Computer Science, vol. 3, pp. 185 -193, 2020. https://doi.org/10.1007/s42044-020-00057-z

[11] Kestur, R. Meduri, A. & Narasipura, O., "MangoNet: A deep semantic segmentation architecture for a method to detect and count mangoes in an open orchard", Engineering Applications of Artificial Intelligence, vol. 77, pp. 59 - 69, 2019.https://doi.org/10.1016/j.engappai.2018.09.011

[12] Rabia Saleem, Jamal Hussain Shah, Muhammad Sharif , Mussarat Yasmin, Hwan-Seung Yong & Jaehyuk Cha, "Mango Leaf Disease Recognition and Classification using Novel Segmentation and Vein Pattern Technique", Applied Sciences, 202. https://doi.org/10.3390/app112411901

[13] Melnyk P, You Z, Li K. "A High-Performance CNN Method for Offline Handwritten Chinese Character Recognition and Visualization", Soft Computing, vol. 24, no. 79, pp. 77 - 87, 2019.

[14] Sundararajan SK, Sankaragomathi B, Priya DS., "Deep Belief CNN Feature Representation based Content based Image Retrieval for Medical Images", Journal of Medical Systems, vol. 43, no. 6, pp. 1 – 9, 2019.

[15] Kumar S, & Singh SK, "Occluded Thermal Face Recognition using Bag of CNN (BoCNN)",

IEEE Signal Processing Letters, vol. 27, pp. 975 - 979, 2020. https://doi.org/10.1109/LSP.2020.2996429

[16] Li J, Mi Y, Li G, Ju Z, "CNN-based Facial Expression Recognition from Annotated RGB-D Images for Human–Robot Interaction", International Journal of Humanoid Robot, vol. 16, no. 4, 2019. https://doi.org/10.1142/S0219843619410020

[17] Jun Liu & Xuewei Wang, "Plant Diseases and Pests Detection-based on Deep Learning: A Review", Plant Methods, vol. 17, no. 1, 2021.https://plantmethods.biomedcentral.com/articles/10.1186/s13007-021-00722-9

[18] U. P. Singh, S. S. Chouhan, S. Jain and S. Jain, "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease," in IEEE Access, vol. 7, pp. 43721-43729, 2019, doi: 10.1109/ACCESS.2019.2907383.

[19] Theano - http://deepl earni ng.net/softw are/theano/.

[20] Caffe - http://caffe .berke leyvi sion.org/.

[21] TensorFlow - https ://www.tenso rflow .org/.

[22] PyTorch - https ://pytor ch.org/.

[23] https://vikaspedia.in/mango-diseases-and-symptoms

[24] https://www.plantsdiseases.com/p/diseases-of-mango.html

[25] https://www.krishisewa.com/disease-management/ 399-disease-mango.html

[26] https://plantwiseplusknowledgebank.org/doi/10.1079/PWKB.Species.18427

[27] Al Adawi A.O, Deadman M.L, Al Rawahi A.K, Khan A.J., Al Maqbali Y.M, "*Diplodia theobromae* associated with sudden decline of mango in the Sultanate of Oman", Plant Pathology, vol. 52, no. 3, pp. 419, 2003. http://dx.doi.org/10.1046/j.1365-3059.2003.00841.x

[28] https://www.agrifarming.in/mango-pests-diseases-and-control-methods-a-full-guide

[29] https://data.mendeley.com/datasets/hxsnvwty3r

[30] Dasgupta, R.; Chowdhury, Y.S.; Nanda, S.Performance Comparison of Benchmark Activation Function ReLU, Swish and Mesh for Facial Mask Detection Using Convolutional Neural Network", Algorithms Intelligence Systems, vol. 31, pp. 355 - 367, 2021.