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Mango Leaf Stress Identification Using Deep Neural Network

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Abstract: Mango is a widely growing and consumable fruit crop. The quantity and quality of production are most important to satisfy the needs of the huge population. Numerous research has been conducted to increase the yield of the crop. But a good number of crop harvests were destroyed due to various factors and leaf stress is one of them. The various types of stresses include biotic and abiotic that impact the mangoes productivity. But here the focus is on biotic stress factors such as fungus and bacteria. The effect of the stress can be reduced in the preliminary stage by taking some affirmative steps such as earlier detection and resolutions for the same. So many advanced techniques and methods have been used extensively to identify and classify certain stresses. This research supports farmers in identifying early-stage stresses in the plant leaf, that enhances the mango quality and quantity. This approach's main objective is to ensure that farmers are accurately informed and driven by accurate results of the diagnosis based on affirmative knowledge. The complete approach is laid down in two folds. Firstly, the region of interest is segmented from input images. The region of interest is used to extract symmetrical features of images and these features are used to create symmetry in the classification and identification. Secondly, the segmented image is processed through Convolutional Neural Network (CNN). CNN model is a multilayer model that automatically extracts features from the inputted image. The proposed technique is compared with various models such as VGG16, VGG19, and RestNet, etc. The proposed technique in this paper outperforms other models. The whole experiment was performed using Google Co-Lab using dataset from a known standard or open-source repository. The data collection is composed of different diseases characteristics compared to a healthy leaf. The different stress approach was chosen for different types of mango leaves like powdery mildew, anthracnose, dieback, phoma blight, bacterial canker, and red rust. The result outcomes proved that the proposed approach was 98.12% accurate to identify stress and can be beneficial in actual application by farmers.

Keywords: Convolutional neural network (CNN); artificial intelligence (AI); biotic disease; segmentation; image processing

1 Introduction

The Plants are essential for the ecosystem and they encounter various barriers due to different types of stresses. They can be the reason for the huge loss of plant production. The preliminary and precise identification of stresses during growth stages would helps to reduce the possibility of ecological harm.

The Mango trees are important for maintaining biodiversity and are a major source of fruits. The king fruit “Mango” is gaining a lot of traction in the agricultural industry. As a result, there is an increasing global understanding of mango plant cultivation as a means of promoting fruit production through sustainable agricultural practices. Stress is an important factor that affects crop production. The symptoms of stress can be found on the leaves, stems, and fruits in general. The signs of stress on the leaf are easy to monitor since they are noticeable on the leaf. Different types of stresses can impact plant leaf such as biotic, abiotic, and combinatorial as discussed in [1,2]. This paper addresses the issue of biotic stress due to bacteria, fungus, etc., and deals with one stress at a time on a plant leaf. The leaf images with stresses have asymmetric features and classification is the way to create symmetry in the stress classes [3]. The Mango trees are susceptible to a variety of stresses, including mango malformation stress, anthracnose, etc.

That’s why farmers use unnecessary pesticides to treat plant stresses in absence of knowledge which affect the yield of plant. As a result, careful treatment is essential for the initial recognition of leaf stresses. However, the manual detection of insects and stress is ineffective and expensive. If the field is broad, the manual identification process takes a long time. Therefore, plant leaf images are one of the best and reliable ways to detect stress in computer vision applications. The images are processed using competent image identification technology which contains filtering, scaling, and other operation. These operation generates a symmetric image with efficiencies in image identification, reduce the expenses, and enhance the identification accuracy [4,5]. As a result, sample images can be taken and fed into the algorithm, which will detect plant stresses. The term “plant stresses” refers to patterns of disease on a plant leaf. For good yields, the earlier detection of stress is required.

Mango leaf stress is difficult to diagnose by manual observation that’s why technology is needed for accurate stress detection at the appropriate stage. Formerly, experts had analyzed and judged plant stresses manually, relying solely on visualization. However, this is extremely difficult in a wide area. This requires a significant amount of time and effort. Several techniques and algorithms are employed to identify leaf stresses but the deep learning techniques are best. A deep neural network has been used to resolve various issues in different fields as given in [6–12].

In this article, a deep neural network is used to tackle mango plant stress issues. Here, the convolutional neural network (CNN) with segmentation is applied to identify leaf stresses using leaf images. CNN inevitably extracts features from an input image. Other classical models never extract features automatically. But, leaf images are taken in different conditions that’s why there is an asymmetry in the leaf image. The image symmetry is achieved by using segmentation and extracting features from the same segmented images.

The major contributions of the paper or objectives:

a) To use the region of interest or stress part of the leaf image to process.
b) The challenges such as (1) changes in the radiance and spectral coefficient of reflection (2) Poor quality of images (3) Image sizes and forms are tackled. These are the reasons for asymmetry in the images [13].
c) The model is evaluated on other parameters that was not used in other work

The complete paper is described in various folds. Section 2 deals with the state of the art. Section 3, describes the material and method. The result analysis and discussion are given in Section 4. Section 5 is the concluding and future work.

2 Related Work

The agriculture sector is completely dependent upon the productivity of plants or crops. The good amount of crop yield is important for economy of a country's. The stress in the plants or trees is a worldwide issue and affects 25% productivity of plants every year. Several factors affect the productivity of plants such as plant stresses and the other environment factors.

Therefore, plant leaf stress detection at an early stage is the most prominent area of research in the past few years. Therefore, an effective stress detection system is required to identify stress. Therefore, huge amount of research has been carried out in agriculture and horticulture.

The support vector machine (SVM) is used in [14] to detect the leaf stress of the mango plant. The system can assist in stress detection without the intervention of experts, saving time by identifying stress using a computer rather than a manual system. The accuracy achieved using this updated model is 80%. Mango plant leaf stresses can be detected scientifically by combining pattern recognition, image detection, and mango fruit extraction methodologies [15,16]. A wavelet transformation segmentation approach with wavelet neural network approach for classification of mango leaf stress. In this work, they have used data of around 1150 images for the segmentation and classification of leaves [17]. The accuracy achieved using the wavelet model is 98.93% that shows its usage [18]. Presented a method for determining the magnitude of mango stress based on leaf photographs and used segmentation, Sobel, and Laplacian filters. Leaf stresses are a major problem in crop production and a threat to worldwide food productivity and quality. It is a tedious task to recognize the leaf stresses with naked eyes. There have been many proposals for using deep learning techniques to detect leaf stresses. Convolutional neural networks were used by the majority of them to create models based on low-resolution images [19]. The author compared the results of the Artificial Neural Network (ANN) model with pre-defined CNN models.

The ANN model results are much better than CNN (AlexNet, VGG16, ResNet model). ANN-based techniques are used in [20,21] to select features and identify stresses in mango leaves; they only consider the stable leaves with Anthracnose stress leaf. CNN has shown superior success (to that of humans) in identifying and classifying problems [22]. The author proposed a Le-Net architecture for the detection of soybean leaf stress with 91.25% accuracy [23]. On a limited dataset, for the detection of plant stresses, the Generative adversarial network (GAN) algorithm is used. Then for the recognition of this dataset, the baseline convolution neural network works with the resulting synthetic sample [24]. Proposed the classification accuracy of 98.75% from the AlexNet model and 96.25% from GoogleNet. The result shows that the performance of deep learning models is better than machine learning. A tea leaf disease detection method using the Non-dominated Sorting Genetic Algorithm (NSGA-II) is proposed in [25]. The proposed method also used Principal Component Analysis (PCA) and SVM-Multi class features algorithm to extract and classify various leaf stresses [26].

The description of stress detection techniques and their accuracy is given in Tab. 1.

Table 1: Description of stress detection techniques with accuracy

Reference	Technique	Species	Stress recognition	(Detection accuracy %)
[27]	Morphological operator and C-mean		Fungal and bacterial	
[28–32]	K-mean		Fungal and bacterial	
[33–40]			Fungal disease	
[41]	Genetic algorithm	Banana	Fungal disease	95.71%

(Continued)

Table 1 (continued).

Reference	Technique	Species	Stress recognition	(Detection accuracy %)
[42]	k-nearest neighbors (KNN)	Tomato	Early blight bacterial spot TYLCV	
[43]	GLCM	All	White blister, downy mildews, powdery mildews and clubroot	62.50%
[44–46]	Image processing	–	All	
[47]	k-mean and neural networks	All	Leaf disease	94%
[48]	K-mean and SVM		Grapes leaf disease	88.89
[49]	NN	Pepper		
[50]	MLP, SOM	Wheat (Triticumsp.)	Yellow rust	99%
[51]	RBF, MLP	Avocado (Persea americana)	Laurel wilt (Lw) disease	98%
[52]	NN-SOM	Cotton (Gossypium sp.)	Reniform nematode	97%
[53]	PNN	Rice (Oryza sativa L.)	Aphelenchoides besseyi, rice leaf roller	95%
[54]	CNN		26 crop diseases	99.3%
[55]	CNN		13 crop diseases	96.3%
[56]	PCA-DNN whale optimization algorithm	Tomato disease	10 diseases	94%

Various methods and techniques have been developed by the researcher to tackle the same issue but no one provided exact and correct information to farmers. This paper was also focused to provide a solution for the same issue with some other parameters which are not considered in the previous approach. In the literature, the authors concentrated on a few mango leaf stresses and they have considered the complete leaf area to process it. This may be the reason for an increase in the error rate. But here in this paper, the proposed approach considers the infected area only.

3 Material and Method

The section covers the dataset description and proposed algorithm.

3.1 Dataset

A dataset consists of mango leaf pictures. The model is trained with 80% of data from the dataset and 20% of data is kept for testing/validation and reference images are shown in Fig. 1. The dataset comprises distinct classes of stress and is taken from a popular standardized repository with multiple classes. The dataset has different classes belonging to different stresses and one for the healthy leaf.

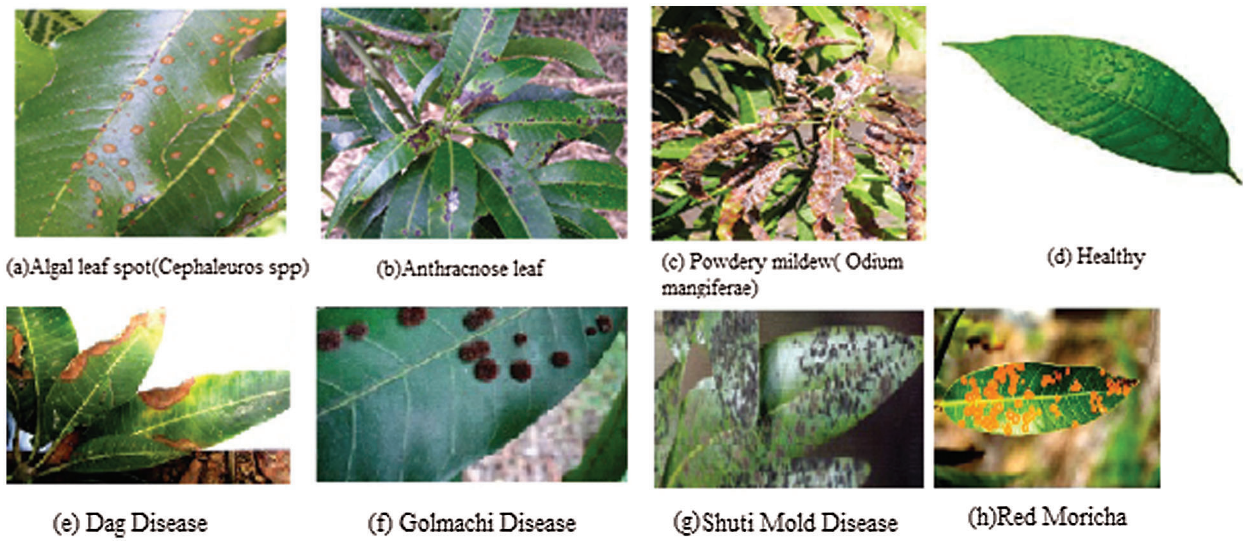

Figure 1: Sample mango stresses and healthy leaf

3.2 Mango Leaf Stress Detection

The stress detection methodology starts with the first phase of data pre-proceeding and labeling. Secondly, pre-processed data is classified using a Convolutional Neural network. The complete process of stress diagnoses is laid down in Fig. 2.

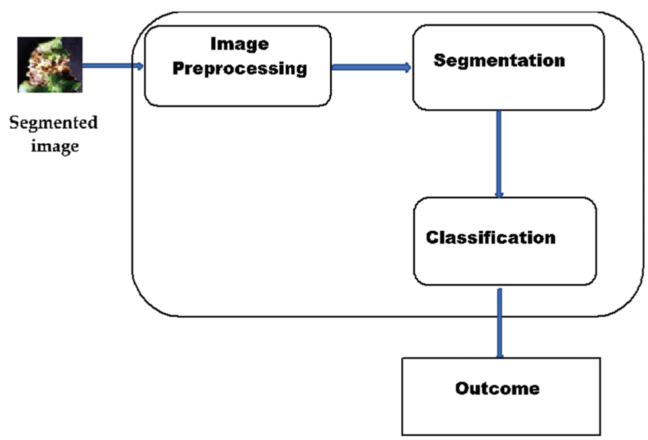

Figure 2: Classifier model

i. Image Pre-processing and Labelling

This is an initial phase, where the raw image dataset was pre-processed to remove noise before inputting it to the CNN classifier. It must be for a model to analyze the structure of the network and dataset to generate better outcomes. Therefore, the dataset is preprocessed initially to collect appropriate features of images which can be used by the model to accurately diagnose or predict the actual outcomes. Here in pre-processing, firstly, the size of each image is normalized as per requirement which is 256*256 pixels. The python libraries are utilized to perform the same task with maximum accuracy. Secondly, all images are converted into grey images.

The pre-processing stage is considered a phase that extracts image features to train the model. These training features are the reason for accurate prediction. After pre-processing, the data is labeled and segregated into different classes.

ii. Classification with Mathematical Model

Here, the CNN is used for classification, one of the most prominent technologies used at present. Here, the model is trained with the feature extracted in the previous phase. In the CNN, the image dataset is processed in different layers and each layer has the following sub-layers. The complete CNN structure is laid down in Fig. 3.

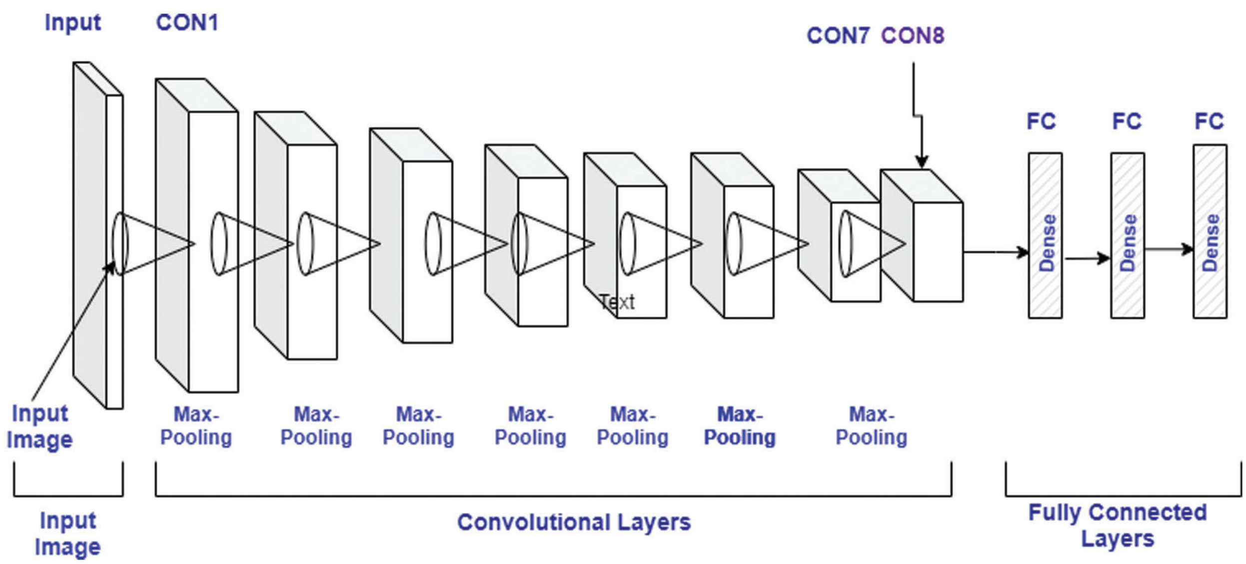

Figure 3: CNN model architecture

a) Input Layer

This represents a set image which passes as input to the CNN. The input image is represented by [height*width*nos of Color channel]. The color images represent the type of image that has 3 channels representing an RGB. The same input is passed through a segmentation and data argumentation before finally inputted to the CNN. The argumentation is performed through different operations such as rotation, cropping, etc. These operations are used to increase the dataset because CNN needs a large amount of data to give an appropriate outcome.

The hyperparameter used to configure Deep neural network are depicted in Tab. 2.

Table 2: Deep neural network tuning parameters

Parameter	Description
Convolution layer	10
Max pooling layer	10
Dropout rate	0.25
Net weight assigned	Uniform
Activation function	Relu
Learning rates	0.01, 0.01, 0.1
Numbers of filter	[32, 64, 128]
Stride	(1, 1)

b) Convolutional Layer

The main operation in the convolutional layer is convolution in which the input image was mapped with a filter of m*m and generates outcome feature maps. The outcome of the convolutional layer was expressed by Eq. (1)

$$A_n^m == \mathbf{f}\left(\sum\nolimits_{\mathbf{k}\in \mathbf{L_n}} \mathbf{A_{kn}^{m-1}} * \ \mathbf{M_{kn}^m} + \mathbf{C_n^m}\right) \tag{1}$$

where,

A_n: Outcome feature maps,

L_n: Input maps,

M_{kn}: Kernel of convolution,

C_n: Bias term.

The degree of the final feature map is expressed by,

$$N = \frac{(\mathbf{X} - \mathbf{M} - 2\mathbf{Y})}{\mathbf{T}} \tag{2}$$

where,

N: output height/length

X: input height/length

M: filter size,

Y: padding,

T: Stride.

Here, padding can be used to store the output. The padding is expressed by Eq. (3):

$$\mathbf{Y} = \frac{(\mathbf{M} \quad - \quad \mathbf{1})}{\mathbf{2}} \tag{3}$$

where, M: filter size.

- ReLU Layer: This also plays an important in CNN and is also known as the Activation layer. This layer is next to the convolution layer and the output of the same will be input to the ReLU. This layer creates linearity in the convolutional process. So, each convolutional layer found associated with a ReLU layer. The important task of this layer is to update all negative activation to zero and thresholding which is given by f(p) = max (0, p). This layer helps the system to learn quickly and remove gradient problems. ReLU activation function is well designed for multiclass classification.
- Max-Pooling Layer: This layer generates the reduce sized output after maximizing the elements of each block. This layer also controls the overfitting problem without the learning process.
- Dropout Layer: This layer is used to drop out the input elements having a probability less than a certain value and this process is a part of the training phase.
- Batch Normalization Layer: This layer plays an important role in between the convolutional and ReLU layer. This layer is used to enhance the training speed and reduce sensitivity. This layer performs different operations (subtractor, division, shifting, and scaling). On the activation layer to normalize its value. Firstly, the activation is subtracted with mean, and divided by the standard deviation which is followed by fluctuating by α and then scaled by □. The batch normalized outcome, B_k is expressed by the Eqs. (4)–(7),

$$
\begin{aligned}
B_k = &\ \mathbf{D}O_{\theta_\alpha} \times (A_k) \\
&\equiv \boldsymbol{\theta}\widehat{A}_k + \ D
\end{aligned} \tag{4}
$$

where $\hat{\mathbf{A}}_k$ is the normalization of activation $\mathrm{A_k}$.

$$\hat{\mathbf{A}}_{\mathbf{k}} = \frac{\boldsymbol{A_k} + \boldsymbol{U_D}}{(\boldsymbol{\sigma}_{\boldsymbol{D}}^2 + \boldsymbol{\varepsilon})^{1/2}} \tag{5}$$

where,

ε: constant

U_D: Mini-batch mean

${\sigma_D}^2$: Mini-batch variance given by,

$$\boldsymbol{U_D} = \frac{\boldsymbol{1}}{\mathbf{d}} \sum_{\mathbf{k}=\boldsymbol{1}}^{\mathbf{d}} \mathbf{A_k} \tag{6}$$

$$\boldsymbol{\sigma}_{\boldsymbol{D}}^2 = \frac{1}{\mathbf{d}} \sum_{\mathbf{k}=1}^{\mathbf{d}} (\mathbf{A_k} - \mathbf{U_D})^2 \tag{7}$$

c) Fully Connected Layer

Here, the neurons of the next layer are connected with neurons of the previous layer and produced a vector and the vector dimensions represent the number of classes.

d) Output Layer

This layer is a combination of softmax and classification. In this layer, firstly, the softmax is used to distribute the probability and the classification is carried out by the network. The softmax is defined by Eq. (8)

$$\mathbf{P}(\boldsymbol{v}_{\mathbf{r}} \ |\mathbf{A},\ \boldsymbol{\theta}) = \frac{\mathbf{P}(\mathbf{A},\ \boldsymbol{\theta}|v_{\mathbf{r}})\ \ \mathbf{P}(v_{\mathbf{r}})}{\sum_{\mathbf{n}=1}^{\mathbf{M}} \mathbf{P}(\mathbf{A},\ \boldsymbol{\theta}|v_{\mathbf{r}})\mathbf{P}(v_{\mathbf{r}})} \tag{8}$$

where,

$0 \leq \mathrm{P}(\mathrm{v_r}|\mathrm{A}\ \ \boldsymbol{\theta}) \leq 1$ and $\sum_{\mathbf{n}=1}^{\mathbf{M}} \mathbf{P}(\mathbf{v_r}|\mathbf{A},\ \boldsymbol{\theta}) = \mathbf{P}(\mathbf{A},\ \boldsymbol{\theta}\ \ |\mathbf{v_r})$ is the conditional probability and class prior probability. Eq. (9) can also be

$$P(v_r|A,\ \theta) = \frac{\mathbf{expd_r}(\mathbf{A},\ \boldsymbol{\theta})}{\sum_{n=1}^{M} \mathbf{exp}\ d_n(A,\ \theta)} \tag{9}$$

written as follows, where

$$d_r = \ln(P(A,\ \theta|v_r)\ P(v_r)) \tag{10}$$

3.3 Stress Detection Algorithm

The identification process was initiated with color images (I_{RGB}). After the input, the segmented image (S_{RGB}) is extracted from the original image (I_{RGB}). The segmented image was further processed with CNN to generate a mask image (M_{mask}). The mask image (M_{mask}) was further divided into different regions K_{tiles}.

Afterward, K_{tiles} was used to select the Region of Interest (RoI) and the same was used to identify stress. The proposed algorithm has been given below:

Algorithm 1: Stress Detection

Input: Image data with different color image ($\boldsymbol{I_{RGB}}$)

Output: Stress Identification.

a) Generate Segmented image ($\boldsymbol{S_{RGB}}$)

b) Generate $\boldsymbol{M_{mask}}$ from $\boldsymbol{S_{RGB}}$

c) Split $\boldsymbol{M_{mask}}$ into smaller regions $\boldsymbol{K_{tiles}}$ (square tiles).

d) for ($\boldsymbol{K_{tiles}}$ in $\boldsymbol{M_{mask}}$) do

e) Classify $\boldsymbol{K_{tiles}}$ into $\boldsymbol{M_{mask}}$ Mango stresses.

f) if $\boldsymbol{K_{tiles}}$ is stressed then Identify Stress

g) end

The next section provides a detail explanation of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4 Result Assessment and Discussion

The research has been carried out with the help of Google Co-Lab-based GPU and python-based Keras libraries. The experiment was performed with varying the batch size, epoch, and learning rate. The experiment was performed with two epoch sizes i.e., 50 and 100, and three learning rates i.e., 0.1, .001, and .0001 learning rates. The results are discussed below in the sub-section:

The experiment was performed with a sample image partitioned into training and testing ratio. The performance of the model was measured on different performance indicators as given:

$$Accuracy\ \ (Acc) = \frac{\mathbf{T_p} + \mathbf{T_f}}{\mathbf{T_p} + \mathbf{T_f} + \mathbf{F_p} + \mathbf{F_n}} \tag{a}$$

$$Precision\ \ (Pre) = \frac{\mathbf{T_p}}{\mathbf{T_p} + \mathbf{F_p}} \tag{b}$$

$$Recall\ \ (Re) = \frac{\mathbf{T_p}}{\mathbf{T_p} + \mathbf{F}_n} \tag{c}$$

$$\boldsymbol{F1 - Sco} = \frac{\mathbf{P} \times \mathbf{R}}{\mathbf{P} + \mathbf{R}} \tag{d}$$

Note that $\mathbf{T_p}$, $\mathbf{T_f}$, $\mathbf{F_p}$, *and* $\mathbf{F_n}$ represent true positive, true negative, false positive, and false negative, respectively.

4.1 Epochs Test

The objective here was to observe the effect of Epochs on device efficiency. An epoch was a complete introduction to a learning machine of the data set. In this research, the experiment is conducted with 50 and

100 epochs size. Fig. 4 shows the test with 50 epochs and Fig. 5 shows 100 epoch sizes with a learning rate of 0.0001. Both show an accuracy rate that was 98.02% and 98%.

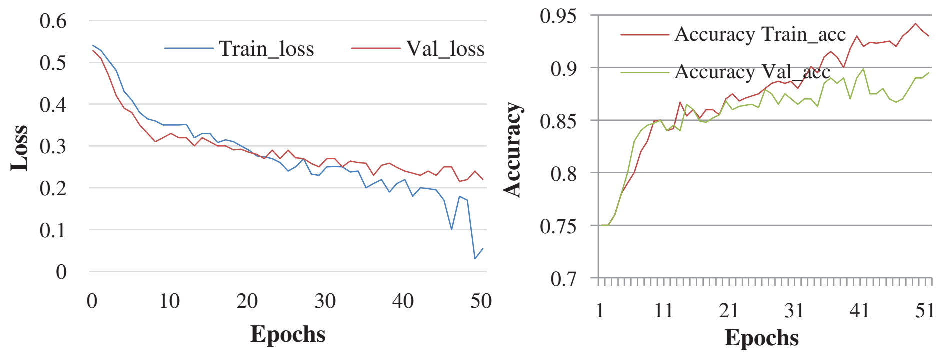

Figure 4: Accuracy and loss learning rate 0.0001

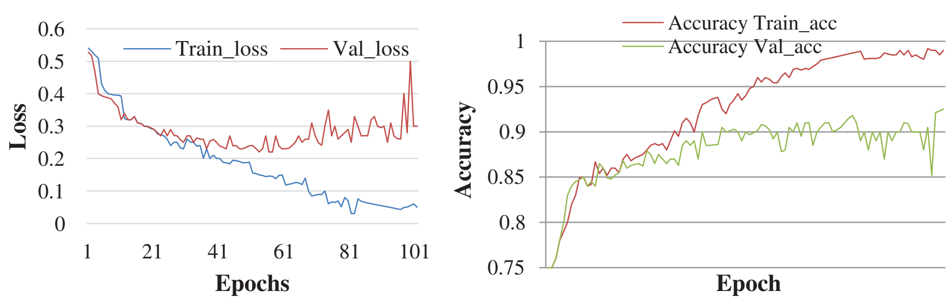

Figure 5: Accuracy and loss with learning rate 0.0001

It is possible to assume that more times will provide a higher percentage of data accuracy based on the research procedure. But the number of epochs is getting longer, the longer the training step involves.

Here, the experiment was conducted with 50 and 100 epochs size. Fig. 6 shows the test with 50 epochs and Fig. 7 shows 100 epoch sizes with a learning rate of 0.001. Both show an accuracy rate that is 98.07% and 98.25%.

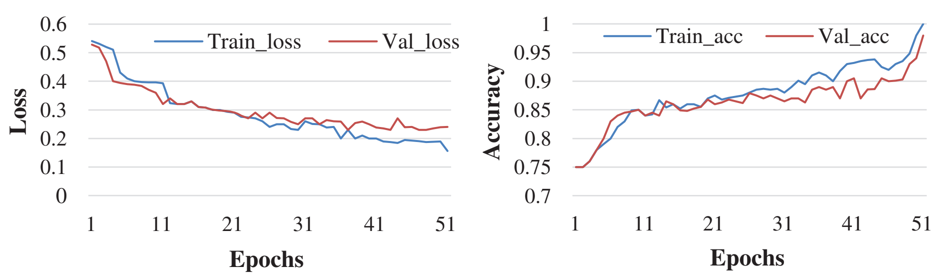

Figure 6: Accuracy and loss learning rate 0.001

Here, the experiment was conducted with 50 and 100 epochs size. Fig. 8 shows the test with 50 epochs and Fig. 9 shows 100 epoch sizes with a learning rate of 0.01. Both show an accuracy rate that is 98.12% and 98.12%.

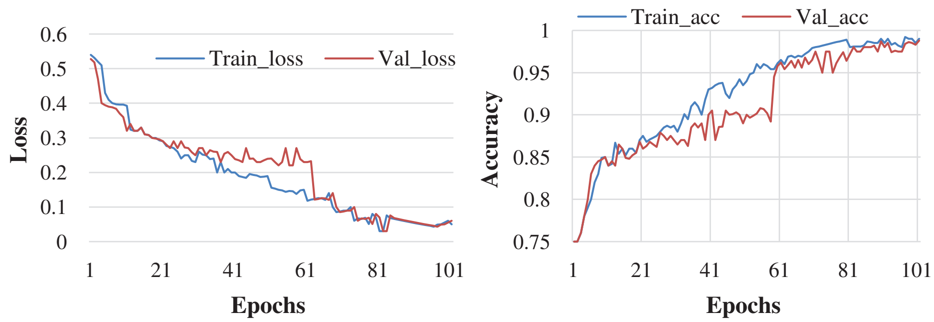

Figure 7: Accuracy and loss learning rate 0.001

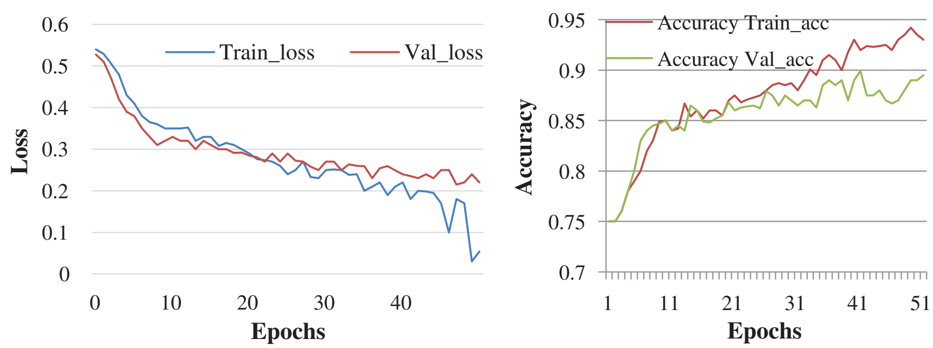

Figure 8: Accuracy and loss learning rate 0.01

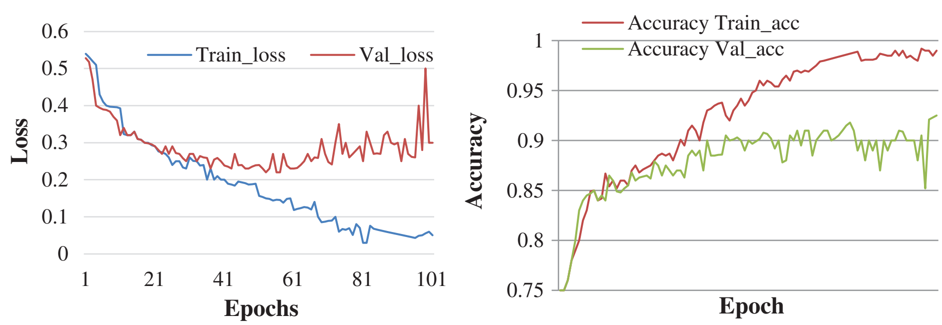

Figure 9: Accuracy and loss learning rate 0.01

The result analysis based on the experiment is laid down in Tab. 3 and the confusion matrix is depicted in Fig. 10:

Table 3: Experiment outcomes

Dataset size	Dimension	Epoch	LR	Accuracy (%)
2800	256 × 256 px	50	0.0001	98.02%.
		50	0.001	98.07%.
		50	0.01	98.12%.
		100	0.0001	98.00%
		100	0.001	98.25%
		100	0.01	98.12%.

Figure 10: Confusion matrix

The precision, recall, and F1-Score of the model is described in Figs. 11a–11c.

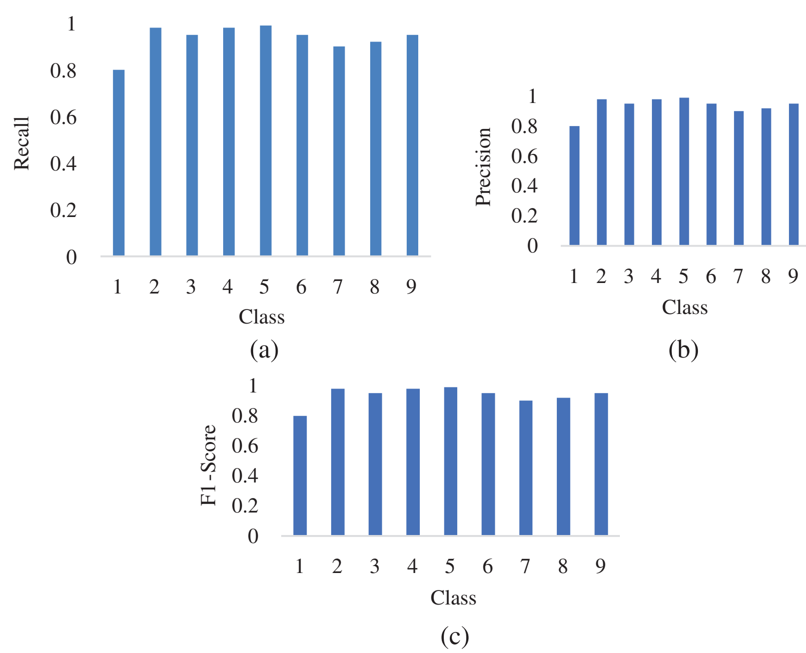

Figure 11: (a) Recall (b) Precision (c) F1-score

Based on the assessment procedure performed, a more accurate percentage of the data with a higher learning rate can be evaluated. The result analysis based on the experiment is laid down in Tab. 4:

Table 4: Comparison of the proposed model with other models

Model	Accuracy rate	Space	Training parameters	Non-trainable
Mobinet	66.75	82,566	18,020552	455262
VGG16	79.52	85245	21000254	532654
InceptionV3	64.25	90255	22546862	658644
Proposed	98.12	22565	1422542	0

5 Conclusion

The article proposes a high-performance deep neural network for identifying and categorizing plant leaf stress. The classification considers morphological attributes such as color, intensity, and leaf dimension of the plant. This article proposes an approach that takes two major steps to identify and classify mango leaf disease. Firstly, the leaf image is segmented, and the targeted area or disease part of an image is extracted. Further, they are processed to extract features to create symmetry in classification [57,58]. Secondly, the segmented image is inputted into the Deep Neural Network model. This article discusses different biotic stresses caused by fungal and bacterial pathogens, specifically Blight, Blast, and Browns, etc. of mango leaves. The result shows that the proposed model outperforms other models such as Mobinet, VGG and ResNet versions and the detection accuracy of the proposed model is 98.12 percent. The plant leaf is impacted by combinatorial stress or multiple stresses of biotic and abiotic stress as discussed in [59,60]. In the future will expand the model to address the issues related to the combination of biotic and abiotic stress variables.

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