Integrating Deep Learning and mSVM for Category of Class Prediction of Spice Plant Leaf Diseases

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Integrating Deep Learning and mSVM for Category of Class Prediction of Spice Plant Leaf Diseases

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ABSTRACT

Early disease detection is fundamental to protect the crops and provide early treatment. Plants with medicinal values are rare and need complete care. Black pepper is a spice herb, highly used as medicinal plant. The diseases prominent in black pepper spice are anthracnose, phytophthora, slow wilt, quick wilt, and yellowing. The proposed work suggests deep learning-based prediction and classification. The proposed work utilizes a benchmark dataset created in real time environment. The dataset is preprocessed, segmented, and labeled into classes under expert supervision. Deep neural network ResNet -50 is trained with novice data. The trained features are saved in an array. This data is matched in linear with extracted feature of Support vector machine SVM, a machine learning algorithm used for disease prediction. This is done by passing and mapping the hyperparameter features of Renet-50 as an array and mapping it to feature array of multiclass support vector machine. Hence there is no requirement of training machine learning separately. This results in fast training and early disease prediction **.**

Keywords: Black pepper, Deep Neural Network, Disease Classification, ResNet50, Support Vector Machine

1. INTRODUCTION

One of the primary sources of income in a developing nation is crop cultivation.Crop loss occurs due to various leaf diseases caused by environmental variation and climate change. Leaf diseases are one of the major factors that result in crop losses. Leaf disease are the important parameters to treat diseases in plant. The estimated crop losses around the globe owing to plant infection are in the billions. Black pepper is significantly used in Ayurvedic medicine because of its therapeutic properties. Black pepper is often referred to as the king of spices. There is a raising demand for better technologies aimed at early disease detection in plants as well, to overcome various issues related to plant disease [1][2]. If fast mechanism is available to cure early-stage disease, then lethal losses in agriculture can be hugely reduced. By checking the disease severity measure, farmers can be alerted and advised to use proper pesticides. One of the most hazardous diseases that affect plants is powdery mildew. The use of fungicides can be optimized through the early detection of mildew using non-destructive approaches. Ecological factors are interdependent with plant diseases. Plant infections often spread unpredictably across fields, making effective crop management challenging. Implementing smart sensing technologies to detect diseases in both isolated and surrounding areas could significantly improve monitoring systems. This is particularly crucial for black pepper farmers, who suffer substantial economic losses each year as diseases not only impact their current crops but also spread to healthy plants. Since each of these illnesses has a unique course of treatment, it's critical to correctly identify any diseases that may be present in a plant [3], [4]. Plant leaves, which are available throughout the year, are easier to photograph digitally and simpler to enumerate in two dimensions. Farmers predict diseases through the traditional technique of visual symptom inspection. In most cases, it is misjudged and frequently wrong. Some researchers have [3] worked on sensor-based plant severity measurement. The author stresses that automatic plant disease detection is essential to identify and detect symptoms. The objective of their study is to identify patterns in the reflected light spectrum, literature-described indices, and mildew severity. The polycarbonate greenhouse was used to grow plants with artificial lighting during a 16-hour photo period. Cucumber mildew severity was rated on a 10-point scale. The powdery mildew infection level in cucumbers and the light reflectance spectrum showed the highest association in the visible light green region, about 550 nm. Which resulted in powdery mildew detection using new indices.

The primary uses of machine learning techniques are in data classification and feature extraction. These techniques have been employed for many years to accurately process digital images [5]. When considered digitally, computer vision consisting deep learning with digital image processing provide an identifiable outcome, ignoring the inadequacy of live images. Deep learning techniques are emerging swiftly and are more popular today than before. Its high applicability in all fields makes its techniques widely spread and popular [6]. It is a scientific field that gives machines the capability to learn without being programmed. Deep neural networks have the high potential to rectify any variations in image features [7]. It takes novel approaches to successfully use these techniques in the agricultural domain, which is both locally and globally changing. An essential first step in automating any process is to simulate human visual abilities.

This study introduces a method for predicting black pepper leaf diseases using computer vision techniques, which can play a crucial role in precision agriculture. Given the scarcity of skilled labor, automated plant disease detection becomes vital for efficiently monitoring vast crop fields. The use of neural networks as classifiers, leveraging their learning capabilities, exemplifies the significant utility of recent technological advancements [8] [9]. The black pepper diseases considered are shown in Figure 1 with their severity type. Authors have discussed the importance of image processing in today's world to diagnose various ailments and diseases and to reduce the overall treatment and experimental costs. They also stressed the difficulty with traditional image capture methods that result in misclassification, cost complexity, and overfitting that occur in real time arguments. Researchers have proposed a framework using Kohonen-based deep learning and the Inception Visual Geometry Group Network to remove the image capturing related obligations. In article [10], the author presents a thorough analysis of recent research on agricultural pest and disease detection utilizing image processing and machine learning methods. The author suggests that due to the low cost and wide availability of digital RGB cameras, there can be focused on the utilization of RGB images. Lawrence Ngugi et al. [14] emphasized that to increase agricultural productivity in a sustainable manner, quick and precise plant disease diagnosis is essential. In the past, abnormalities in plants brought on by viruses, pests, nutritional shortages, or harsh weather have been identified by human experts with traditional and laboratory experiments. But doing so is costly ,time-consuming and occasionally impracticable. To get around these challenges, the application of image processing techniques to plant disease identification has been a hot research topic

Zhang et al. [15] worked on the fusion of super pixel clustering gradients algorithms, a plant diseased leaf segmentation and recognition approach. First, a super pixel clustering technique is used to divide the color sick leaf image into a few little super-pixels. To segment, the K-means clustering technique is then used. Finally, four PHOG descriptors are concatenated to create a vector by extracting the PHOG features from the three-color components of each segmented lesion image and its corresponding grey-scale image. The effectiveness of the suggested strategy is demonstrated by the experiment results on two plant leaf disease image data sets. Shao Xiang et al. [18] have proposed a method based on UNet for segmentation and recognition of rice bacterial leaf streak illness in rice leaves. The authors have used semantic segmentation and compared the performance with two types of models, i.e., UNet and Deep Labv3. The semantic approach was implemented using pixel wise classification for rice leaves. They have suggested that further improvement in the segmentation can be seen with multi-scale feature aggregation and attention mechanisms. But the experiment carried out is still not sufficient to claim high accuracy in severity determination in all the cases of different diseases. There are limitations in disease segmentation severity level estimation.

This project proposes an excellent hybrid technique to minimize overall processing time. In this work the benchmark image data is trained using deep learning on training data and then machine learning based multiclass support vector machine is used on testing data for further classification. It is observed that the classification is fast enough. This paper include methodology as section 2, in section 3 architecture and proposed algorithm is described and section 4 includes results and discussions.

2. MATERIALS AND METHODS

2.1. IMAGE ACQUISITION

Image acquisition involves collecting images for subsequent analysis. This process is carried out using a suitable high-intensity camera, which is essential for capturing real-world images and conducting an in-depth study of them. The very first step is data acquisition. Data is collected from the black pepper farm in real time

[11]. The leaf images were taken with a high-end digital camera Sony Ericsson and Nikon Coolpix DSLR. The image quality is maintained such that the disease indication is clearly visible on the leaf [12]. These helped in distinguishing one disease from another on the same leaf species. Such that in later stage of computer vision-based classification is easier.

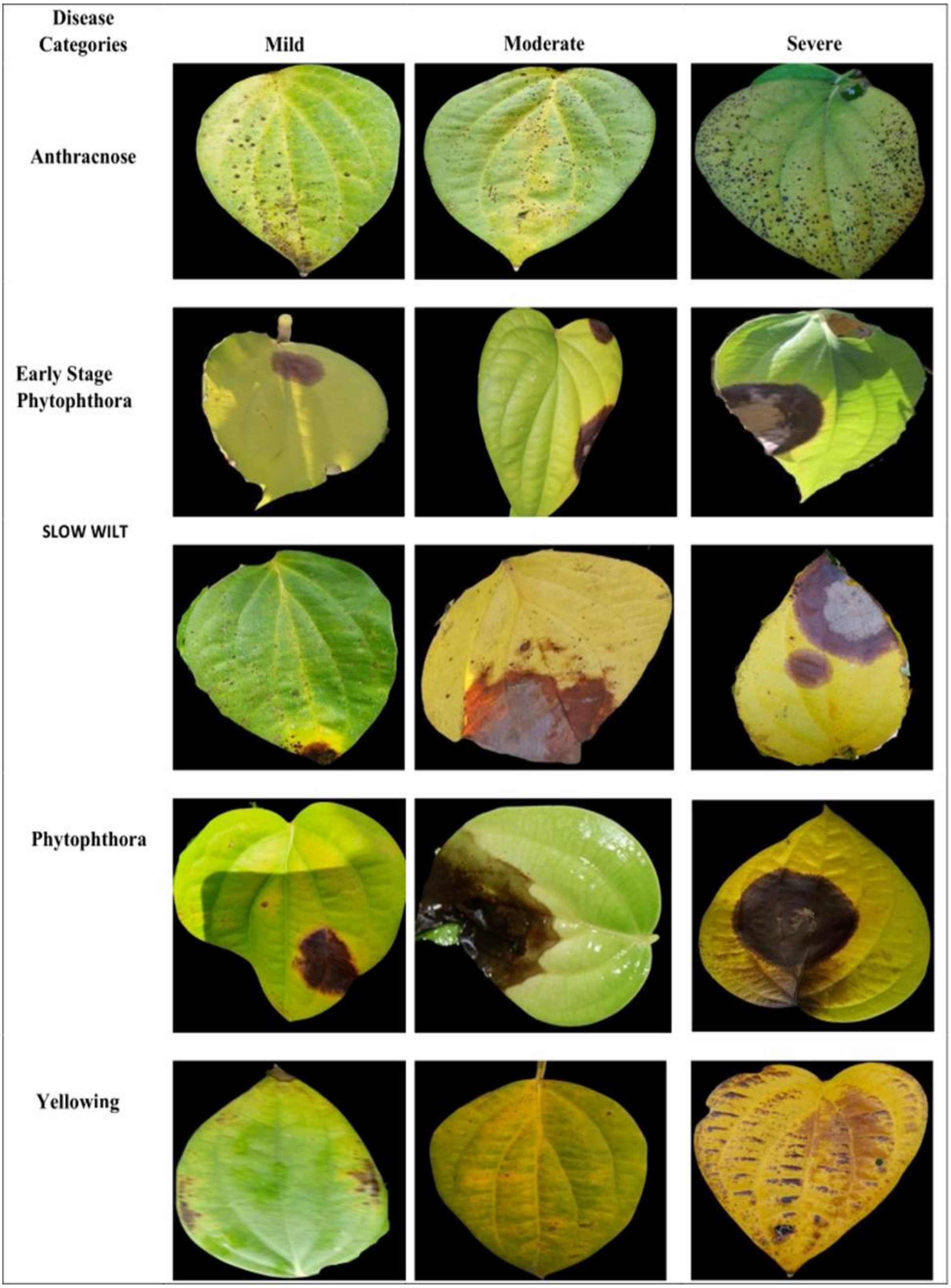


Figure 1. Black pepper diseased leaf sample data

2.2. IMAGE PRE-PROCESSING

Pre-processing is the next step after image acquisition. At this stage the overall quality of the acquired image is improved in terms of various parameters such as light intensity, color, shade, complex background, different sizes, orientation, brightness, noise removal, etc. This process is the most important step in image processing and computer vision for dealing with any kind of digital data [13],[16].Pre-processing techniques benefit the implementation of advanced deep neural techniques by providing a clear set of uniform data with minimal variations in the given set of data. Images are enhanced and resized to support better segmentation. PNG images are considered for the project.

2.3. IMAGE SEGMENTATION

Segmentation is a technique to further process the digital image in a more meaningful way for obtaining a better region of interest. The segmentation technique involves discarding irrelevant and unimportant details from the images. In this experiment, the K- means clustering algorithm is applied for image segmentation. The basic idea behind segmentation was to divide a single image into several clusters and pictures and select only the diseased object of interest (part) from the complete image. The segmentation is possible using the k-means algorithm, as in this method, the segmentation is done with respect to distances from a randomly chosen cluster centroid and the connecting-intensity of the image, which is measured in terms of the sum of distance squared [17]. K-means clustering is an iterative process that partitions the image data with the pixel information and clusters them, grouping them in different clusters based on the nearness' of the centroid. Hence, clustered segmentation. After this, convert the given image from RGB to La*b*. This is done as the color segmentation becomes easier with La*b*. La*b* consists of color zones divided into three. Luminosity is common, and then the features are a* and b*. The workings of K- means clustering are shown in the form of a graph in Figure 2.The three-color work reduces the task of clustering into three groups [18]. The Grey Level Color Cooccurrence Matrix (GLCM) is used to extract statistical features, also called texture features. The most densely visible cluster image is chosen, and its severity is measured. The evaluation of 13 different features from the region of disease effected leaf parts is limited to those that are derived statistically from Grey Level Cooccurrence Matrices (GLCM). These features include Correlation, Contrast, Energy, Mean, Homogeneity, Standard Deviation, RMS, Kurtosis, IDM, Smoothness, Variance, entropy, and Skewness. Since the given image now belongs to only two-color dimensions, feature extraction and comparison become easier [19]. This feature change is matched with the region of the affected diseased image compared to that of the original image.

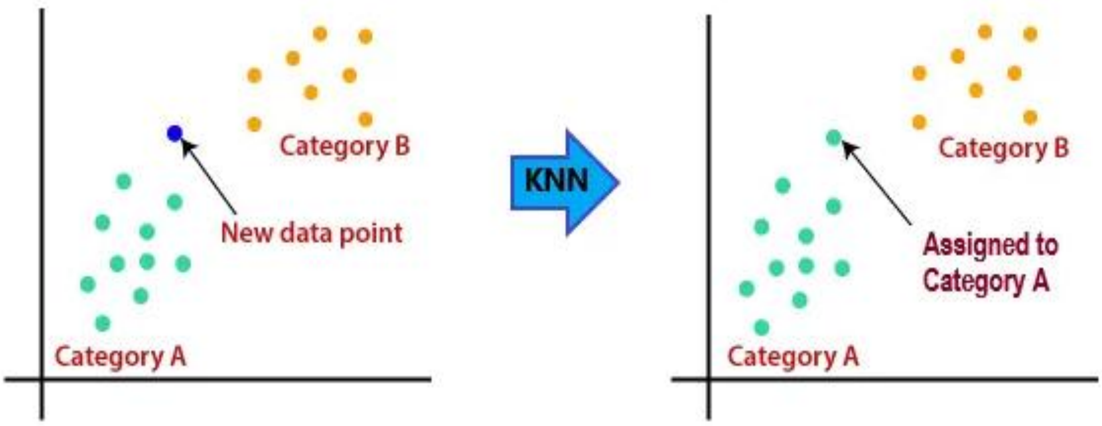


Figure. 2. K-means Clustering Technique

The comparison done is based on the area of the affected region obtained through clustering and that of the original image, and the severity is measured [20]. This is next displayed as a percentage of the affected part compared to that of the original image.

2.4. MULTICLASS SUPPORT VECTOR MACHINE

Support vector networks, sometimes referred to as support vector machines, are models for supervised machine learning. It has corresponding algorithms that analyze the data for regression and classification. The term support vector machine refers to samples that are on the margin formed by creating a maximum-margin hyperplane for an SVM trained on data from the classes. When there are a greater number of margins and classes, it is called a multiclass support vector machine .Support vector machines are a valuable tool for categorization due to their tendency to perform well in many situations and not over-fit. Support vector Machines (SVM) is not a new technique but are still powerful. This is the algorithm where a hyperplane originates in an n dimensional space that divides the data point into potential classes. The hyperplanes are positioned as near to the data points as feasible. In terms of distance, SVM are the data points that are closest to the hyperplane. Because of their closeness, they have a bigger influence on the hyperplane's exact location than other data points. Figure 3 displays the graphical representation of the multiclass support vector machine classification performance model . The three spots, represented in blue and a single in green, are located on the lines in the graph and represent support vectors. Multiclass classification facilitates categorizing data into two categories and classifying it as binary. Data points are projected into a high-dimensional space to achieve linear separation between each pair of classes. This approach, known as the one-to-one strategy, involves creating a binary classifier for every pair of classes. Another method, called the one-to-rest strategy, uses a binary classifier for each class by treating it as distinct from all others. A single SVM is capable of performing binary classification between two classes. To classify data points from an M-class dataset, breakdown strategies are applied, where the one-to-rest approach utilizes M SVM classifiers, one for each class.

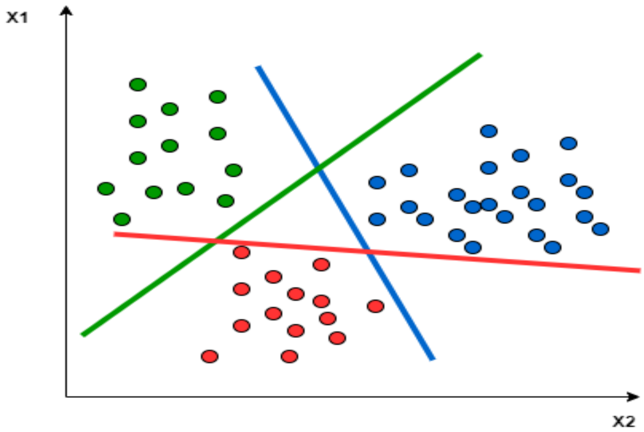


Figure 3. Classification using Multiclass Support Vector Machine [ref]

MATHEMATICAL EXPRESSION FOR MULTICLASS SUPPORT VECTOR MACHINE

The machine learning algorithm trains a logistic regression classifier $\mathbf{h_\theta^{(i)}(x)}$ for each class i to predict the probability that y=i. This process is one versus all. On a new input x, to make a prediction, pick the class i that maximizes $\mathbf{max}_{(i)}\ \mathbf{h_\theta^{(i)}(x)}$

In other way →

$$\left.\begin{aligned} S_j &= f(X_i, W)_j \\ &= WX_i \end{aligned}\right\} \text{score of the jth class of } i^{th} \text{ Vector } (X_i, Yi)$$

$$S_{yi} = f(X_i, W)_{yi} \rightarrow \text{Should be maximum}$$

$$S_{yi} - S_j \geq \Delta$$

$$\mathbf{L_i = \Sigma_{j \neq Yi}\ max\ (0, } S_j - S_{yi} + \Delta\mathbf{)}$$

2.5. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks, or CNNs, have drawn a lot of interest recently and have grown to be a well-liked machine learning technique for image classification. Deep Learning algorithms are another name for these groups of algorithms. The neural network is extended by these algorithms [19]. While preserving the relationships between pixels, convolution uses smaller input data squares to learn visual features. Two inputs are required for this mathematical process: an image matrix and a filter, or kernel. The author of the proposed work employed an input image for computation. Then, a few fully linked layers are added after repeated convolution and pooling procedures. To automatically train the disease, a convolutional neural network is employed. A system like this can be put into use instantly. Figure 4 depicts basic CNN architecture. A neural network's input layer, output layer, and between layers of neurons comprise the initial stage. A neural network functions as the brain of a machine, enabling it to recognize and learn patterns from test data. When the network includes multiple layers, it is referred to as a deep neural network, characterized by a greater number of hidden layers compared to the standard input and output layers. CNN consist of multiple convolutional layers, each followed by a pooling layer. Between these layers, activation functions are applied.

The convolutional layer processes the input image by applying filters, modifying the pixel intensities to extract features. Activation functions control the state of neurons and transmit signals to subsequent neurons. Pooling layers then reduce the dimensionality of the convolutional output, with techniques such as Max pooling, Min pooling, and Average pooling commonly used.

In this project, a CNN is implemented to classify black pepper (spice) plant leaf images into disease categories, utilizing Max pooling for dimensionality reduction.

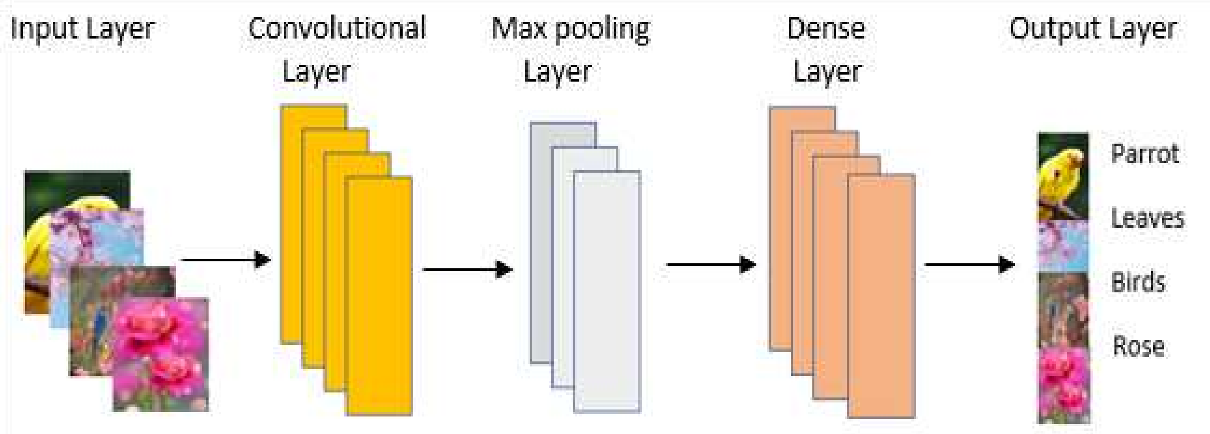


Figure 4. CNN Architecture

2.6. RESNET-50

ResNet-50 is a popular deep learning classifier that has many layers of CNN in it, with some skip layers. Basically, the architecture of Resnet-50 consists of six major parts. The inner pre-processing model has a fully connected last and output layer, and in between input and output, it has four layers. The arrangement of these internal residual blocks differs from one implementation to another as per the experimental requirements. Some of these median network layers are skip layers [22]. That means some of the middle neural network layers are skipped for higher network layers while performing classification accordingly. Figure 5 shows ResNet 50 models.

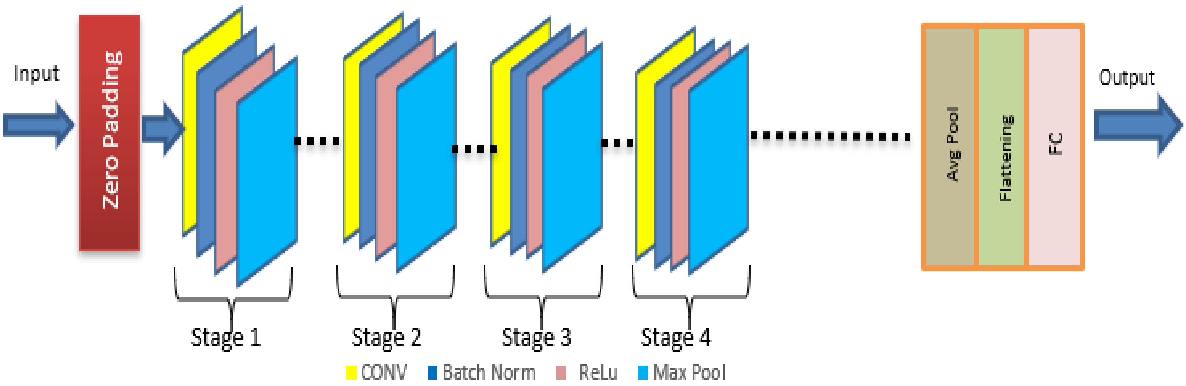


Figure 5. ResNet50 Architecture Model

The architecture of the skip model is shown in Figure 6. The activation function is ReLU, and the arrow in the Figure 6 shows the skipped lower neural network layer.

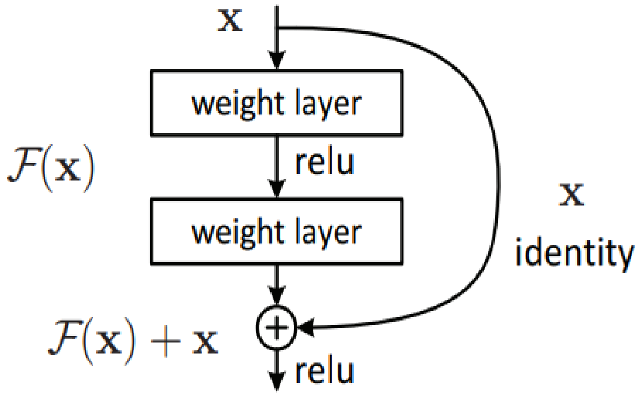


Figure 6. Resnet Residual Block [ref]

3.ARCHITECTURE OF PROPOSED MODEL

The deep neural network is trained on a complete dataset of 1300 images. Multiclass SVM is trained using CNN features of deep learning algorithm Resnet-50.Intitially Resnet-50 model is trained with the novel black pepper leaves dataset. In this process the cascading is maintained by extracting the non-linear digital image input data ,which is mapped and transformed into greater dimension plot as part of linearly disconnected data. This method provides a high degree of prediction and is a robust technique even if there are minor training errors. Hyperparameter values for the deep learning as well as machine learning models are chosen carefully to train the given models to enhance performance [23]. Figure 7 depicts the conceptual model of hybrid cascaded category of class prediction using multiclass SVM using CNN features (Resnet-50). The classifier, m-SVM is trained through hyperparameters chosen for ResNet50 and is used to predict only the test data. The training feature comparison by mSVM to those of CNN activation features is fast. This way, the machine learning based classifier evaluates the test image data and makes predictions to foresee the category class of the diseased test image faster. Algorithm 2 represents stepwise process.

<u>Algorithm :</u>

New Hybrid Cascaded Category of Class Prediction (HCCP) based on deep learning and machine algorithm.

Input → S = Original feature set, S1 , S2 , S3 , S4 , ,…….. SN
C = Class Labels

Output → P_Classifiers =Accurate category of class prediction

---

Begin

1. S_Select ← Null

2. A ← Number of features derived from activation function from trained ResNet-50

(i) Resize to 256 * 256 *3 & Enhanced.
(ii) Convert rgb to La*b*

3. for j←1 to N do

Initialize A← null
A[i]← a[i]]
Create an empty cell array and store the CNN activation features in columnar

4.end for.

5.B ← Train the multiclass SVM classifier using fast linear solver and arrange the classifier output feature in another empty array cell created in columnar form.
{ B[j]← null }

6.for j← 1 to N do

B[j]←b[j]]

7.end for.
8.max_1 ←A[i]
9. for K ← 1 to N do
if A(k)≥ max_1 then
max_1 ←A(k)
l← i
endif
10.end for.
11.max_2 ← B[l]

12. for k← 1 to N do

if B[k]≥ max_2 then
max_2 ← B [k]
P← k
endif
13.end for
14. Evaluate **A[k] ≅ b[k]**

15. Predict category of class

$P_{\_Classifier}$ ← category of class, S(Select)

16. end
17.end

This way there is drastic reduction in the number of feature parameters to be considered while testing and validation.

Utilizing performance measures that are based on True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) outcomes, the effectiveness of the suggested method for detecting black pepper leaf disease is assessed. The following formula can then be used to calculate the

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN)$$

Precision forecasts measure the proportion of correct predictions among all expected positive outcomes.

$$\text{Precision} = TP/(TP+FP)$$

The percentage of positives among all genuine positives is reliably predicted by recall.

$$\text{Recall} = TP/(TP+FN)$$

The F1 value considers recall (R) and precision (P) rates.

$$F1 = (2*\text{Precision}*\text{Recall})/ (\text{Precision} + \text{Recall})$$

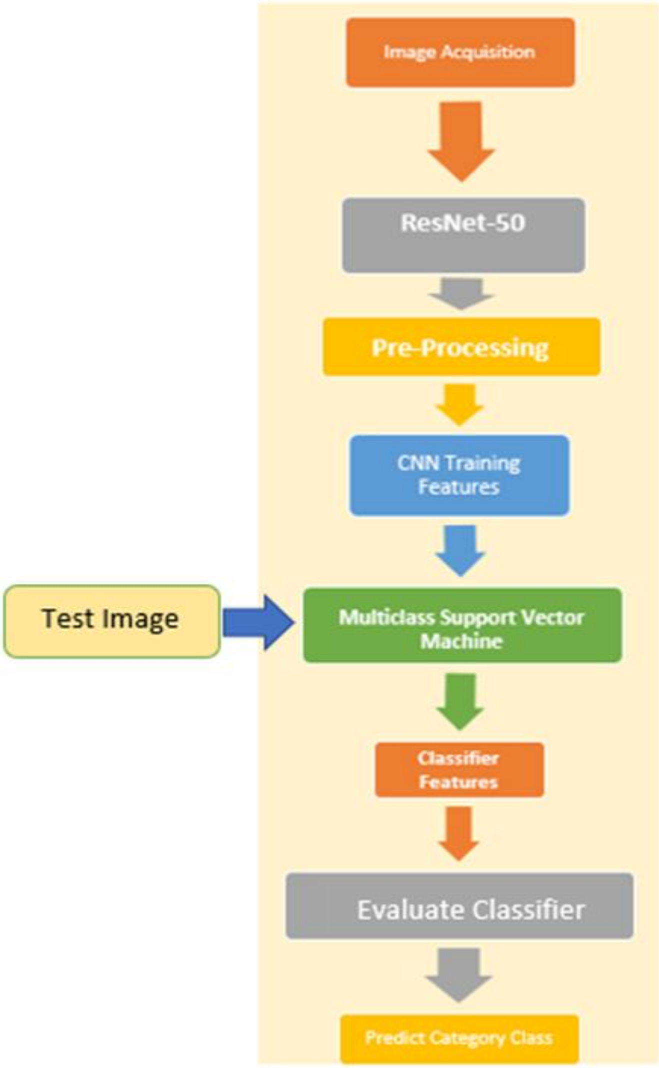


Figure 7. Hybrid Cascaded Category of Class Prediction using Multiclass SVM using Resnet-50

Features considered for severity measurement.

• Contrast: It is related to the gray scale variance in the image.
• Correlation: A practice implemented mathematically to find how two elements are close to each other.
• Energy: It refers to a change in intensity or brightness in the given image. This is an important image compression parameter.
• Mean: It is a component of special filter, used to reduce noise in the image.
• Homogeneity: Homogeneity refers to similarity among images based on pixel components.
• Standard Deviation: It is calculated by means of statistical data and calculated as square of the mean square. The expression for standard deviation is represented as

$$\sigma = \sqrt{(\frac{1}{N} + \sum_{n=1}^{N}(x_i - \mu))} \quad \text{eq.1}$$

Where σ is the standard deviation.

N= Number of observations in sample.
Xi =Is the ith observation in sample.
M = The mean sample.

• RMS: This parameter is root mean square value and returns scalar or row vector for a given input.
•Kurtosis: It is the image feature that approximates resolution and noise in the image. Low Kurtosis results in low resolution with low noise.
• IDM: The full form is inverse difference moment. It shows up the local homogeneity regarding image.
• Smoothness: The smoothness characteristic is required in digital image processing to suppress and noise level.
Variance: Variance shows the spread of pixel value. Mathematically represented as

$$\sigma^2 = \sqrt{(\frac{1}{(N-1)} + \sum_{n=1}^{N}(x_i - \mu)^2)} \quad \text{eq.2}$$

Where σ is the variance,

N = Number of observations in given sample.
Xi = is the ith observation in sample
M = the mean sample.

• Entropy: It is the statistical metric that determines the unpredictability of the bits used to encode an image.
• Skewness: The asymmetric mean distribution of a digital image is called skewness. It usually ranges from -5 to 5.

For the proposed research two algorithms are designed, one to obtain disease severity and another to make prediction of category of classes. These are represented as Algorithm.

4.Results and discussions

The proposed research work was carried out successfully. The disease severity for each of the categories in the given dataset is calculated. Further, for the classification task, a unique approach by combining deep learning and machine learning is accomplished. The hybrid cascaded technique is implemented in an exclusive way, the features of the trained CNN are stored in an array through the activation function. And only these hyperparameters are used to train mSVM. image. The process is expressed through two algorithms. This classifier with fast linear solver is used to test the test dataset. The sample pre-processed /enhanced images using MATLAB software, is shown in Figure 8(a) input and Figure 8(b) enhanced output. Figure 9 show Image Augmentation for (a) Random reflection x axis and (b)Random rotation (c) Random rescaling. Accuracy in percentage of predicted black pepper leaf diseases is shown in Figure 10 and Figure 11 shows the sample output for the black pepper leaf disease severity measurements. The severity estimation is incorrect if the disease symptom is not prominent on the leaf image. Figure 12 shows sample category of class prediction with class object count. Figure 13 displays diseased leaf cluster selection. Figure 14 and Figure 15 depicts the confusion matrix for ResNet50 deep neural network model. Confusion matric output is used for finding ROC curve and AUC comparison graph, Figure 16. This is implemented for a small dataset of 50 images in each class.

From the confusion matrix it is seen that for healthy leaf category prediction is high. Clouded leaf images will never give satisfactory output. The present result can be improved with a greater number of data considered. Precise field care may be taken if the images are regular. monitored. High sophisticated techniques such as deep learning and advanced instruments such as drones can be used for agricultural field surveillance for better performances. Drone-collected image data can be stored in databases for later use in research and references. Disease prediction using computer vision techniques is used in precision agriculture. Figure 17 shows the accuracy and loss graph for the disease prediction of black pepper leaves.

Figure 8 (a). Input image Early-Stage Phytophthora

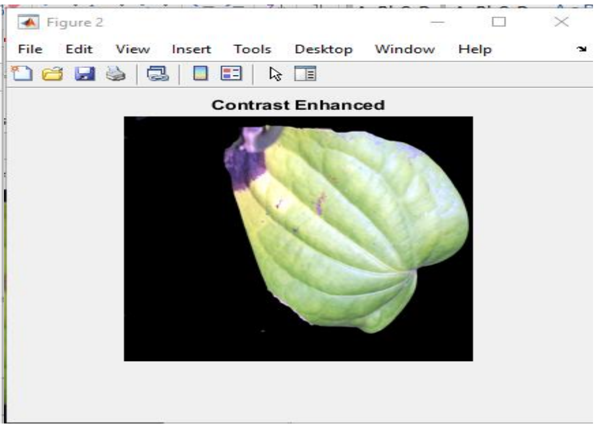


Figure 8 (b). Enhanced Image Output

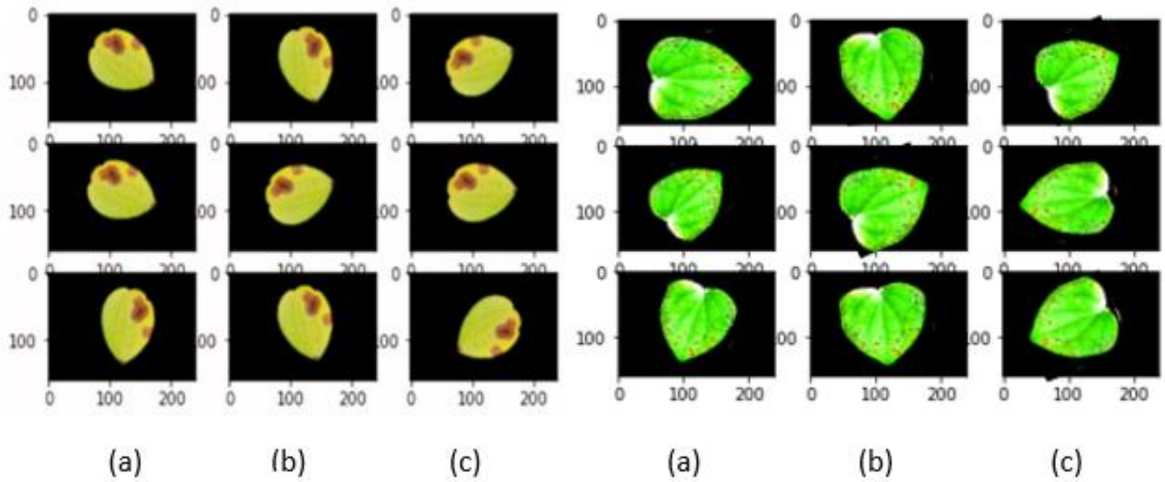


Figure 9. Image Augmentation (a) Random reflection x axis (b) Random rotation (c) Random rescaling

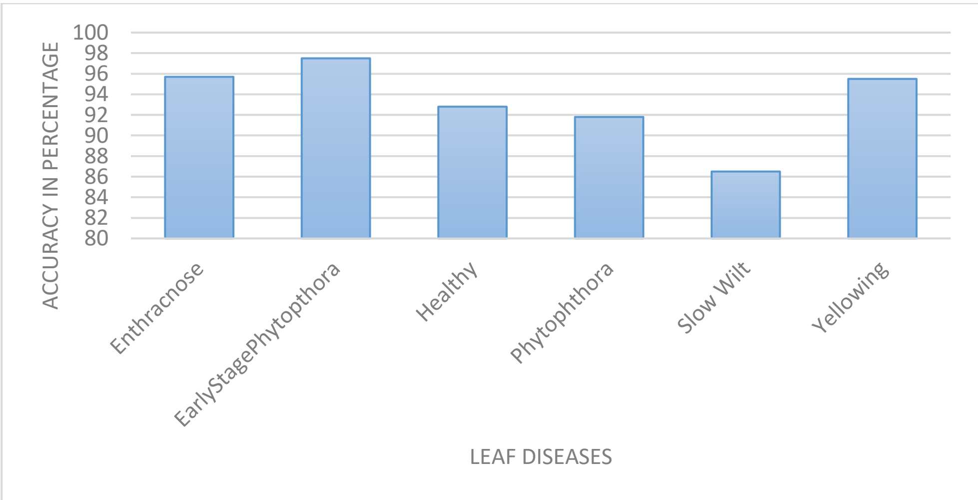


Figure 10. Predictability of black pepper leaf diseases as accuracy percentage

Diseased Leaf Samples	Input Query Image	Enhanced Image	Cluster Output	Diseased Area Prediction [Output]	Severity Level
Anthracnose				ans = 'Affected Area is: 15.0115%'	Mild
Phytophthora				ans = 'Affected Area is: 95.0507%'	Severe
Early Stage Phytophthora				ans = 'Affected Area is: 39 %'	Severe
Slow Wilt				ans = 'Affected Area is: 19.0224%'	Moderate
Yellowing				ans = 'Affected Area is: 100%'	Severe

Figure 11. Sample Input images severity prediction

Prediction: Test Data Category

Label	Count
EarlyStagePhytophthora(ESP)	113

fx ans =

Figure. 12. Category of Class Prediction with count.

Command Window

tbl =

6×2 table

Label	Count
Anthracnose(ANT)	100
EarlyStagePhytophthora(ESP)	113
Healthy_Image(HLT)	110
Phytophthora(PHY)	104
SlowWilt(SW)	101
Yellowing(Y)	110

Figure. 13. Leaf Class Prediction with count.

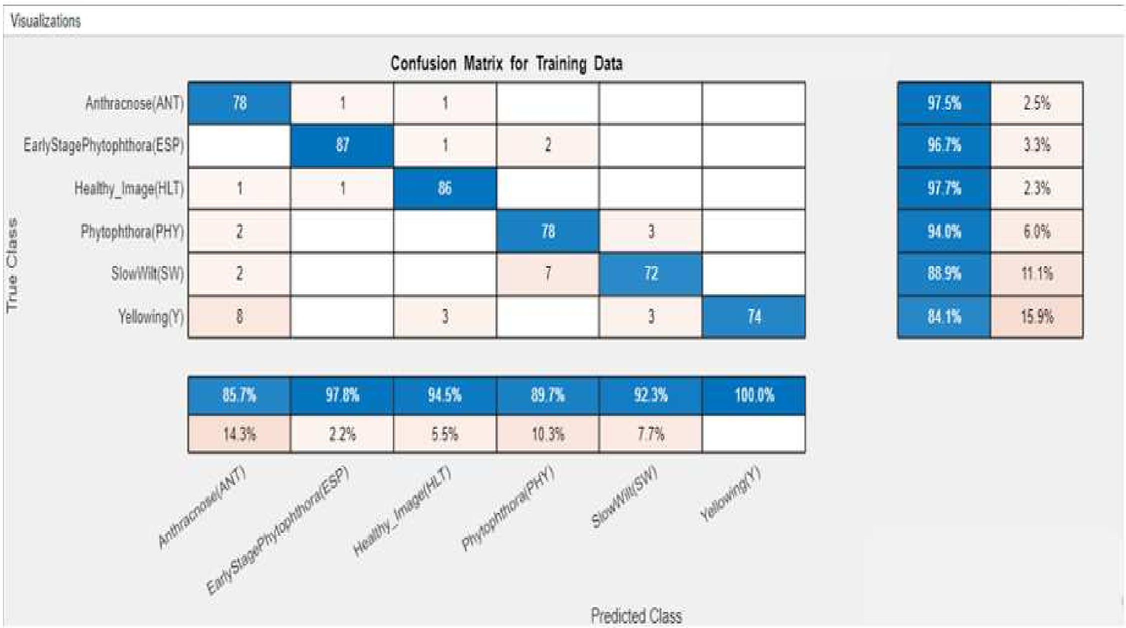
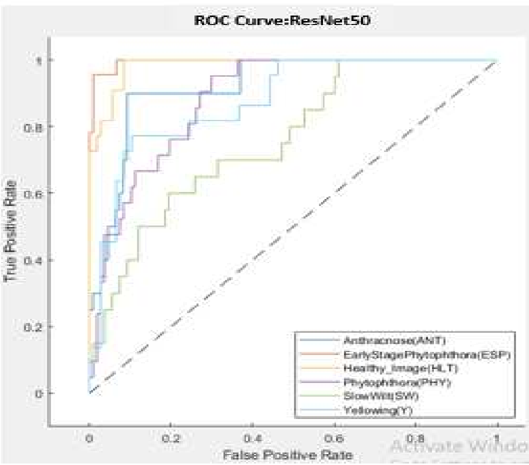


Figure 14. Confusion matrix training set

Figure 15. Confusion Matrix validation test

The hyperparameters of convolutional neural network are shown in Table 1



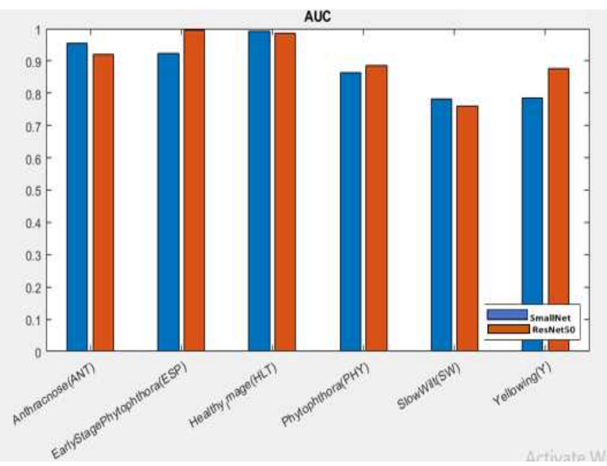


Figure 16(a). ROC curve for ResNet50 Figure 16(b). AUC graph for ResNet50

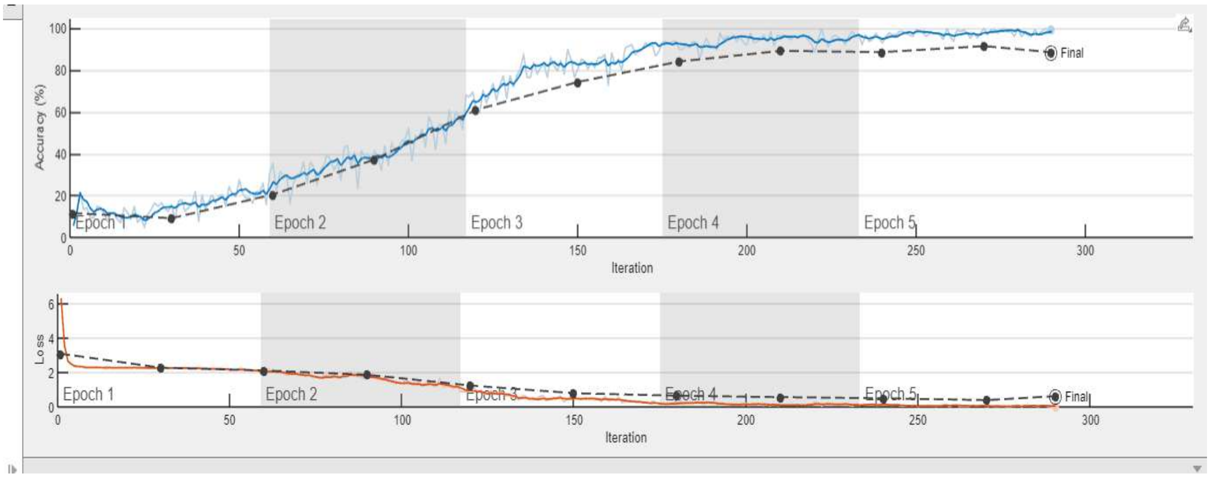


Figure 17. Predictive accuracy and loss graph for black pepper leaf disease

Table 1: Hyperparameters and their Descriptions

S. No	Hyperparameters	Description	Value/Parameters
1	Partition(Data)	Division of data for training and testing purposes.	Training: 70%, Testing: 30% OR Training: 60%, Testing: 40%
2	Size of Input Image	Dimensions of the input image required by the model.	224 × 224 × 3 OR 227 × 227 × 3
3	Function(Loss)	Represents the error between predicted and actual outputs	Range: 0 to 1.00
4	Batch Size-Small	Batch size, typically powers of 2, not recommended for datasets smaller than 2000.	64, 128, 256, 512, etc.
5	Rate of Learning (initial)	Starting value for the learning rate of the neural network	0.001 OR 0.0001
6	Learning Rate Schedule	Adjustment method for the learning rate based on predefined values.	Time Decay, Step Decay, Exponential Decay
7	Number of Epochs	Number of times the model iteratively trains on the entire dataset.	10, 25, 30
8	Learn Rate (Factor)	A positive scalar comparing the learning rate of a definite parameter to the universal rate.	10
9	Bias Learn Rate	The learning rate for the bias of the neural network	10
10	Validation Patience	Maximum number of attempts to improve performance during validation epochs.	40
11	Validation Frequency	Minimum frequency at which the model is validated.	10
12	Performance Metrics	Metric to evaluate the classification performance of the model.	Confusion Matrix
13	Optimizers	Functions to adjust the weights and learning rates of the neural network.	SGDM, Adam, RMSprop

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