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PREDICTION AND CLASSIFICATION OF TEA LEAF DISEASES USING DEEP LEARNING TECHNIQUES ELeNet

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Abstract
Tea is the most critical beverage of people next to the water. So, tea production is essential in India. To increase the crop, yield early-stage diagnosis of tea leaf disease is essential. Generally, Tea leaves are affected by 100 types of diseases, but 15 of which occur in leaf and buds. Among these disease blister blight, anthracnose, brown blight, red leaf spot and fungal leaf spot, white scab, grey blight may affect the quality and quantity of the tea production. So, data mining plays a vital role in the early diagnosis of tea leaf disease and assess the crop yield. Diagnosis of plant disease is typically based on disease characteristics. Developing and implementing a diagnostic structure for tea plant illnesses would, therefore, assist farmers in ensuring precise and timely identification of tea plant illnesses. Such improvements would lead to better techniques of control that would restore problems due to disease economically and efficiently. This research starts the new method to predict and classify the tea leaves disease. Finally, this research forecast crop yield by identifying the major diseases that are limiting yield. For this the following objectives are framed.

1.INTRODUCTION

India is the largest tea producer. Seventy per cent of tea is consumed in India. India is one of tea consumer among the top 5 producers. Tamil Nadu produces 64 per cent of South Indian tea. Tea plantations are concentrated on hills stations such as Nilgiris, Valpari and Theni. Tea leaves are often affected by diseases due to virus and bacteria. Therefore, it will affect crop yield and production. Diagnosis of plant disease is typically based on disease characteristics. Moreover, qualified tea plant pathologists are scarce, and the constraints of background awareness of tea growers tend to an inability to recognize disease occurrences in a timely and efficient way.

Developing and implementing a diagnostic structure for tea plant illnesses would, therefore, aid farmers in ensuring precise and timely identification of tea plant illnesses. Such improvements would lead to better techniques of control that would restore problems due to disease economically and efficiently. Also, these advances would contribute to ensuring more exceptional tea quality while lowering labour and agricultural manufacturing expenses and, most importantly, enhancing returns and the sustainable development of tea production. Microscopic identification and spectroscopic techniques are current methods of diagnosing plant diseases. However, these methods are time-consuming and expensive.

Plant pathologist may incorrectly diagnose diseases. These methods are exact, but they required specialized labour, their intensive and instrumentation. In recent year the fast development of intelligent agriculture has led; to solve the different problems in agriculture. Also, the impact of these techniques used in early diagnosis of plant disease and crop yield. This research starts the new method to predict and classify the tea leaves disease. Finally, it predicts the crop yield percentage of tea. Hence it will improve production and pesticide usage.

III. TYPES OF DISEASES IN TEA LEAF

Tea leaves are affected by 100 types of diseases, but 15 of which occur in leaf and buds. Among these disease blister blight, white scab, grey blight, anthracnose, brown blight red leaf spot, birds eye spot and fungal leaf spot may affect the quality and quantity of the tea production. Therefore, data mining plays a vital role in the early diagnosis of tea leaf disease and assess crop yield.

The diseases of the plant in two forms are:

- Infectious diseases caused by Fungi, Bacteria, and Viruses.

- Non-infectious diseases or disorders caused by mineral toxicities, soil acidity, nutrient deficiencies, or environmental factors.

Bacterial Disease Symptoms

The tiny pale green spots which soon come into view as water-soaked is the characteristic of this disease. Then it appears as dry, dead spots as, e.g. brown or black water-soaked spots on the foliage, sometimes with a yellow halo, generally identical in size in the bacterial leaf. Under dry conditions, the spots have a speckled appearance.

Viral Disease Symptoms

Among all plant leaf diseases, the most difficult to diagnose is the disease caused by the virus. Viruses produce no tell-tale signs that can be readily observed and often easily confused with nutrient deficiencies and herbicide injury. Insects carry these diseases are Aphids, leafhoppers, whiteflies and cucumber beetles insects. Mosaic virus look for yellow or green stripes or spots on foliage. Leaves might be wrinkled, curled and growth may be stunted. (a) Bacterial leaf spot, (b) mosaic virus Bacterial and Viral disease on leaves.

Fungal Disease Symptoms

Among all plant leaf diseases, those caused by a fungus, some of them are discussed below and, e.g. the fungus phytophthora infesters cause the disease called late bite. It first appears on lower, older leaves such as water-soaked, grey-green spots, these spots darken and then white fungal growth forms on the undersides when the fungal disease is matured.

The fungus Alternariasolani cause the disease called early bite. It first appears on the lower, older leaves such as small brown spots with concentric rings that form a bull's eye pattern, and it spreads outward on the leaf surface causing it to turn yellow when the disease is matured. In downy mildew yellow to white patches on the upper surfaces of older leaves occurs. These areas are covered with white to greyish on the undersides. (a) Bacterial Leaf Spot (b) Fungal Leaf Spot (c) Late blight (d) early blight Figure 1.


(a) Bacterial Leaf Spot **(b) Fungal Leaf Spot**


(c) Late Blight **(d) Early Blight**

Figure 1: Fungal, Bacterial and Viral Affected Disease on Leaves

III.EXISTING WORK

Sun et al. (2019) present SLIC_SVM based leaf diseases saliency map extraction of the tea plant. For improving the removal of tea plant leaf disease saliency map under complex backgrounds, a new algorithm combining Simple Linear Iterative Cluster (SLIC) with SVM is proposed. The significant point is detected by Harris algorithm, and

Firstly, superpixel block is obtained by SLIC algorithm, fuzzy salient region contour is extracted by employing convex hull method. Secondly, superpixels block in the striking region and background areas are extracts the four-dimensional texture features, and then the map classification is obtained by classifying the super pixel blocks with the help of SVM classifier.

Yang (2019) developed tea diseases detection based on fast infrared thermal image processing technology. Tea is economically damaged because of its large yield in china since it is an economic crop. In order to estimate tea diseases and to study for developing an effective, simple, and suitable computer vision algorithm is to find tea diseases area using infrared thermal image processing technique. The study finds that the area of tea diseases has a certain regularity in the infrared image grey distribution. By using this rule, two characteristic parameters into a classifier to help achieve rapid tea disease detection, the accuracy of detection of a small amount which increases were extracted.

Hossain et al. (2018) Recognition and detection of tea leave diseases using support vector machine. All around the world, the famous beverage is tea, and in Bangladesh, cultivation of the tea plays a vital role. Several diseases affect the proper growth of tea leaves, leading to its reduction; the production of tea is thus hindering. Therefore, the condition is identified at the starting stage, solve all problems by appropriate treatment, or through the pruning technique the leaves, which prevent the spread of the disease. In order to crack this problem, image processing is the best option to detect and diagnose the disease. This is a novel approach due to the number of features compared to earlier research, without adversely sacrificing the success rate of the classifier; more than 90 per cent retains accuracy.

Dhakad et al. (2018) discuss leaf disease detection using image processing. About 70 per cent of the Indian economy depends on agriculture. Diverse ranging is Indian agriculture from impoverished farm villages to developed farms using modern agricultural technologies. Promoting the application of advanced information technology in agriculture will solve a series of problems facing by farmers such as rainfall and temperature, severely the crop yield gets affected. Loss in production is led by lack of exact information and communication. The study has overcome these problems, and in that way, it has been designed. Based on remote sensing, this system provides an intelligent monitoring platform framework and system structure for facility agriculture ecosystem based on remote sensing. Development of automatic leaf disease detection system using advanced computer technology such as image processing help farmers in the identification of disease at an early or initial stage and provide useful information for its control. Image processing involves image acquisition, image pre-processing, image segmentation, feature extraction and classification. Through testing based on 261 diseased images, the quality evaluation index, the accuracy precision, recall, and F-Value are 98.5 per cent, 96.8 per cent, 98.6

per cent and 97.7 per cent respectively. The proposed method performs better than the other three SLIC methods.

IV DATA COLLECTION

Data for this study is collected from 'Mahavir Plantations Pvt. Limited', High Forest Estate, Nalacuthu Estate, Valpari, Coimbatore District. The database had 120 samples of tea leaf images. There are different types of diseases affected by a tea leaf such as blister blight, net blister blight, white scab, bud blight, leaf blight, grey blight may affect the quality and quantity of the tea production.

V. PROPOSED CLASSIFIER

The proposed method is modified Efficient LeNet deep learning algorithm.

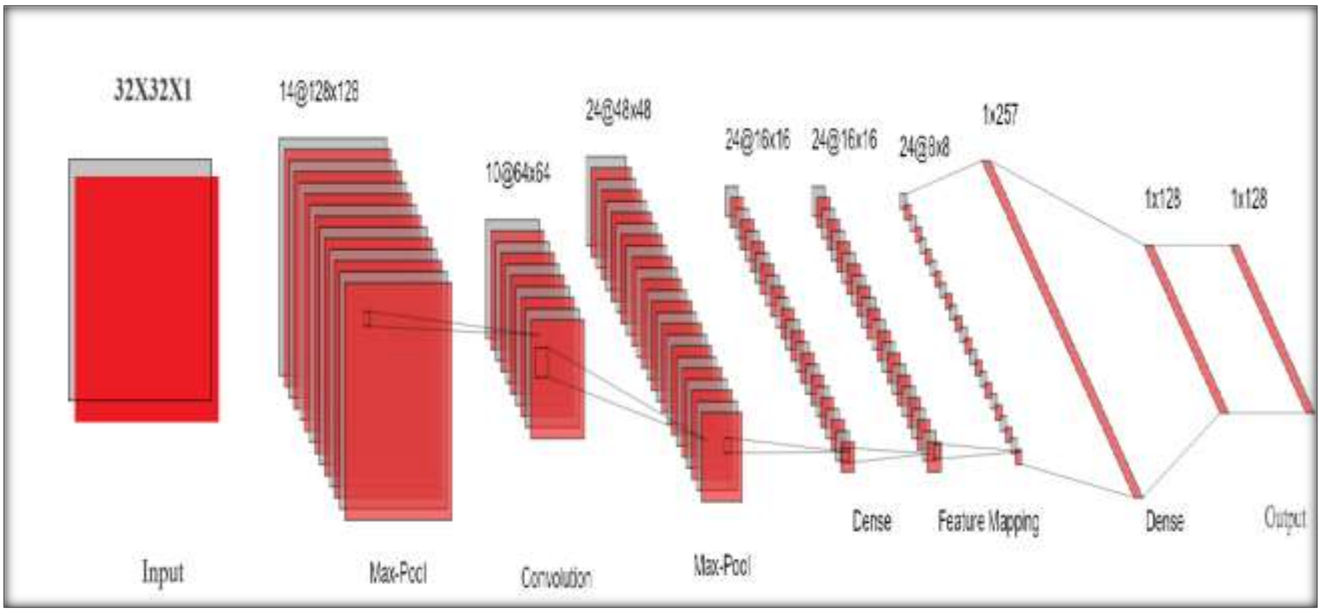

Figure 2 Architecture of Proposed ELeNet

The first layer is the input layer with feature map size 32X32X1. Next, we have an average pooling layer with filter size 16X16 and stride 2. The resulting feature map is 128X128X14. Since the pooling layer doesn't affect the number of channels. Then the first convolution layer with 16 filters of size 8X8 and stride is 4. The activation function used at his layer is tanh. The output feature map is 64X64X10. After this comes the second convolution layer with 16 filters of 5X5 and stride 1. Also, the activation function is tanh. Now the output size is 10X10X16. Again comes the other average Max pooling layer of 4X4 with stride 6. As a result, the size of the feature map reduced to 24X24X48. The dense layer has 120 filters of 16X16 with stride 4 and activation function tanh. Now the output size is 128. The next is a fully connected layer with 84 neurons that result in the output to 84 values and the activation function used here is again tanh. The last layer is the output layer with 10 neurons and Softmax function. The Softmax gives the probability that a data point belongs to a particular class. The highest value is then predicted. This is the entire architecture of the Lenet model. The number of trainable parameters of this architecture is around sixty thousand.

VI. RESULT AND DISCUSSION

The classification of diseased plant leaves performed by using ELeNet and learning vector quantisation techniques which have been analysed for the 118 input leaf images. From the confusion matrix of the respective classifier, the performance metrics evaluated. In Experiment divided into two parts

1. Classification of Disease and non-disease leaf

2. Detection of the particular leaf as disease or not disease

Here four performance metrics had been calculated to measure the efficiency of the classification results. (i.e.) Accuracy, Precision, Recall ratio, F_measure. To measure the quality of the classified diseased leaf images, the performance is analysed by using four parameters, which includes Accuracy (AC), Recall ratio, Precision and F_Measure.

Accuracy (AC)

Ratio of correctly predicted observation to the total observations (preferred in balanced datasets)

Accuracy =(TP + TN/TP + FP + FN + TN)

Precision

Ratio of correctly predicted positive observations to the total predicted positive observations

Precision=(TP/TP + FP)

Recall ratio

Ratio of correctly predicted positive observations to all observations in actual class

Recall ratio= (TP/TP + FN)

F_Measure

The F-Measure computes some average of the information retrieval precision and recall metrics. Root means the squared method is used to calculate the RMS error.

$$\text{F-measure} = \sqrt{}(\text{True negatives} - \text{True Positives})^2 + (\text{False Negatives} - \text{False Positives})^2$$

Table 1: Accuracy Comparison of Different Classifiers

Existing Approaches	CNN	SVM	CNN-PSO	Proposed ELeNet
Accuracy	90.23	75.06	88.56	98.02

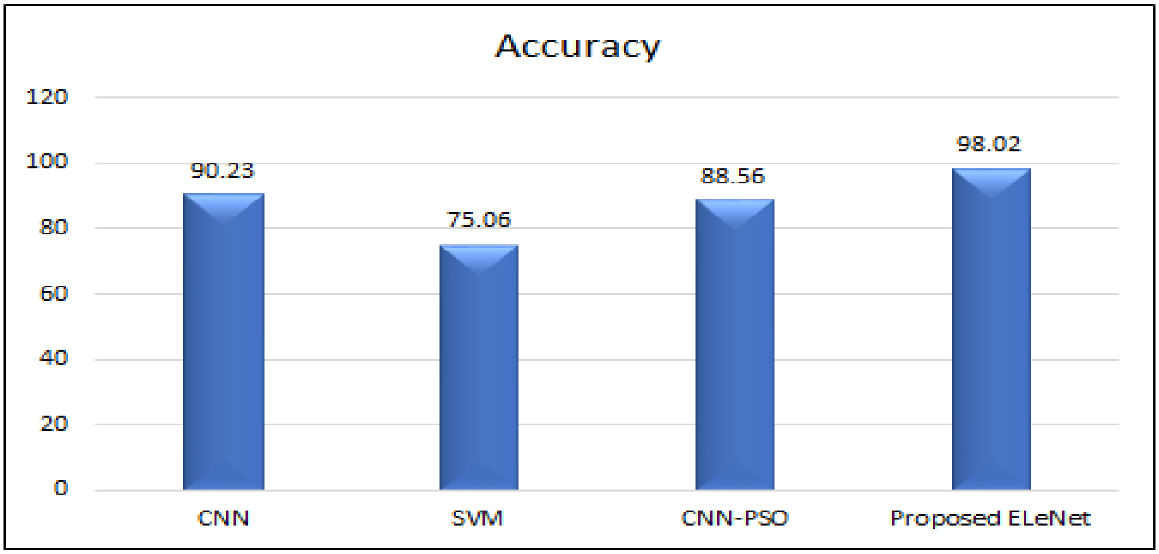

Figure 3: Comparison of Accuracy of Different Classifier

Figure 3 presents the comparison of convolution neural network and convolution neural network with particle swarm optimisation and SVM and proposed ELeNet. In Figure 3, X-axis classifier and y-axis value of accuracy, which show that CNN_PSO show 88.56% significant accuracy and CNN 90.23% these accuracies highly significant from SVM and ANN. These accuracy increase in case of CNN because convolution the features and non-linear mapping so effective features given effective accuracy but in CNN_PSO optimise features and proposed ELeNet achieved 98.02% accuracy than other methods

Table 2: Precision Comparison of Different Classifiers

Existing Approaches	CNN	SVM	CNN-PSO	Proposed ELeNet
Precision	90.34	43.73	74	94.56

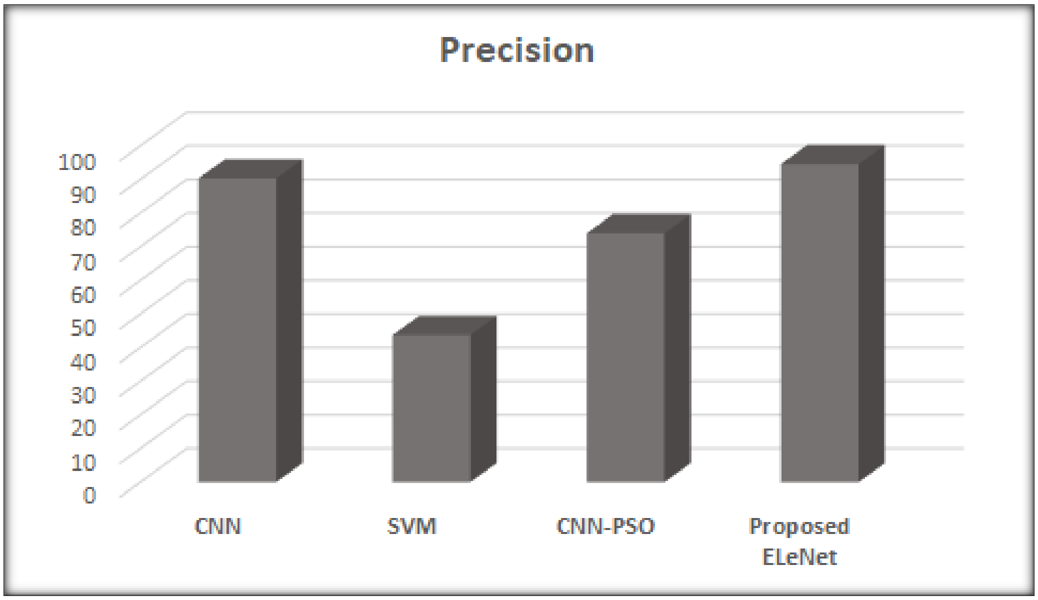

Figure 4: Comparison of Precision of the Different Classifier

Figure 4 presents the comparisons of convolution neural network and convolution neural network with particle swarm optimisation and SVM with ELeNet. In Figure 4 X-axis classifier and y-axis value of precision, which show that CNN_PSO show 74%, CNN 90.34%, SVM 43.73% and proposed method show 94.56 than other methods.

Table 3: Recall Comparison of Different Classifiers

Existing Approaches	CNN	SVM	CNN-PSO	Proposed ELeNet
Recall	92.14	42.73	75.45	96.78

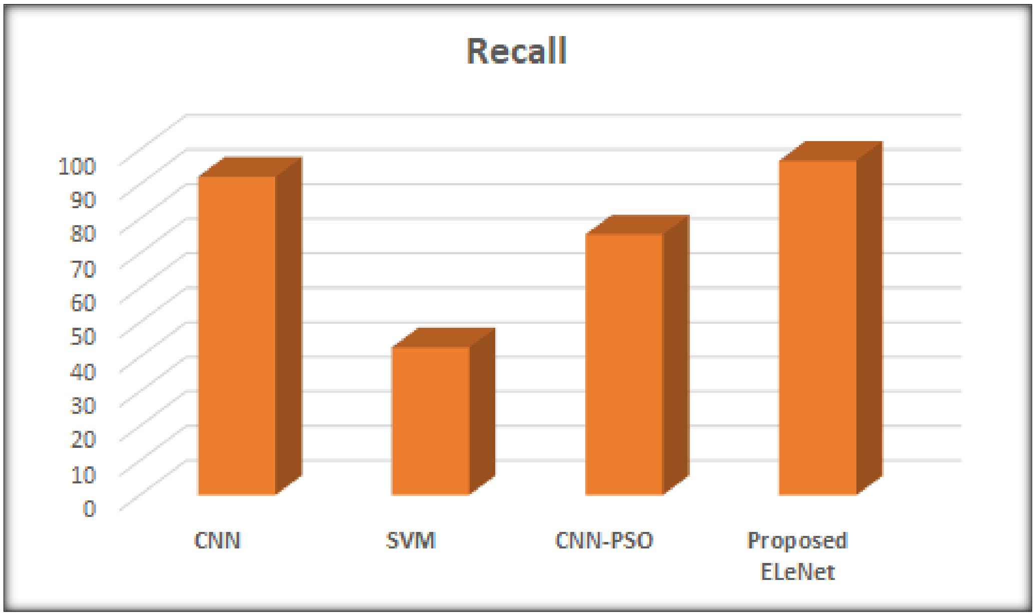

Figure 5: Comparison of Recall of Different Classifier

Figure 5 presents the comparisons of convolution neural network and convolution neural network with particle swarm optimisation and SVM with proposed ELeNet. In Figure 5 X-axis classifier and y-axis value of recall which shows that ELeNet show 96.78% significant recall and CNN shows 92.14%, SVM shows 42.73 these recall lower than proposed.

Table 4: F-Measure Comparison of Different Classifiers

Existing Approaches	CNN	SVM	CNN-PSO	Proposed ELeNet
F-measure	93.7	42.67	76.56	97.67

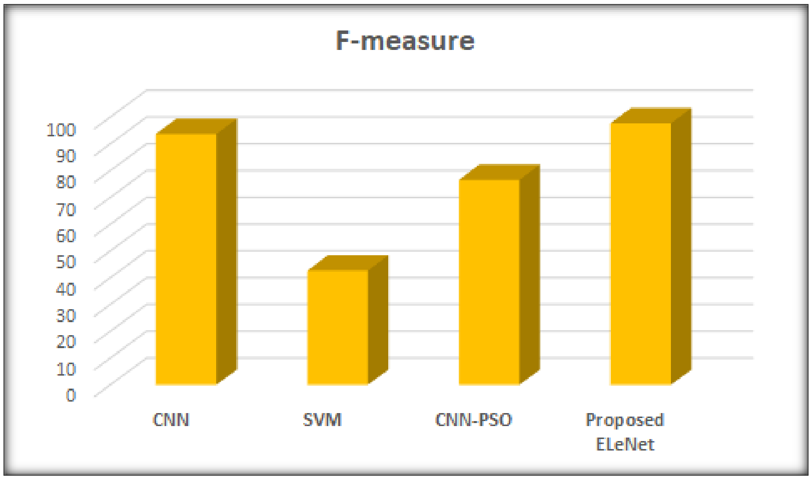

Figure 6: Comparison of F-Measure of Different Classifier

Figure 6 presents the comparisons of convolution neural network and convolution neural network with particle swarm optimisation and SVM with proposed ELeNet. In Figure 6, X-axis classifier and y-axis value of F-Measures, which show that proposed ELeNet shows 97.67% significantly higher than others. CNN_PSO show 76.56% and CNN 93.7% and SVM shows 42.67%.

Table 5: Comparison of Different Classifiers

Existing Approaches	CNN	SVM	CNN-PSO	ELeNet
Accuracy	90.23	75.06	88.56	**98.02**
Precision	90.34	43.73	74	**94.56**
Recall	92.14	42.73	75.45	**96.78**
F-measure	93.7	42.67	76.56	**97.67**

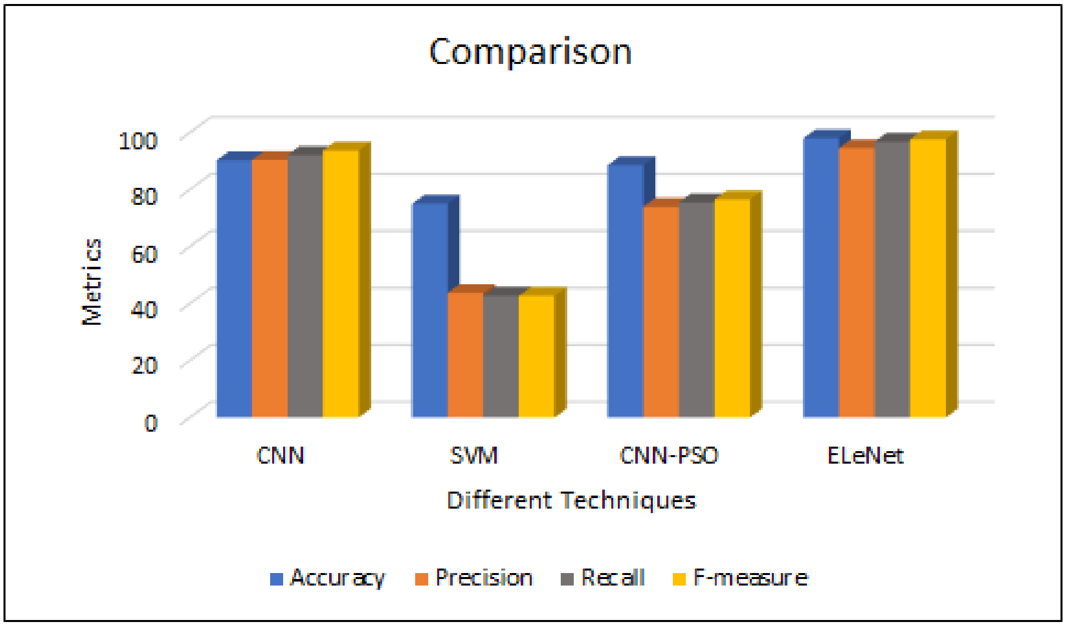

Figure 7: Comparison of F-Measure of Different Classifier

Some diseases can occur in tea plants throughout the year, although some diseases occur at distinct times. Consequently, the time of year when diseases are diagnosed may differ, which would affect the accuracy of disease recognition. A further complication inaccurate disease diagnoses may be that two or more diseases can infect tea leaves. The occurrence of a disease within a leaf would likely result in physiological weakness that could lead to infection by a second disease. Thus, the above confounding factors may explain lessened accuracy in disease recognition by the tested models.

Also, the performance of the proposed ELeNet was compared against three other methods described previously. The accuracy of the proposed ELeNet was slightly lower

than of the three algorithms mentioned above. However, more types of diseases were used in the present study compared to those used to evaluate the accuracy of the other two models. Consequently, the method proposed here to classify tea tree diseases is superior to the two other previously described algorithms.

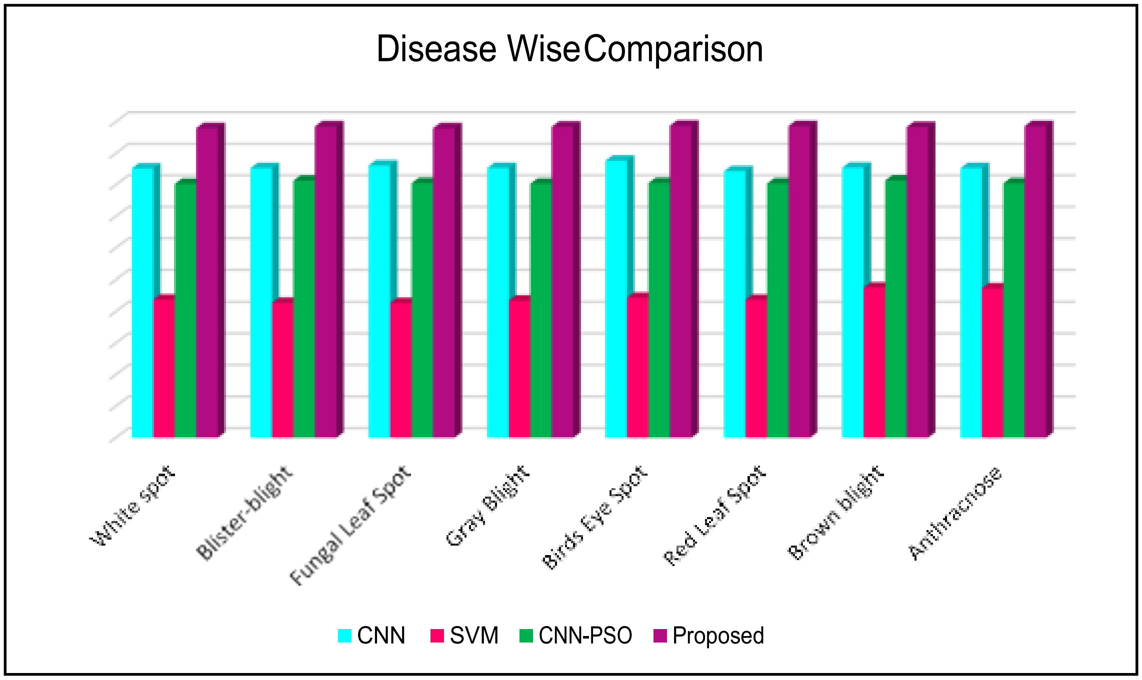

Figure 7.19: Accuracy (as a %) of Disease Classification for each of the Three Classification Models for the Eight Candidate Tea Diseases

In this research, the accuracy of the CNN, CNN-PSO, SVM and proposed ELeNet classifiers in determining disease states for tea leaves from images were evaluated. The results of these analyses are shown in Figure 7.9-7.13. Error matrices were used to evaluate the accuracy of tea leaf disease recognition classifiers (Tables 7.6–7.8). Figure 7.19 presents accuracy percentage of disease classification for each of the three classification models for the eight candidate tea diseases. From these data, the various tea leaf disease recognition algorithms generally identified the majority of diseases correctly. However, the proposed ELeNet algorithm performed better than the SVM, CNN, CNN-PSO algorithms. Among the different diseases, the bird's eyespot disease was best distinguished by the Proposed ELeNet, which is likely due to its obvious phytopatho logical symptoms and ease of discernment. White spot disease was the next most accurately classified disease, while all other diseases were classified at accuracies between 84–93%. The grey blight, red leaf spot, and brown blight were classified

with the least accuracy, which is due to the similarity in pathological characteristics among the three diseases. Some disease symptoms are too similar in their later stages to be distinguished, like grey blight and brown blight diseases, which both exhibit annulations during later stages. Moreover, the symptoms in the early and middle stages of these diseases are also difficult to distinguish. Alos, to the above cases, the symptoms during the early and middle stages of some diseases are also very similar. For example, the symptoms of white spot and bird's eye spot diseases both include reddish-brown spots at early stages. Also, both anthracnose and brown blight diseases are typified by waterlogged leaves during early disease stages, while differentiation occurs during later stages.

Table 6: Error Matrix showing the Classification Accuracy of the Proposed ELeNet Algorithm

	White Spot	Bird's Eye Spot	Red Leaf Spot	Gray Blight	Anthra-cnose	Brown Blight	Blister Blight	Fungal Leaf Spot	Sensitivity	Accuracy
White spot	111	3	0	0	3	0	0	0	94.87%	
Bird's eye spot	1	117	0	0	0	0	1	1	98.32%	
Red leaf spot	0	0	95	7	0	8	0	1	85.59%	
Gray blight	0	0	4	96	3	7	0	1	86.49%	98.23%
Anthracnose	5	0	1	6	97	1	2	0	88.18%	
Brown blight	0	1	15	2	0	97	2	0	84.35%	
Blister blight	5	1	5	12	1	2	96	0	87.42%	
Fungal leaf spot	1	1	2	2	1	0	1	98	93.33%	

Table 7: Error Matrix showing the Classification Accuracy of the SVM Algorithm

	White Spot	Bird's Eye Spot	Red Leaf Spot	Gray Blight	Anthra-cnose	Brown Blight	Blister Blight	Fungal Leaf Spot	Sensitivity	Accuracy
White spot	79	11	0	2	19	1	0	5	67.52%	
Bird's eye spot	12	89	0	4	1	10	1	3	74.79%	
Red leaf spot	2	4	59	23	2	19	4	2	53.15%	
Gray blight	0	0	13	70	8	17	5	3	63.06%	60.91%
Anthracnose	19	0	5	13	56	11	11	6	50.91%	
Brown blight	0	2	19	17	3	73	2	1	63.48%	
Blister blight	4	2	7	6	1	3	28	2	62.18%	
Fungal leaf spot	9	10	12	13	3	4	5	54	51.43%	

Table 8: Error Matrix showing the Classification Accuracy of the CNN-PSO Algorithm

	White Spot	Bird's Eye Spot	Red Leaf Spot	Gray Blight	Anthra-cnose	Brown Blight	Blister Blight	Fungal Leaf Spot	Sensitivity	Accuracy
White spot	83	13	0	3	15	1	2	2	70.94%	
Bird's eye spot	6	100	0	6	1	5	1	1	84.03%	
Red leaf spot	1	1	80	17	0	11	4	1	72.07%	
Gray blight	0	0	9	81	6	14	3	1	72.97%	70.94%
Anthracnose	13	0	4	10	73	8	9	2	66.36%	
Brown blight	0	5	16	15	3	75	0	1	65.22%	
Blister blight	5	1	12	21	5	15	76	2	67.35%	
Fungal leaf spot	6	5	9	10	4	4	3	67	63.81%	

VII. CONCLUSION

This chapter has presented Multi-Layer Perceptron ELeNet alogithm. This algorithm classifies the eight tea leaves diseases. this algorithm is compared with existing algorithms the comparison shows the ELeNet algorithm has a improved rate of 98.02% accuracy when compared to CNN algorithm 90.23%.