Transforming Coconut Farming with Deep Learning Disease Detection

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Transforming Coconut Farming with Deep Learning Disease Detection

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Abstract: Early detection of plant diseases is crucial for effective prevention and control of food insecurity in agriculture. Coconut trees are vulnerable to various pathogens such as fungi, bacteria, viruses, and nematodes, which can cause significant quantitative and qualitative losses. In this study, we suggested a strategy that applies the resulting hybrid model (NNSVCLD), which is created by modifying SVM and CNN, to extract deep features from images and classify out of 5 diseases to which class it belongs. Comprehensive testing is carried out on Kaggle dataset, and performance measures like accuracy, precision, recall, specificity, and F1-rating are assessed and examined. According to the experimental results, the introduced version outperformed the other cutting-edge hybrid learning models in terms of accuracy, precision, recall, and F1 rating for different folds. The proposed method shows accuracy with 98.9% for three, 99.3% for five folds, and 99.4% for 10 folds respectively. The efficacy of the model is further supported by the precision, recall, and F1-scores for each category, which range from 98.7 to 99.4%.

Keywords: Coconut Caterpillar Infestation (CCI); Weligama Coconut Leaf Wilt Disease (WCLWD); Ensemble learning; Support Vector Machine; Neural Network Support vector coco leaf disease (NNSVCLD)

1. Introduction

Coconut, a versatile tropical fruit, is an essential crop in many countries, serving as a significant source of income and nutrition for millions of people. However, coconut cultivation faces numerous challenges, including diseases that can significantly reduce yields and threaten livelihoods[1,2]. Early detection and management of these diseases are crucial for sustainable coconut production. Coconuts (Cocos nucifera L.) are palm trees that are beneficial to humans from their fruit to their trunks. Actually, according to[3], India is the world's third-largest coconut producer. Southern Indian states make up a substantial portion of the world's coconut crop. The ailments that impact coconut plantations' output inevitably have a detrimental effect on the pertinent industrial units and the family's livelihood, which is entirely reliant on the coconut economy. Root (wilt) disease (RWD), stem bleeding, Ganoderma - Basal Stem Rot (BSR), leaf blight, leaf rot, and bud rot are a few common diseases that affect coconut trees. Termites, black-headed caterpillars, rhinoceros beetles, coconut eriophyid, and red palm mites are some of the pests that live in coconut trees[4].

Coconut Caterpillar Infestation (CCI) and Weligama Coconut Leaf Wilt Disease (WCLWD) are the most harmful pests and diseases on coco fields, causing significant damage in a short amount of time[5,6] deep learning for coconut disease detection[7-9] presents an exciting opportunity to improve the resilience and productivity of coconut cultivation. By harnessing the power of artificial intelligence and computer vision, we can develop robust, accurate, and scalable systems that empower farmers with the tools they need to safeguard their coconut crops and livelihoods[10-12].

Traditional methods of disease detection in coconuts rely heavily on visual inspection by agricultural experts, which can be time-consuming, subjective, and prone to human error. With the advancements in deep learning, there's an opportunity to revolutionize coconut disease detection by leveraging computer vision techniques to automate and enhance the process. The detection of coconut tree illness can be effectively achieved with the use of Artificial Intelligence (AI) techniques like Convolutional Neural Network (CNN) and Deep Learning (DL), which are highly favoured in this field[13].

In this research paper, a model for smart agriculture called Neural Network Support Vector Coconut leaf Disease Detection and Classification (NNSVCLD) is presented. As a preliminary stage, the median filtering-based noise removal technique is followed by the given NNSVCLD technique. Furthermore, the impacted leaf sections are identified using the neural network method. In addition, the useful feature vectors are extracted by using the Support Vector Machine approach as a feature extractor. The results were assessed under various folds after the experimental analysis was carried out using the NNSVCLD model.

The remaining part of the document is arranged as follows. Next section describes a review of related work in the area, followed by a methodology part that covers dataset collecting and model construction which includes training, testing, hyper-parameter adjustment, and performance evaluation. The results section summarizes performance metrics for each severity level. The acronyms used is paper are presented in Table 1.

Table 1. The Acronyms used.

S N	List of Abbreviations	
1	SVM	Support vector Machine
2	CNN	Convolutional Neural Network
3	NNSVCLD	Neural Network Support vector coconut leaf disease
4	Acu	Accuracy
5	Pre	Precision
6	Re	Recall
7	MCC	Matthews correlation coefficient (MCC)
8	ROC	Receiver Operating Characteristics
9	AUC	Area Under Curve

2. Literature Review

Various authors have used deep learning methods for disease detection and classification in the coconut. Multiple coconut leaf diseases can be detected using a CNN-based model. The model was trained using a dataset of photos of impaired and healthy coconut leaves[14-16]. S. R. Dubey et al. in[17] have used k-means and multi-class SVM for apple disease classification. M.A. Khan and other authors have discussed different types of diseases in coconuts and their prevention[18-24]. Along with LSTM (long short-term memory) and DNN (deep neural networks), Klompenburg in[25] concluded from their thorough research that CNN is a commonly used deep learning technique in this sector. ANN, KNN, Random Forest, MLR, and SVR models were compared for hybrid model prediction accuracy using a variety of performance criteria by Gopal and Bhargavi in[26]. It was concluded that the hybrid MLR- ANN model offered more accurate results than other models. The literature is organized by dataset accuracy and research methods as shown in Table 2.

Table 2. Previous studies.

Author	% Accuracy	Approach used
[27]André S. Abade,	97.62	Convolutional Neural Networks (CNN)
[28]J Sujithra,	55	SVM and Neural network (NN)
[29]S. Priyadharshini	Both 93	SVM &KNN
[30]Dr. G Manjula,	95	. SVM
[31]D. Nesarajan,	93.54&93. 72.	CNN and SVM.
[32]Wang	88.53 & 99.64	Faster R-CNN and Mask R-CNN
[33]Vidhanaarachchi	97	CNN
[34]Barman	100	ANN and SVM
[35]Narayanan	64	A CNN model
[36]Vinoth	96.7	CNN model
[37]Abdullah, Noor Ezan,	70	Principle component analysis (PCA
[38]D. Banerjee, V	. 86.03	(SVM)x
[39]DhapithaNesarajan	93.7, 83.2, &20.9	EfficientNetB0, ResNet50, and VGG16 b
[40]V. Pooja	92.4	SVM
[41]AttaponPalananda,	94.05	MobileNetV2
[42]Sibiya, M	92.85	CNN
[43]Ferentinos, K.P.	99.53	CNN
[44]Too, E.s C et al.	96 and 98	ResNet with 50, 101 and 152 layers
[45]Muhammad Shakaib Iqbal	99.75	Mask R-CNN
[46]Jain	97.7	Hybrid
[48]Jain	97.7	NLRSGD
[49]Sandip Thite	92 &94	MobilenetV2&Resnet
[12]Singh, Piyush Verma	96.94	2D-CNN

Recent research has shown that these strategies are excellent in achieving high accuracy while also addressing problems such as data paucity and unpredictability in disease symptoms. However, there are still a number of obstacles to overcome, such as real-time deployment, environmental constraints, and data imbalance.

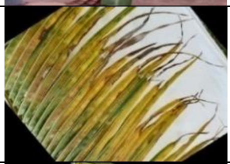
3. Dataset

The Coconut Leaf Dataset for Pest Identification dataset by ShravanaTirtha[47)] used in this paper. This dataset contains 5036 coconut diseased leaves which are divided into five categories:

1. Coco caterpillar infestation (CC1) named a
2. Coco caterpillar infestation Leaflets (CCI_L) named b
3. Weligama Coco Leaf drying (WCLD) of leaves named c
4. Weligama Coco leaf yellowing (WCLY) named d
5. Weligama Coco leaf Flaccidity (WCLF) named e

The dataset[46)] consists of 20% testing data and 80% training data. The sample photos for each of the five image categories are displayed in Table 3.

Table 3. Coconut leaf dataset with sample images.

S. No	Coconut Image	Name of the image	No of Images	Reason
a		Coconut Caterpillar infestation (CC1)	990	Pests that feed on the leaves or other parts of plants
b		Coco caterpillar infestation Leaflets (CCI_L)	795	Caterpillars can be pests that feed on the leaves or other parts of plants, causing damage.
c		Weligama Coco Leaf drying (WCLD)	1089	Lack of water, pests, or environmental stress.
d		Weligama Coco leaf Flaccidity (WCLF)	1079	Due to lack of water or other factors affecting turgor pressure in plant cells
e		Weligama Coco leaf yellowing (WCLY)	1084	nutrient deficiencies, pests, diseases, or environmental stressors.

The size of each category has been shown in Fig. 1. Violin plot shows that CCIL is uniformly distributed as per size. It has been verified with results.

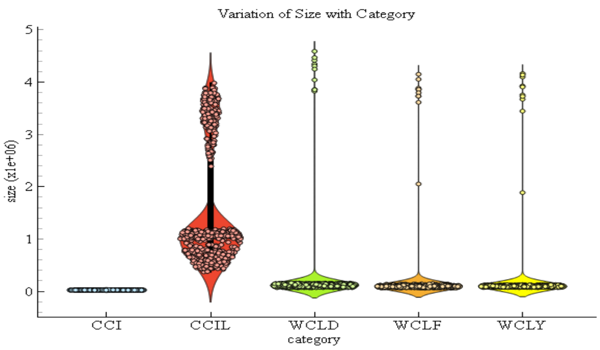


Fig. 1: Violin plot of variation of category with size of coconut leaves.

4. Approach

Convolutional Neural Networks (CNNs) are a highly-liked, cutting-edge neural network architecture that works well in computer vision applications. CNN is manually created in this study to categorize images of coconut trees to identify illnesses. The layers that make up CNN are the input, convolution, pooling, flatten, fully connected, and output layers[45,49)]. When applied to traditional classifiers, the ensemble method boosts performance and accuracy. Ensemble deep learning is a hybrid technique that combines two classifiers, such as support vector machines and convolutional neural networks, and evaluates their parameters. Figure 1 shows the proposed methodology to classify coconut-diseased leaves.

5. Proposed Algorithm

Steps of the NNSVCLD Algorithms:

- A total of 5036 observations are used as the input dataset.
- The data set is divided into a 20% testing piece and an 80% training portion.

- The initial resolution of images stored in RGB color space was decreased to 224 pixels on both the left and right sides.
- To evaluate the accuracy of the findings, three-fold, five-fold, and ten-fold cross-validations were carried out.
- The line SVM and CNN (Inception V3) models provided the framework for the creation of the hybrid classifier.
- The CNN Model's Inception V3 network is utilized to extract features. This model makes use of the Relu activation function and features completely connected layers. There is a 0.1 dropout rate in place.
- The average of all the pertinent scores determines the final classification. In Fig.2 flow chart of the proposed methodology is shown.

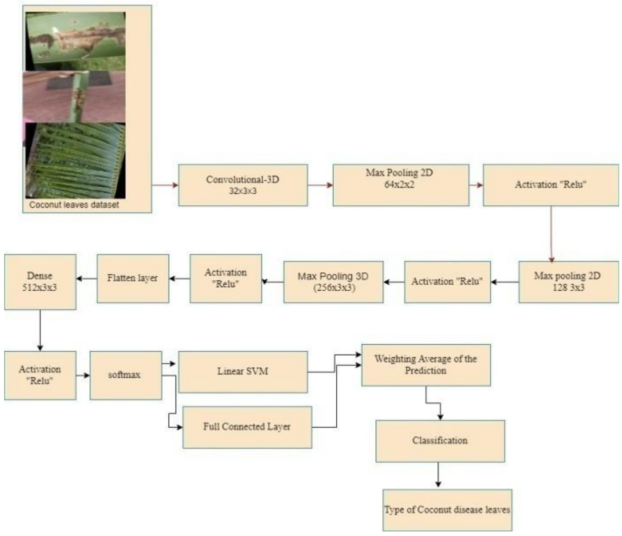


Fig.2: Flow Chart of the proposed methodology.

6. Performance Evaluation

The F1 score, area under the curve (AUC), and recall/hit rate are also crucial metrics. It was determined how well certain parameters performed. Using the Confusion Matrix, calculate your "Classification Accuracy, F1 Score, Precision, and Recall Value". The expressions for those factors are listed below:

$$Acu = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\mathrm{Pre} = \frac{TP}{TP + FN} \quad (2)$$

$$\mathrm{Re} = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = \frac{2 * \mathrm{Re} * \mathrm{Pre}}{\mathrm{Re} + \mathrm{Pre}} \quad (4)$$

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{((\mathrm{TP+FP}) * (\mathrm{TP+FN}) * (\mathrm{TN+FP}) * (\mathrm{TN+FN}))}} \quad (5)$$

"TP True positive, TN True Negative, FP False Positive, FN False Negative"

The ROC curve at a threshold of 3 is depicted in Figures 3(a), 3(b), 3(c), 3(d), and 3(e) for (CC1), (CCL1), (WCLD), (WCLF) and, (WCLY) respectively. Colors of the ROC curve: orange for SVM, purple for the ensemble (NNSVLC) method, and green for NN. Figures 4(a), 4(b), 4(c), 4(d), and 4(e) display five-fold ROC curves for (CC1), (CCL1), (WCLD), (WCLF), and (WCLY). Figures 5(a), 5(b), 5(c), 5(d), and 5(e) show the ten-fold ROC curve for (CC1), (CCL1), (WCLD), (WCLF), and (WCLY), in that order. The comparison of several techniques for 3, 5 and 10 folds for (CC1), (CCL1), (WCLD), (WCLF), and (WCLY) is displayed in Table 4.

Table 4. Comparing various algorithms for three, five, and ten folds.

K Folds	Model	AUC	CA	F1	Pre-cision	Recall	MCC
3	CNN	100	98.7	98.7	98.7	98.7	98.4
3	SVM	100	98.7	98.7	98.7	98.7	98.4
3	NNSVCLD	100	98.9	98.9	98.9	98.9	98.7
5	SVM	100	99	99	99	99.1	98.8
5	NN	100	99.1	99.1	99.1	99.1	98.9
5	NNSVCLD	100	99.3	99.3	99.3	99.3	99.1
10	CNN	100	99	99	99	99.1	98.9
10	SVM	100	99.2	99.2	99.2	99.2	99
10	NNSVCLD	100	99.4	99.4	99.4	99.4	99.3

The confusion matrix for the threefold model is shown in Table 5-7, the confusion matrix for the fivefold model is shown in Table 8-10, and the confusion matrix for the tenfold model is shown in Table 11-13 for the NN SVM and NNSVCLD models.

Table 5. SVM Model's confusion matrix for three-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	98.9	0	2.1
	d	0	0	0.3	99.1	1.7
	e	0	0	0.8	0.9	96.2

Table 6. NN ModelModel’s confusion matrixfor three-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	98.3	0	1.7
	d	0	0	0.1	98.7	1.3
	e	0	0	1.6	1.1	97.3

Table 7. HybridModel’s confusion matrix for three-folds.

		Predicted				
		a	b	c	d	e
Actual	a		a	b	c	d
	b	a	99.8	0	0	0
	c	b	0.2	100	0	0
	d	c	0	0	98.9	0.1
	e	d	0	0	0.1	99

Table 8. SVM Model’s confusion matrix for five-fold.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	99.4	0	1.1
	d	0	0	0.6	99.3	1.7
	e	0	0	0	0.7	97.2

Table 9. NN Model’s confusion matrix for five-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	98.5	0.3	0.8
	d	0	0	0.2	99	0.6
	e	0	0	1.3	0.7	98.5

Table 10. Hybrid Model’s confusion matrix for 5-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	99.5	0.1	0.6
	d	0	0	0.6	99.2	0.7
	e	0	0	0.5	0.7	98.7

Table 11. SVM Model’s confusion matrix for ten-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	99.3	0	1.7
	d	0	0	0	99.2	1.1
	e	0	0	0.7	0.8	97.2

Table 12. NN Model’s confusion matrix for ten-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	99	0.3	0.8
	d	0	0	0.1	99	0.7
	e	0	0	0.9	0.7	98.4

Table 13. Hybrid Model’s confusion matrix for ten-folds.

		Predicted				
		a	b	c	d	e
Actual	a	99.8	0	0	0	0
	b	0.2	100	0	0	0
	c	0	0	99.5	0.1	0.6
	d	0	0	0.6	99.2	0.7
	e	0	0	0.5	0.7	98.7

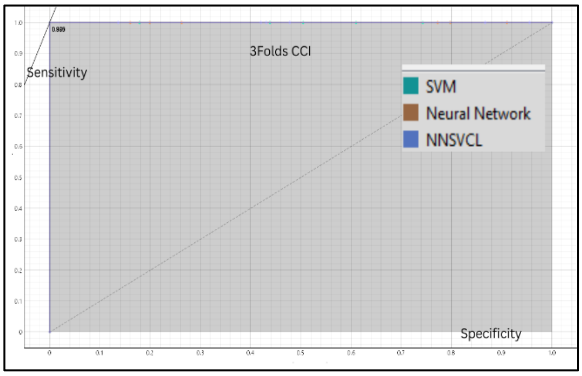


Fig. 3:(a) ROC of CCI for 3 folds.

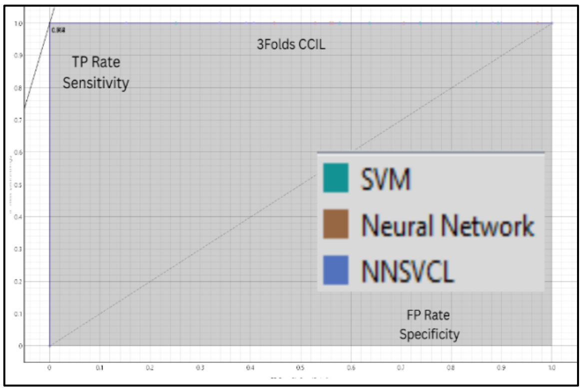


Fig. 3:(b) ROC of CCIL for 3 folds.

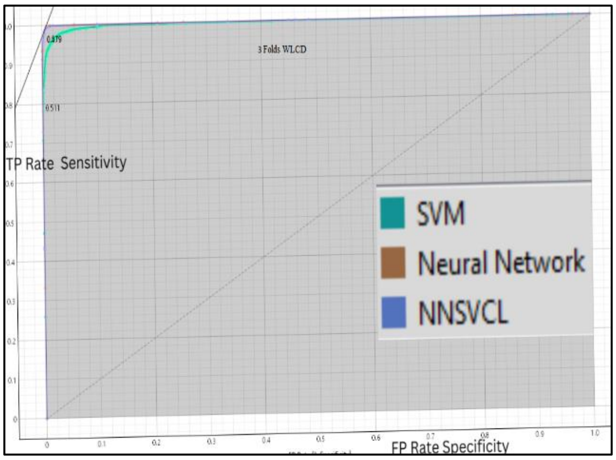


Fig. 3:(c) ROC of WLCD for 3 folds.

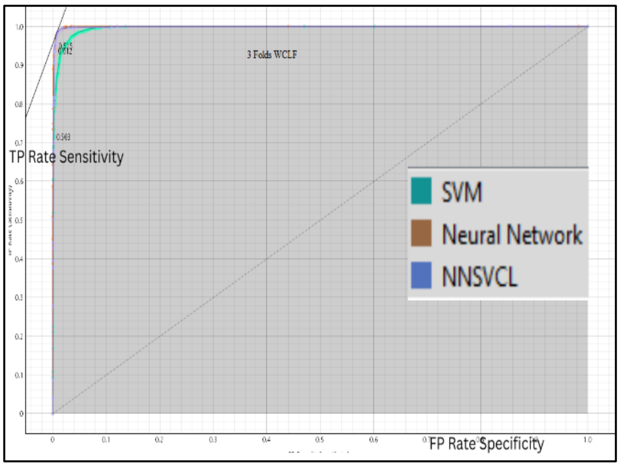


Fig. 3:(d) ROC of WCLF for 3 folds.

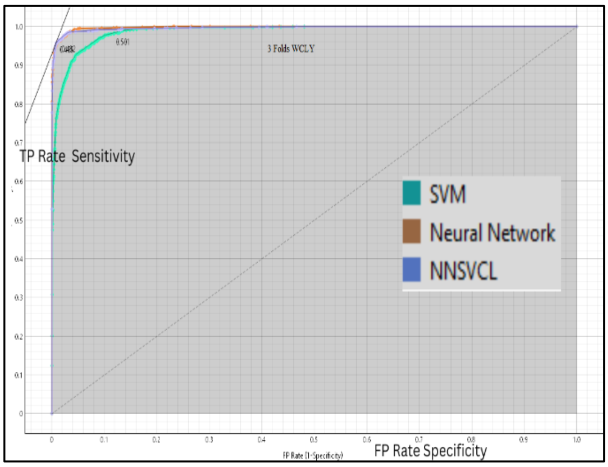


Fig. 3:(e) ROC of WCLY for 3 folds.

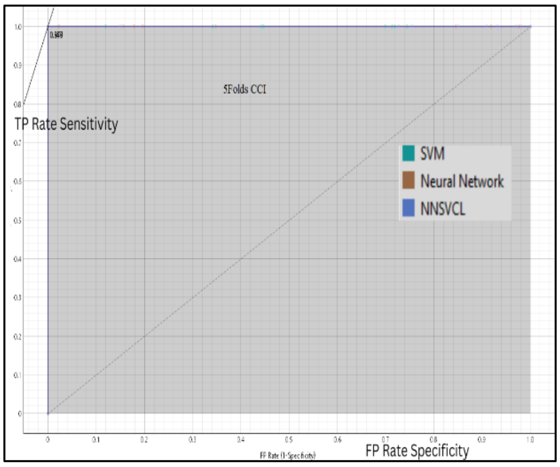


Fig. 4:(a) ROC of CCI for 5folds.

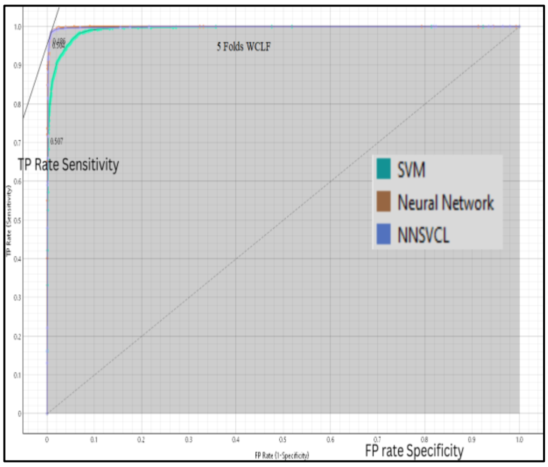


Fig. 4:(b) ROC of CCIL for 5 folds.

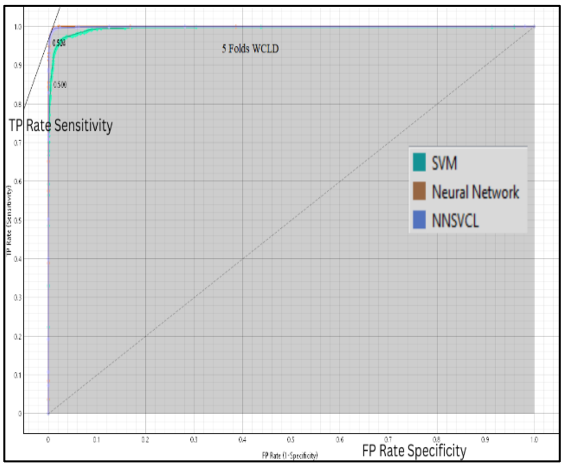


Fig. 4:(c) ROC of WCLD for 5 folds.

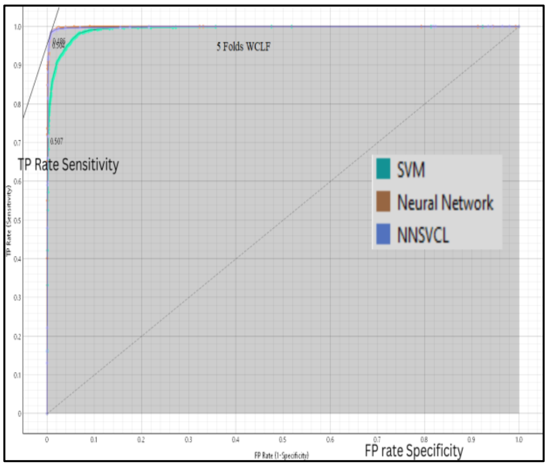


Fig. 4:(d) ROC of WCLF for 5 folds.

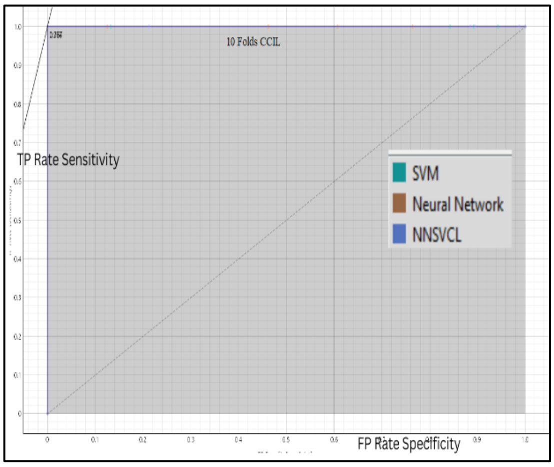


Fig. 5:(b) ROC of CCIL for 10 folds.

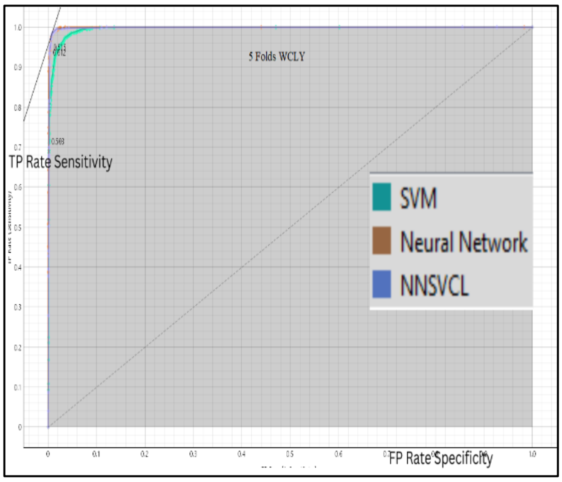


Fig. 4:(e) ROC of WCLY for 5 folds.

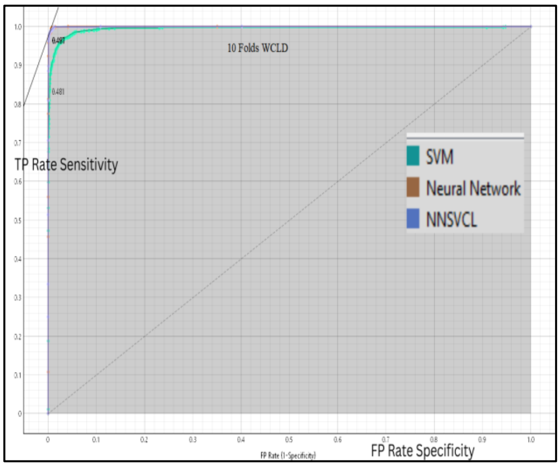


Fig. 5:(c) ROC of WCLD for 10 folds.

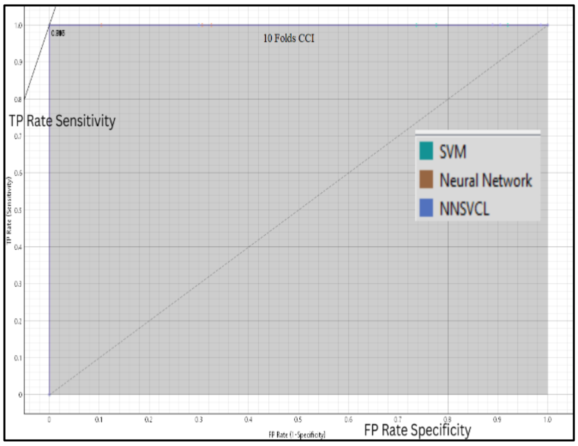


Fig. 5:(a) ROC of CCI for 10 folds.

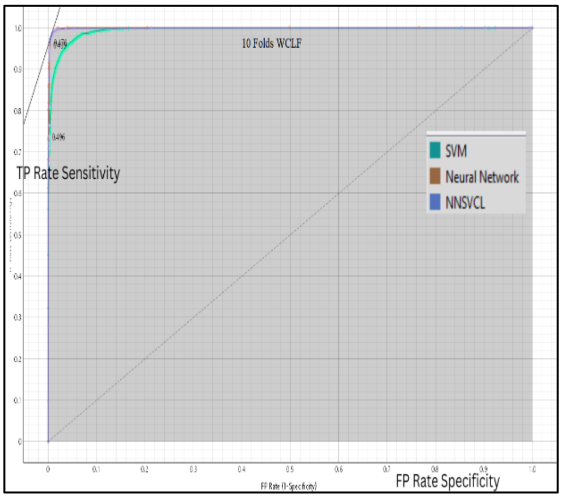


Fig. 5:(d) ROC of WCLF for 10 folds.

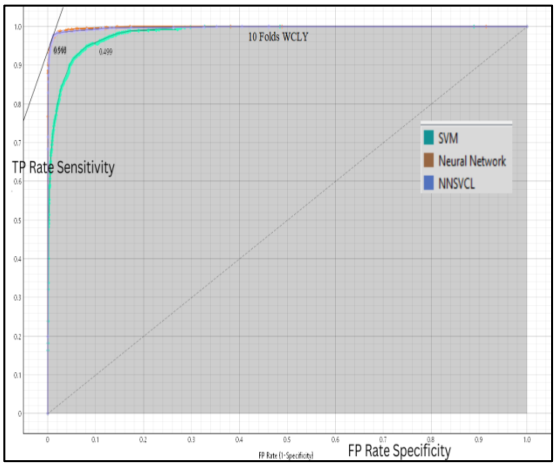


Fig. 5:(e) ROC of CCI for 10 folds.

7. Conclusion

Precision Agriculture aims to improve coconut leaf productivity and early disease detection. Deep learning technique paired with high resolution datasets have an accuracy of 99%. Urbanization has led to a shortage of skilled farmers, making it challenging to spot diseases at the appropriate stage. The proposed algorithms benefit farmers by providing cost-effective image –based crop monitoring solutions. Predict illnesses in coconut trees quickly and accurately, with least money and labour. Using deep learning techniques improves categorization accuracy in agricultural vegetation mapping. We suggested automated coconut diseased leaves classification assembling models for deep learning. The upper layers of two-component classifiers (Inception V3, SVM) were eliminated by transfer learning. Transfer learning allowed two component classifier (Inception V3, SVM) to identify features of diseased coconut leaves and link them to Relu classifier, for classification. various parameters such as “Accuracy, Precision, Recall and F1 score” of component classifier was confirmed for three, five and ten folds’ validations on the leaflet dataset infected with coconut disease. To test set performance for three, five, and tenfold cross Validations, we employed a weighted aggregate of classifiers to classify using NNSVCLD. It shows that for tenfold all the performance matrices have shown the best results. NNSVCL outperformed as compared to SVM particularly for WLCD, WLCF, and WCLY. As number of fold increases the various performance matrices have also been improved specifically for hybrid method NNSVCLD.

The future of coconut leaf disease detection using deep learning is bright, with significant chances for improvement. The development of synthetic data for model enhancement, enabling real-time detection, mixing various data types, enhancing model generalization, and incorporating disease detection into larger precision agriculture systems are important areas for expansion. In order to ensure healthier coconut farms and increase overall agricultural productivity, deep learning will become increasingly important as AI, computer vision, and agriculture methods continue to advance.

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