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Research Article

A Novel Classifier for Plant Health Monitoring: A Focus on Banana Leaf Disease Detection Using Deep Learning

Ravi Kumar Tirandasu[1]*, Prasanth Yalla[2]

[1]*Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.*
ravi.tirandasu@gmail.com

[2]*Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.*
prasanthyalla@kluniversity.in

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ABSTRACT

Crop productivity and food security in modern agriculture are largely dependent on efficient monitoring and early identification of plant diseases. With a focus on the identification of leaf diseases, this study investigates the use of machine learning algorithms in the context of plant health monitoring. To extract pertinent characteristics from photos of plant leaves, the study makes use of sophisticated image processing techniques. This results in a large dataset that can be used to train and assess machine learning models. The proposed approach makes use of a comparison study to assess how well different machine learning algorithms recognise and categorise distinct leaf disease kinds. High-resolution photos of plant leaves displaying disease signs are collected as part of the approach, which also include preprocessing the data to improve feature extraction and utilising labelled datasets to train machine learning models. After that, the models are evaluated on hypothetical data to see how well they generalise and perform in actual situations. In this paper an Ensembled CNN Leaf Disease Detection Classifier (ECNNLDD) used to predict the healthiness of a leaf which classifies whether is healthy or unhealthy which is a 2-class problem and compared with the existing classifier like Decision Tree and SVM algorithm in which the proposed classifier Ensembled CNN Leaf Disease Detection Classifier outperformed when compared with the existing classifiers. The findings of proposed classifier gave the best accuracy in agriculture by offering an intelligent and automated solution for early detection and diagnosis of plant leaf diseases. The integration of Deep learning into plant health monitoring systems holds the potential to revolutionize farming practices, enabling farmers to adopt timely and targeted interventions, thereby minimizing crop losses, and promoting sustainable agriculture.

Keywords: Early Detection, Decision Tree, Healthy Leaf, EnsembledCNN Leaf Disease Detection Classifier, Crop productivity.

INTRODUCTION

Maintaining global food security depends heavily on agricultural production. However, a number of diseases that affect crop quality and output create a danger to crop health. Conventional disease detection techniques frequently depend on manual inspection, which can be laborious and imprecise. The use of deep learning methods to agriculture has shown a lot of promise recently, providing effective and precise methods for the identification and categorization of leaf diseases [1]. The goal of this research is to improve plant disease diagnostics by utilising ML & deep learning techniques. The main goal is to create reliable models that can correctly recognise and classify diseases from photos of plant leaves. Farmers may obtain accurate and timely information by automating this process, which empowers them to take preventative action to safeguard their crops. A country's capacity to generate high-quality agricultural goods is critical for its economic success. The identification of plant-damaging areas may be the key to averting a drop in agricultural productivity and production. Many commonly used techniques from the fields of machine learning, image processing, and neural network [2] approaches have been utilised to identify and detect disease on agricultural goods. This paper proposes a pre-processing and segmentation technique for crop disease diagnosis that utilises neural network technology and filtering.Leaves are essential for providing information on the type and quantity of horticultural produce in agricultural crops. Diseases lower agricultural product quality and productivity. The scientific community has given plant diseases a lot of thought, concentrating on their biological characteristics [3]. It is not only the human eye that can identify diseases. The main aim of this article is divided into 4 steps.

1) In the first module aids in determining if leaves are healthy or unhealthy.

2) To create plant disease control strategies and minimise the losses they generate.

3) To create a system capable of precisely identifying agricultural illness.

4) To offer treatment for the illnesses and pests that was found.

Through the provision of an effective and precise tool for the early identification and categorization of leaf diseases, this research advances precision agriculture. By automating this procedure, farmers may make better judgements, reduce the effect of illnesses on crop production, and encourage sustainable farming methods [4]. One important step in resolving issues with global food production and guaranteeing food security for future generations is the use of deep learning techniques into agriculture.

An important worry for farmers across the world is the effect that leaf diseases have on crop productivity. Numerous pathogens, including as fungus, bacteria, viruses, and environmental variables, can result in leaf diseases. These illnesses have a variety of negative effects on agricultural productivity, including decreased photosynthesis [5], fertiliser absorption, and general plant health. The Table1 shows the major factors why farmers losing their yield every year.

Table 1: Understanding the Major Factors Contributing to Yearly Yield Losses Among Farmers

Impact on Farmers' Yield	Consequences and Challenges
Reduced Photosynthesis and Yield Loss & production	Interference with photosynthesis affects energy production which results in Poor crop development and lower biomass production Decreased overall crop yield
Impact on Crop Quality	Discoloration, deformities, and changes in taste or nutrition results in lower market value for affected crops.
Increased Cost of Control Measures	Additional expenses for pesticides and fungicides results in Over-reliance on chemical treatments may pose environmental concerns
Challenges in Early Detection	Visual inspection may not detect symptoms in the early stages results in Delaying detection leads to rapid disease spread
Need for Sustainable and Precision Agriculture	Growing demand for environmentally friendly solutions results in emphasis on precision agriculture for targeted interventions
Role of Technology in Disease Monitoring	Integration of image-based systems and sensors for early detection results in Real-time data for timely intervention and monitoring
Climate Change Considerations	Dissemination of information on best practices and resistant varieties
Impact of climate change on disease prevalence and severity	Need for understanding and adapting to changing disease dynamics

PROBLEM DEFINITION

Agriculture in India is vital to the nation's economic growth. In India, the agricultural industry employs around half of the labour force. The world's leading producer of pulses, rice, wheat, spices, and spice-related items is India. The quality of the thing'sfarmersproduces, which is dependent on plant growth and production, determines how far their economies can go. For this reason, it is essential in agriculture to identify plant diseases. Diseases that inhibit plant development are quite likely to affect plants, which impacts the environment of the farmer. When a plant disease is identified early on, it is best to utilise an automated disease detection approach. Leaf is major part of the plant where plant diseases can appear [6]. Using pictures of the leaves to manually detect plant diseases takes a lot of time. It is necessary to build computational tools to automate the process of classifying and identifying diseases using leaf photos. So, in this article we have taken Banana leaf for Leaf Disease Detection and plant health monitoring system. Figure 1 shows the overall architecture of proposed ECNNLDD classifier in predicting healthiness of leaf detection.

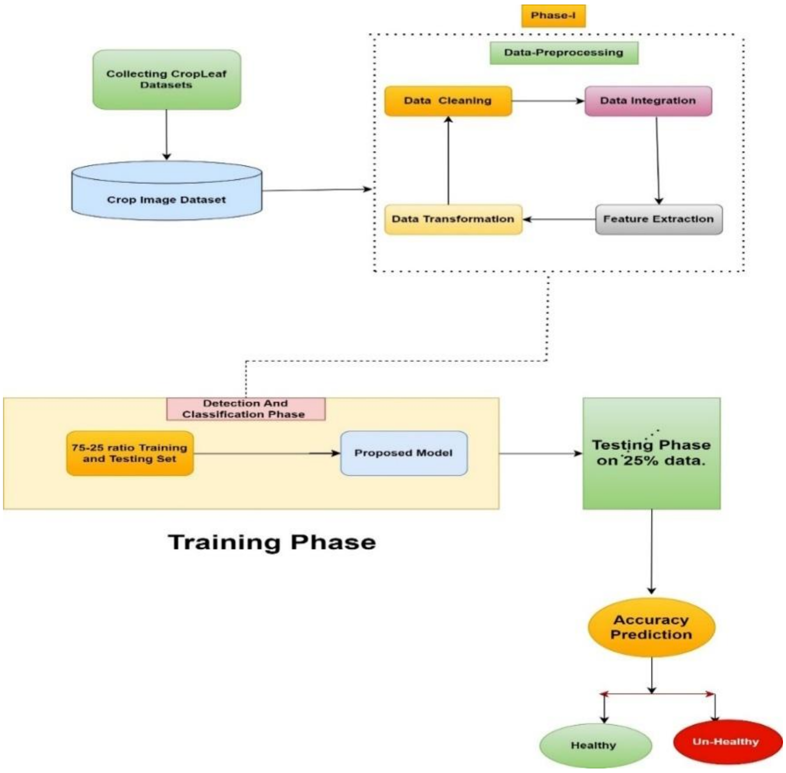


Figure 1: Proposed Architecture of ECNNLDD (Proposed)

LITERATURE SURVEY

In this section we discussed about the current updates in leaf health monitoring system. Table 2 shows the literature collection.

Table 2: Literature review on advancements in CNN for Image Recognition

Author Name & Year	Culture	Disease	Technique of ML	Accuracy
Lee, S.H et.al.(2021)	Crop	To classify Banana leaf diseases	SVM,NB	Achieved a overall accuracy of 89%
Singh, J et.al. (2021)	Crop	Plant-disease detection using a deep-learning model	Deep Learning	It requires large amounts of data to train the network 90%
Li, Y et.al. (2021)	Crop	To classify disease in tea leaves	Neural Networks	91%
Cevallos, C et.al. (2021)	Rice	For detecting the different types of diseases	Neural Networks	92%

		on rice crop		
A. Devaraj, et.al (2020)	Crop	Classification and disease detection is performed by software	CNN	This efficient method for disease detection will prevent the farming loss. 92%
Mukhopadhyay et.al. (2020)	Cotton	For detecting the different type of disease that occurring for the cotton plant	ANN	Grey level Co-occurrence matrix is utilized for the extracting features. 91%
Shital Prasad[22]	Crop	Early Blight, Coffee sena	Advance SVM	89%
HX KAN[2017]	Medical Plant	Cassia Tora	SVM classifier	92.3%
Ashraf-El-Kereamy	Crop	26 Disease	Deep Learning	92.8%
ZareenNaowal[2016]	Jute	Soft root,leaf Blight	Multi SVM	86%
Quinz Yao[2016]	Rice	Rice sheath	SVM,LR	91.3%
Vijai Singh[2016]	Crop	Leaf Spot etc.,	Genetic Algorithm	92.6%
Bassam-AL-Qarallah[2017]	Cucumber	Powdery Mildew	SVM,RF	N/A
VsamaMokhtra[2008]	Banana Leaf	Leaf Miner	SVM Based	88%
T.Pumpfi[2010]	Crop	Sugar etc.,	Spectrum Vegetation Indices	90%
S.Arivazhagan[2013]	Crop, Banana etc.,	Late Scorch	NB,SVM	89%
NumihKurniwoti[2009]	Paddy Leaf	Narrow Brown spot	Ostu Method	91.7%
Farah TazimPinki[2017]	Paddy	Brown spot	SVM	90.4%
Dheebh AI Bashisw[2011]	Crop	Leaf Blast	NB,SVM	89.4%
S. Phadikar, J. Sil, and A. K. Das (2012) Mrunalini R. Badnakhe&Prashant R. Deshmukh (2012)	Crop	Narrow Brown	Mean Filter	90%
Qing Yao, Zexin Guan et al. (2009)	Crop	Brown spot	Median Filter	91%
Sanjeev S Sannakki et al. (2011)	Paddy	Used to blur images	Gaussian Filter	90%
KittipongPowbunthorn, WanratAbudullakasim and JintanaUnartngam (2012)	Paddy	Remove noise	Morphological Operation	89%
Mr. V. A. Gulhane&Dr. A. A. Gurjar (2011)	Crop	Partial derivatives equations (PDE) based denoising	Anisotropic Diffusion	92%
Qing Yao, Zexin Guan et al. (2009) S. Phadikar, J. Sil, and A. K. Das (2012)	Rice, Paddy	Simple to implement	Otsu algorithm fails when the global distribution	91.4%

KittipongPowbunthorn, WanratAbudullakasim et al. (2012)			occurs	
S. Bani-Ahmad, M. Reyalat et al. (2011)	Paddy	Applied on histogram	Local Entropy Based Thresholding Method	92%
Sanjeev S Sannakki et al. (2011) Dheeb Al Bashish, Malik Braik, and SuliemanBani-Ahmad (2010)	Cotton	Easily detection and implementation.	K-Means Clustering Method	91%
P. Kumsawat et al. (2008) Mr. V. A. Gulhane&Dr. A. A. Gurjar (2011)	Paddy	Use training data to solve complex problem and easily detect errors.	Neural Network Based Method	94%

METHODOLOGY

Plant specialists can discover and diagnose plant illnesses by just basic visual observation, which is the current way for diagnosing plant diseases. In these conditions, to monitor large agricultural fields, make use of the given approach [7]. It's also possible that farmers in other countries lack access to the required tools or are unaware that they may seek advice from specialists. As a result, consulting with experts comes at an increased time and financial expense. In certain cases, it would be advantageous to track many plants using the suggested method. So, in this scenario the proposed classifier gives much better accuracy when compared with the existing classifiers. Finding plant diseases is the main goal of this research [8,9]. Plant diseases are identified by the use of feature extraction, segmentation, and classification algorithms. Digital cameras or similar devices are used to capture pictures of leaves from different plants, and the photos are then used to categorise the damaged regions in the leaves. In the suggested framework, a ELDC and a deep neural network named as Ensembled CNN for Leaf Disease Detection is used to identify plant disease. An inexpensive, open-source software solution for the accurate identification of plant diseases is suggested by this study. Our task involved improvisation: We comprehended how segmentation algorithms, feature extraction algorithms, classification algorithms, and so forth operated. We looked at the automatic process for detecting diseases and how well it works in the real-time project. For research, training, testing, and disease detection, we used Banana plant leaves [18].

These days, plant diseases are one of the biggest concerns for farmers [10]. Farmers sometimes don't know which insecticide or pesticide to put on a certain infected plant because they don't know what kind of disease it is. This leads to the incorrect pesticides being sprayed, harming the plants and lowering plant production.

In order to solve this issue, we have devised a system that can quickly and accurately detect a number of common illnesses that affect Banana plants by looking at their leaves.

Numerous diseases that might significantly harm the leaves of Banana plants can affect them. Banana leaf diseases encompass several serious conditions, such as:

1) Black Sigatoka
2) Panama Disease
3) Bacterial Wilt
4) Anthracnose
5) Banana Streak Virus
6) Leaf Spot Diseases
7) Yellow Sigatoka

The proposed classifier works in 2 phases for detecting disease. In Phase-I we used Image-Processing i.e., CNN Model [11] for feature extraction which can yield a confusion matrix. In Phase=II we apply ML algorithms to find the accuracy prediction in detecting the plant disease which predicts whether the plant is healthy or un-healthy. In literature survey most of the researchers concentrated on few parameters like Panama Disease, Bacterial Wilt, etc.. So, in the present article we have chosen BananaStreakVirus (BSV) for predicting the plant disease. The combination of 2 or more models results in a single model known as Ensembled model so, the proposed classifier known as ECNNLDD classifier which is used in the current paper for predicting plant disease the process of how the proposed model works is shown in Figure 2. The proposed model may benefit for farmers in early detecting of disease which can yield good crop results in making profit rather than loss.

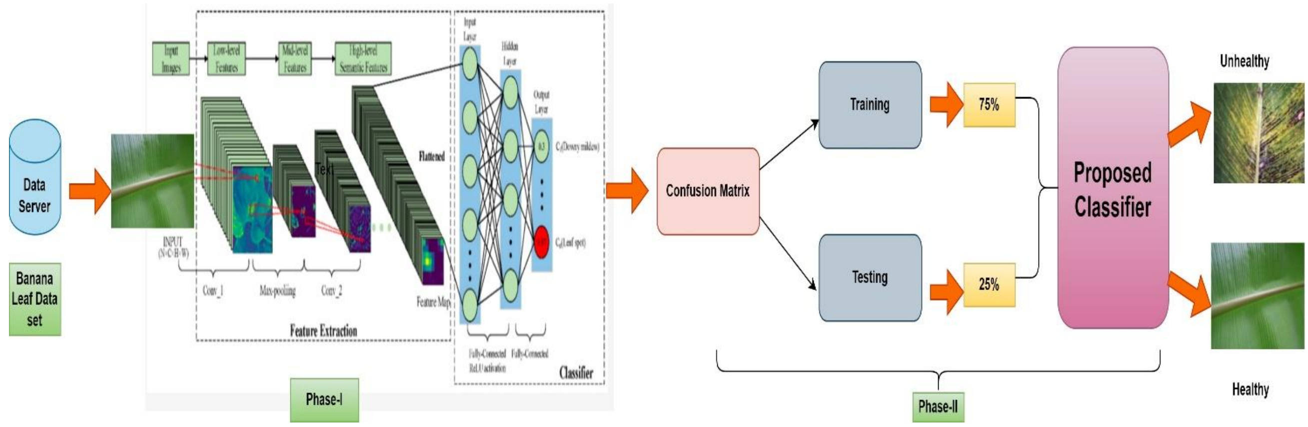


Figure 2: Feature Extraction and Process using ECNNLDD (Proposed) Classifier

4.1: Data Set Collection

The Dataset used to predict the sick plant leaf is taken from Kaggle repository. After the image has been taken, it is uploaded to the system and the image processing [12] step is carried out in Phase-I using proposed model which receives the final image as an input to it. This picture serves as the testing data that will be used to assess the precision of our technology. Prior to being put to the test on our machine learning model, the image is fit, scaled, and coloured using a variety of methods.

4.2: Data Set Features

The dataset consists of enormous volumes of raw data that must be trained to extract any meaningful information. The photos of Banana plant leaves that are either healthy or un-healthy which is represented as a 2-class problem. The dataset contains the images of Banana leaf using preprocessing technique for image processing we used Gaussian filter to perform preprocessing.

Transferring unprocessed data into an accessible and understandable format.

Steps in the pre-processing of leaf images:

Step-1: Take Original image.

Step 2: A picture in grayscale

Step 3: Following the thresholding process.

Step 4: Following a top-hat procedure.

Step 5: Following the bounding box, the final picture.

4.3. Gaussian Filter:

It is a linear filter which is known as low pass filter which is used to reduce noise. The size of the kernel or matrix that will be used to the reduce noise in the picture is first determined followed by softening some areas of a picture [13].

The Gaussian function, which is as follows, computes the values inside the kernel is given in Figure 3.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

1) For the disease diagnosis model to function as accurately and precisely as possible, a large database is required. We have 180mb of leaf photos in total, 75% for Black Sigatoka Panama Disease, Bacterial Wilt, Banana Streak Virus, and Leaf Spot Disease. To create a consistent dataset, each of these photos has been scaled, altered, and polished to a single quality and dimension. This dataset serves as our training set, governing the platform's initial stages of digital picture processing. The Figure 4 shows the images of Banana leaves unhealthy and healthy.

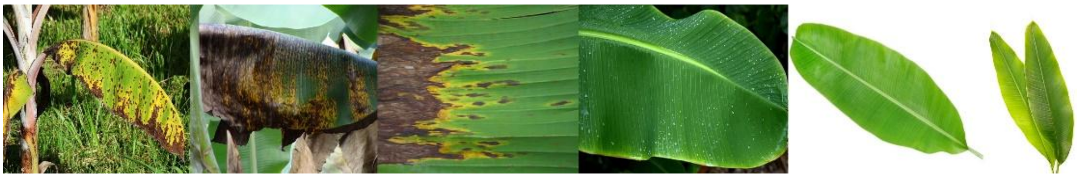


Figure 3: Healthy / Unhealthy State Classification of Banana Leaf

4.4 Digital Image Processing (DIP):

Banana leaf diseases may be accurately detected and diagnosed with the use of digital image processing techniques. Generally, for this to happen we need to perform preprocessing technique and finally the augmented image of the leaf has to be detected which is shown in Figure 5.

Phase -I: In phase-I take the image dataset as input.

Next Data is pre-processed i.e., by image resizing, image enhancement, and image denoising and finally colour correction.

Once the data has been pre-processed the next task is to extract the features which must be distinguished from healthy and diseased like Colour, Texture, Shape etc.

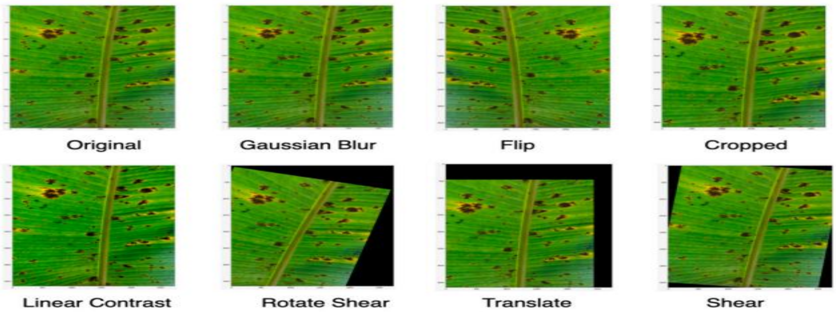
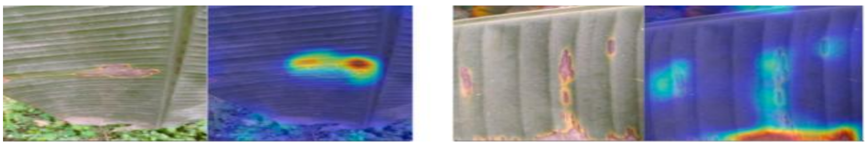


Figure 4: Image Augmentation Techniques Overview (Affine Transformations)

In the Next Step image segmentation must be done. Segmenting a picture entail dividing it into useful parts or segments [14] especially for the purpose of detecting Banana leaf disease. The stages involved in segmenting a picture are as follows:

Image is divided into a few smaller groupings known as Image segments. To put it simply, segmentation is the process of assigning labels to pixels. This assists in decreasing the complex nature of the image where the disease has attacked, Figure 6 shows segmentation process i.e., segmented disease area.



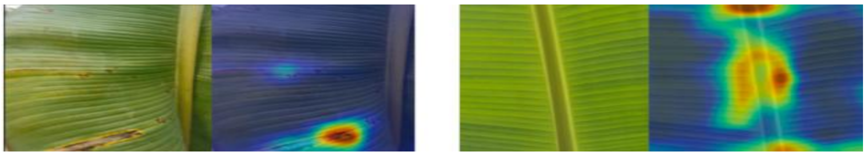


Figure 5: Visualization and Analysis of Segmented Disease Areas of Banana Leaf

From Phase-I for each image a predicted class label is assigned (ie 0 or 1) where 0 is healthy and 1 is unhealthy. So, the o/p from Phase-I will be a 2-class confusion matrix.

In Phase-II from the confusion matrix obtained in Phase-I is trained i.e., 75% we choose for training purpose and 25% for testing purpose. Figure 7 shows the confusion matrix for a 2-class problem.

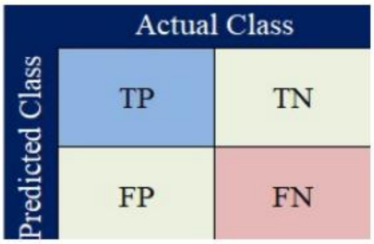


Figure 6: Confusion matrix for a 2-class Problem

PERFORMANCE METRICS & RESULTS

The evaluation metrics are crucial for evaluating machine learning models' efficacy and determining which model is best suited for a certain job. Selecting the validation measures that are most important to the current issue must be done after carefully weighing several options [15].

Precision: The accuracy of a model's positive predictions can be determined by its precision. This formula is used to compute it:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: Recall is a metric that indicates the percentage of real positive cases that the model accurately predicts. It is sometimes referred to as sensitivity or true positive rate (TPR). This formula is used to compute it:

$$\text{Recall (TPR)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F-score: This is often referred to as the F1-score, is an accuracy metric that strikes a compromise between recall and precision in models. It is determined by applying the following formula, which is the harmonic mean of accuracy and recall:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy: In machine learning, accuracy is a widely used evaluation metric that assesses how accurate a model's predictions are overall. It is determined by dividing the total number of predictions the model makes by the number of accurate forecasts. The accuracy formula is:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Algorithm: Phase -I

1) Collect images of healthy and diseased banana leaves.

2) To increase dataset variability, preprocess the photos by shrinking them to a uniform size, normalising pixel values, and applying data augmentation techniques.

3) Utilise pre-trained models for transfer learning, or pre-train the basic models on the gathered dataset.

4) Obtain predictions for the test dataset or newly found images from each base model after training.

5) Utilising an ensemble technique combine the predictions.

6) Generate a categorical data from the image data set.

Algorithm Phase-II

1) Categorical data is the input in phase-II i.e., Confusion Matrix

2) Choose 75%:25% ratio of data for finding the accuracy.

3) Assigning Labels and Features.

4) Split X and Y for use in Proposed Model.

5) Define, compile and train the Model.

6) Test the model for classification i.e., healthy, or unhealthy.

7) Find the accuracy of the model.

8) Stop

Table 3 shows the confusion matrix obtained for the proposed classifier after preprocessing for predicting whether the Banana Leaf is classified as 0 or 1 [16] (Where 0-healthy and 1= unhealthy).And Table 4 show the accuracy prediction from the confusion matrix obtained from phase-I and Figure 8 shows overall performance metrics of the proposed classifier.

Table 3: Confusion matrix of Proposed Classifier obtained After Phase-I

	Actual Class	
Predicted Class	39969	2034
	1544	22433

Table 4: Model Validation Table of Proposed Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	94.99	94.76	94.56	30,927
1(Unhealthy)	93.12	93.89	93.44	34,963
Accuracy			94.88	65980
MacroAvg	94.12	94.21	94.45	65980
WeightedAvg	94.10	94.21	94.12	65980

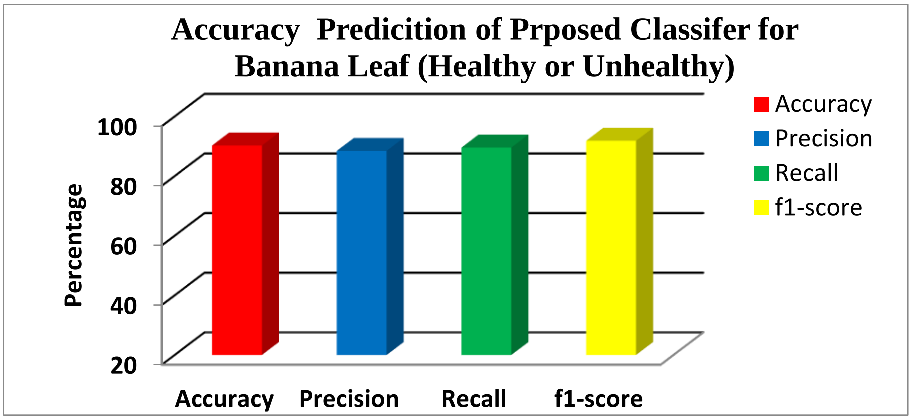


Figure 7: Computational Efficiency: Time and Resource Usage of the Proposed Classifier

Decision Tree: Decision trees, a type of non-parametric supervised learning technique, are applied to regression and classification problems. It has a structure that resembles a tree, with internal, leaf, branch, and root nodes. A dataset may be subjected to multi-class classification by utilising the DecisionTreeClassifier class. The DecisionTreeClassifier, like other classifiers, takes two arrays as input: an array Y (intrinsic values, shape) for the class labels and an array X (sparse or dense) for the training data. One tool for assessing a data set's attribute value is a decision tree. The node at the top of the decision tree is known as the root node. Based on visible symptoms, the decision tree offers a fundamental foundation for diagnosing typical diseases of banana leaves. First, it looks for leaf edge yellowing, which is a frequent sign of several diseases affecting banana leaves. If found, it indicates either Yellow or Black Sigatoka, depending on whether there are any corresponding spots [17]. The tree then looks for leaf mottling or streaking, which is indicative of the Banana Bunchy Top Virus, if no yellowing is seen. The leaf is deemed healthy if neither sign is seen. The Figure9shows the decision tree construction to check banana leaf is healthy or unhealthy. And table 5 shows the confusion matrix of Decision Tree classifier obtained after Phase-I and table 6 shows the overall performance metrics of Decision Tree and in Figure 10 shows performance analysis of DT classifier.

```
                 Is there yellowing of leaf edges?
                          /       \
                        Yes        No
                         |          |
Black Sigatoka   Is there mottling or streaking on the leaf?
                        /          \
                      Yes           No
                       |            |
              Yellow Sigatoka     Healthy
```

Figure 8: Tree Visualization: Decision Tree Structure

Table 5: Confusion matrix of Decision Tree Classifier obtained After Phase-I

	Actual Class	
Predicted Class	33969	5239
	4433	22339

Table 6: Model Validation table of Decision tree Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	88.64	86.64	87.54	30,927

1(Unhealthy)	87.96	85.89	86.23	34,963
Accuracy			85.12	65980
MacroAvg	86.12	85.21	85.45	65980
WeightedAvg	86.10	86.21	85.12	65980

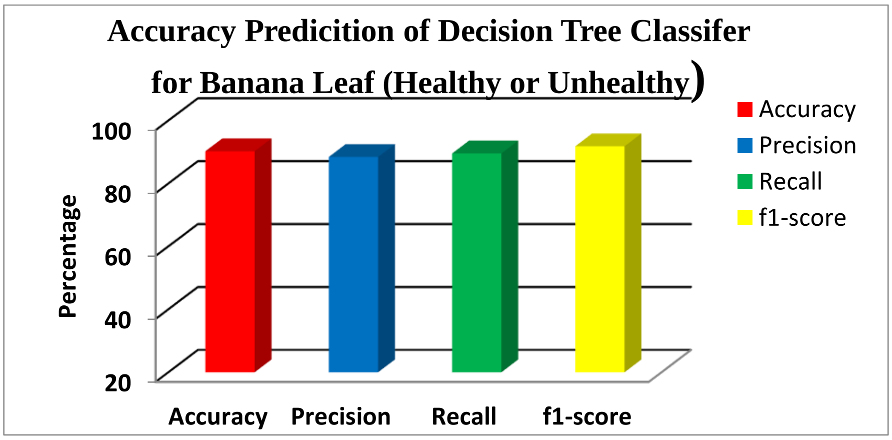


Figure 9: Computational Efficiency: Time and Resource Usage of the Decision Tree Classifier

SVM: An effective supervised learning approach for regression and classification problems is called Support Vector Machine (SVM). The way it operates is by determining which hyperplane best divides the data points into distinct groups. The following are the steps to classify the data to predict whether the Banana Leaf is healthy or unhealthy [18].

Make use of categorical data obtained from phase-I.

Train_test_split was used to divide the data into training and testing sets.

Using svm.SVC, build an SVM classifier using a linear kernel.

Fit is used to train the classifier on the training set of data.

X = np.load('banana_leaf_features.npy') # Features

y = np.load('banana_leaf_labels.npy') # Labels

Split data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

accuracy = accuracy_score(y_test, y_pred)

print accuracy.

Stop

	Actual Class	
Predicted Class	36224	4216
	2213	23327

Figure 10: Confusion matrix of SVM Classifier obtained After Phase-I

Table 7: The Model Validation table of SVM Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	90.64	89.64	89.54	30,927
1(Unhealthy)	90.96	89.89	89.23	34,963
Accuracy	____	____	90.84	65980
MacroAvg	90.12	89.21	89.45	65980
WeightedAvg	89.10	89.21	89.12	65980

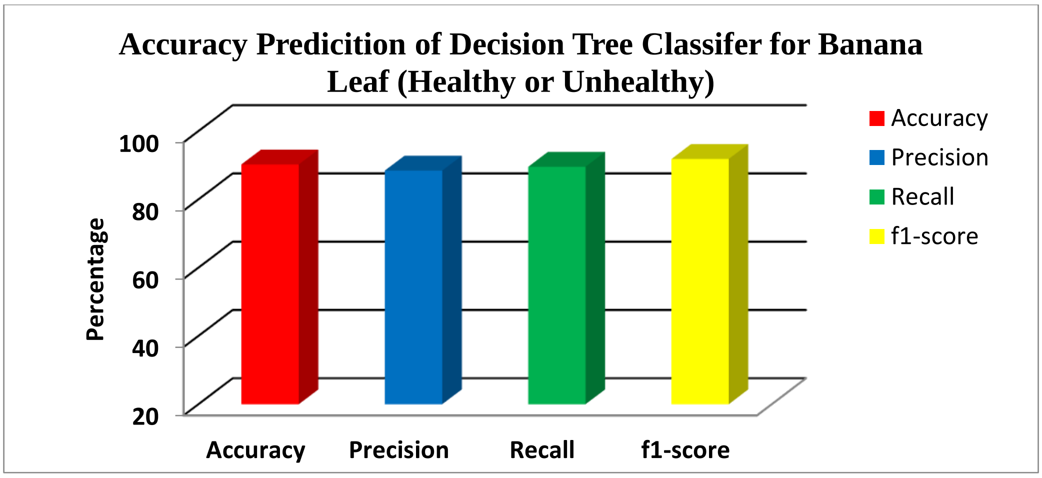


Figure 11: Computational Efficiency: Time and Resource Usage of the SVM Classifier

Lastly, Figure 13 displays the overall comparison of all three classifiers in which, when compared to the other two classifiers, the suggested classifier, ECNNDD has provided the best accuracy, ~ 95%.

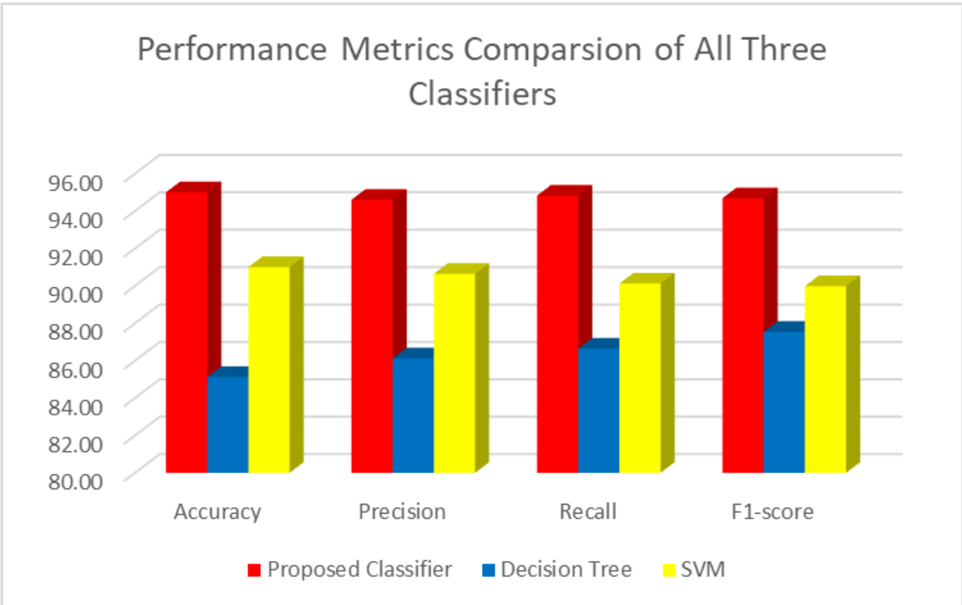


Figure 12: Accuracy Comparison Table of all 3 classifiers

CONCLUSION & FUTURE WORK

In Summary, the application of ECNNLDD classifier for banana leaf disease prediction exhibits potential in offering farmers a dependable and effective way to identify and treat diseases in banana plants. We can precisely categorise banana leaves into healthy and unhealthy groups by utilising machine learning algorithms and image analysis. This allows for prompt interventions to reduce crop losses and guarantee food security. Through this study, we have shown how well Proposed classifiers work to differentiate between several banana leaf diseases, such as Banana Bunchy Top Virus, Yellow Sigatoka, and Black Sigatoka. We built proposed model that gave best accuracy in predicting the course of disease by gathering a dataset of labelled pictures of banana leaves and extracting relevant features. The groundwork laid here will be reinforced, and ultimately, the application of machine learning in predicting the leaf is healthy or unhealthy will develop, by tackling data limitations, enhancing model performance etc., This may be accomplished by running the programme on a GPU (Parallel Processing) instead of a CPU, which increases acceleration ratio while requiring less processing time and improves accuracy.

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