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Sustainable Leaf Plant Disease Based on Salp Swarm Algorithm for Feature Selection

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ABSTRACT

Sustainable plant protection and the economy of plant crops worldwide depend heavily on the health of agriculture. In the modern world, one of the main factors influencing economic growth is the quality of agricultural produce. The need for future crop protection and production is growing as disease-affected plants have caused considerable agricultural losses in several crop categories. The crop yield must be increased while preserving food quality and security and having the most negligible negative environmental impact. To overcome these obstacles, early discovery of satisfactory plants is critical. The use of Advances in Intelligent Systems and information computer science effectively helps find more efficient and low-cost solutions. This paper proposed a multiclass classification model that aims to detect diseases in three types of fruit using the leaves plant images dataset. These three types of fruit are (Apple, Cherry, and Strawberry) where Apples have three disease dataset categories (Apple Scab, Black Rot, and Cedar Rust) as well as healthy apple dataset, Cherry have Powdery Mildew disease dataset category and healthy dataset, and Strawberry have leaf Scorch disease dataset category and healthy dataset. These datasets are based on the Kaggle website. These multiclass classifications need several steps of processing; the first step is preprocessing the dataset by resizing all images to the same size, segmentation, and removing noise; then, feature extraction from color and texture features; the next step is feature selection to find optimal features by using the Salp Swarm algorithm (SSA); and classification by using machine learning models (Random Forest), (CatBoost), and (XGBoost). In the final step, evaluation of the performance was used to select several matrices: Accuracy, precision, recall, and F1-score.

1. Introduction

United Nations has outlined 17 Sustainable Development Goals (SDG) [1], Which aim to prevent poverty, achieve prosperity, and preserve the planet for everyone by 2030 [2]. For any agricultural community, plant health is crucial. Plants are vital components of all life on Earth and are essential to our environment [3]. Plant disease identification delays and inconsistencies lead to lower yield

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levels in quantity and quality. Twenty to forty percent of the world's yearly productivity is lost due to pests or plant diseases [4]. The most crucial aspect is the potential for early detection of plant leaf diseases, which could prevent plant damage, contribute to the sustainability of agriculture, and improve agricultural production. It could maintain sustainable environmental development and prevent a food disaster for the world population [5]. As the human population increases, so does the need for food. According to the World Health Organization (WHO), 70 percent of the world's food needs to be produced by 2050. Therefore, many technologies and facilities have been used in agriculture to maximize crop productivity [6]. Artificial intelligence (AI) continues to advance, and the potential of AI extends beyond its self-optimization; it plays a crucial role in driving sustainability across various industries, including agriculture [7]. This research aims to develop a robust system using advanced computational techniques by AI applications such as computer vision, machine learning, and metaheuristic to classify disease plants more accurately, as well as early detection and implementation in less time and at a low cost [8]. This research is organized into six sections: Section Two reviews the related work, and Section Three represents datasets used in this research. After that, Section Four preprocesses disease Fruit Leaf Plant images taken from datasets; Section Five extracts features and then selects the best features in Section Six; Section Seven, classification by using machine learning and evaluates the performance of the models.

2. Related Works

Many researchers have published studies on the diagnosis of plant diseases, mainly focusing on the detection of leaf diseases using image-processing techniques and machine learning. This area of research has a long history and continues to attract significant attention from the scientific community, highlighting its ongoing relevance and importance. In 2021 Venkatasubramanian, S. [9]. The Chaotic Salp Swarm algorithm (CSSA) and Bi-directional Long Short Term Memory (Bi-LSTM) technique are used to classify and detect process disease of apple and tomato leaves. Where a deep learning network was used to train the dataset taken from the PlantVillage dataset of damaged and healthy plant leaves. In this research is estimated that the trained model achieves a test accuracy of 96%. In 2021 Jain, S., & Dharavath, R. [10]. This research takes images of maize, rice, and grape leaf plant disease detection by processing the image segmentation, feature extraction, optimization, and classification algorithms. It proposes a memetic salp swarm optimization algorithm (MSSOA), which is transformed into binary MSSOA to search for the optimal number of features that give the best classification accuracy. The performance of the proposed algorithm for feature selection is implemented for automatic disease detection of maize, rice, and grape plants, yielding classification accuracy of 93.6%, 79.1%, and 95%, respectively. In 2023 Danwadkar, E. a. T. S. [11]. The proposed system involves training a 14-layered CNN model using hyperparameters in the Google Colab GPU environment. This model has undergone training for a total of 50 epochs. 80% of the images were used for training, while 20% were used for testing. Within the testing set, 10% was allocated for validation purposes. The maximum number of epochs at which the image loss percentage decreased. In this model utilized six pooling layers, six convolutional layers, one flattened layer, and one Dense layer. Contains a batch of 32 images, each with a size of 256*256 pixels and three color channels (RGB) represented by red, green, and blue, to identify tomato leaf diseases. This 14-layer model has achieved a validation accuracy of 96%. In 2024 Konik, M. R., & Swapnil, A. A. [12]. In this research main purpose is the identification of paddy diseases. The plant diseases that attack paddy at different stages of development are Brown Spot Disease (BSD), Leaf Blast Disease (LBD), and Leaf Blight Disease (LBD). Three types of diseases were studied, and one group of healthy paddy leaves was also considered. Some of the agents that cause paddy diseases include bacteria, fungi, and other microorganisms. Machine learning techniques were used for image segmentation, and an automated detection method and classifications were used to find the best accuracy. To measure the classification of this paper, K-Fold cross-validation techniques have been used. When 4 classes of paddy leaf are applied to Random Forest (RF), Decision Tree (DT), Logistic Regression, and SVM as the Support Vector Classifier (SVC), the highest accuracy of 94% is achieved by Random Forest. In 2024, Kumar, R., Bharti, and Kumar, A. [13] used machine learning to detect diseases in plants. They obtained a dataset of plant images representing various crops, such as (Apple, Cucumber, Tomato, and Grape), and the disease types were collected from different sources. They used preprocessing, including standardization, quality enhancement, feature extraction, algorithm selection, and model training using k-nearest neighbors (KNN), Naive Bayesian, and Random Forest algorithms, which were chosen for their classification tasks. Model performance was used for parameter tuning and validation on separate subsets of the dataset. The higher accuracy was obtained at 89% from Random Forest.

3. Proposed model

The Proposed model has been presented in Figure 1, which uses machine learning classification and metaheuristic optimization in feature selection to identify the classification of diseases in Fruit Leaf Plants.

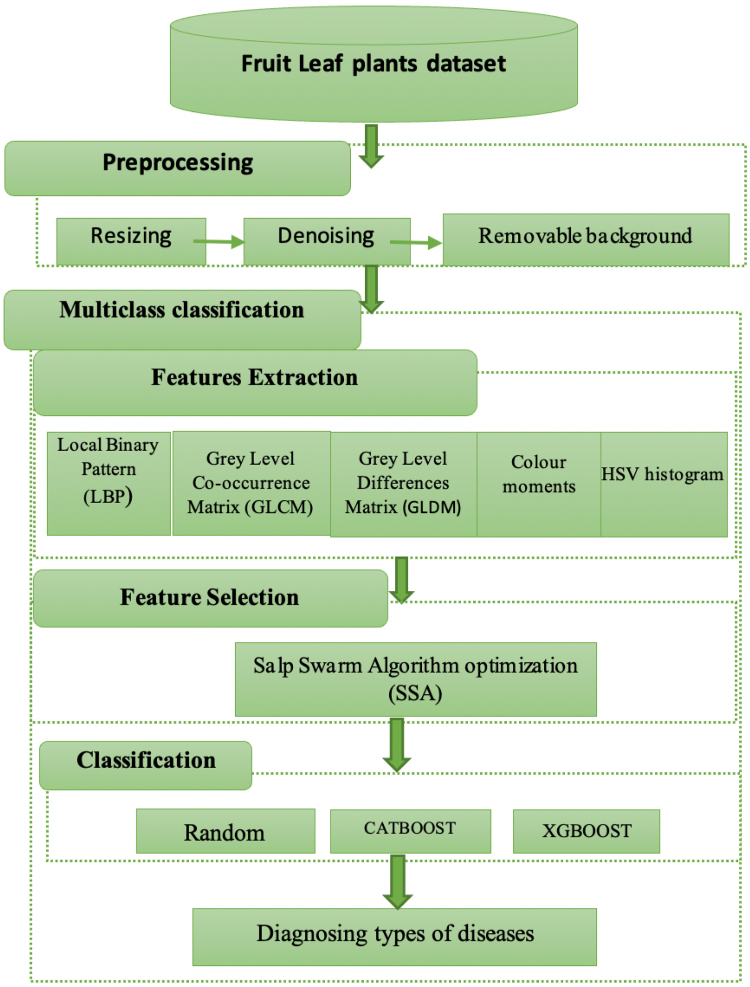


Fig. 1. Diagram of the proposed model

4. Datasets

This paper proposed a multiclass classification model that aims to detect diseases in three types of fruit using the leaves plant images dataset taken from the Kaggle website[14]. These three types of fruit are (Apple, Cherry, and Strawberry) where Apples have three disease dataset categories (Apple Scab, Black Rot, and Cedar Rust) as well as healthy apple dataset, Cherry have Powdery Mildew disease dataset category and healthy dataset, and Strawberry have leaf Scorch disease dataset category and healthy dataset. These datasets are based on the PlantVillage dataset. Apple disease images consist of 500 images for Apple Scab, Black Rot 500 images, Cedar Rust 400 images, and Healthy Apple 500 images. Cherry disease datasets include Powdery Mildew 500 images and Healthy Cherry 500 images. The Strawberry dataset contains 500 images of Leaf Scorch disease and 500 images of Healthy Strawberry. For classification, 80% of the image dataset was used in training and 20% in testing.

5. Preprocessing

It is essentially a step when dealing with disease leaf plant images, especially for tasks like classification. The preprocessing takes several steps, such as (Resizing, segmentation, and denoising). The main task entails adjusting the dimensions of all images to the same size of 200x200 pixels. The removable background in several operations achieves the segmentation. The first operation is to convert RGB (red, green, blue) to HSV (hue, saturation, value) color space and apply the images under the range of upper and lower saturation values and binaries. Where the range of the lower saturation takes [0, 0, 0] and the upper saturation takes [179, 60, 255]. The second operation created two masks, one for the black and the other for the green, combining them to get a single mask that ignores both colors. The range of the lower black mask is [0,0,0], and the upper is [180,255,30], while the green mask has a range in the lower [40,40,40] and the upper [90,250,250]. The reason for using these masking is that the black mask is helpful to ignore the parts of the leaf that are black due to disease or shadow; a green mask is helpful to ignore the healthy parts of the leaf and focus only on the diseased areas. The next operation is applying Gaussian Blur to reduce noise. A morphological operation (erosion and dilation) is used to remove small- unwanted parts. After that, create a mask for the image background and get a rectangle size 3*3 containing the needed object. Finally, the GrabGut algorithm is applied over the mask to the image to extract the object representing the leaf of the plant. The GrbCut algorithm is a method for extracting the foreground in an image. It uses a mask of the image and models of the background and objects to determine which parts of the image belong to the foreground (the object of interest) and which belong to the background. It can be useful in this context to separate the diseased parts of the leaf (the foreground) from the rest of the image (the background). Figures 2(a) and (b) illustrate the samples of the original and preprocessing images from the Fruit Leaf Plants Images datasets.

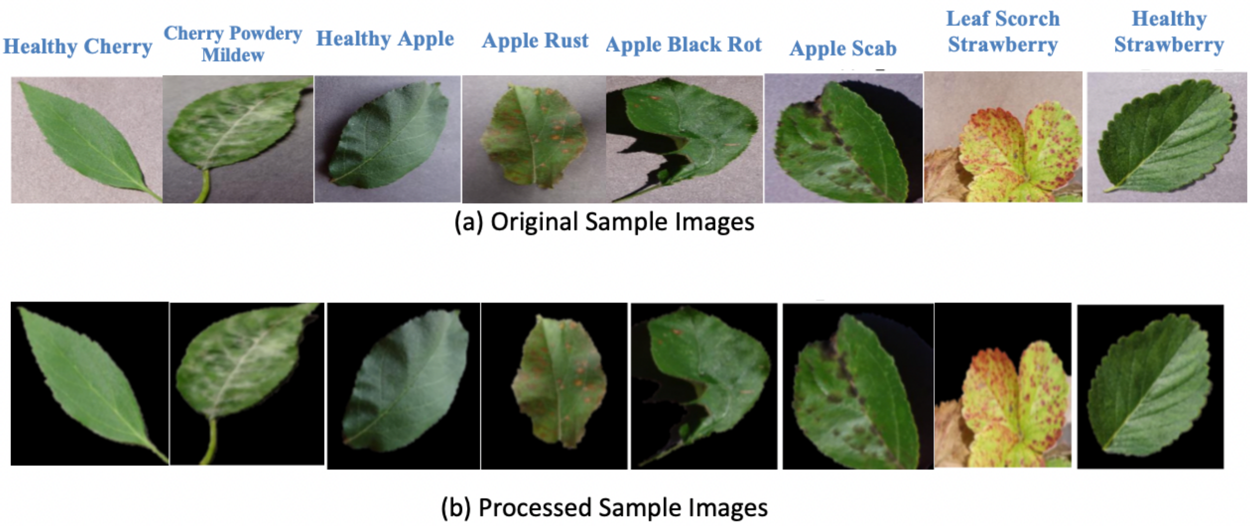


Fig. 2. (a) and (b) Images of Fruit Leaf Plant datasets

6. Feature Extraction

Feature extraction is a crucial process in the accuracy of a classification algorithm that relies significantly on the chosen features. Feature extraction reduces the number of dimensions to effectively and concisely represent the important aspects of a specific area in the image region.

In this paper, two types of features are extracted: color feature and texture feature. The diseased region exhibits a discernible color different from the healthy region. This color remains consistent within samples of the same class but varies across samples of different classes. Similarly, the specific type of disease strongly influences the characteristics of the affected area, making it an important indicator. Also, the more important part of disease identification is a texture feature, representing more information related to the diseased region. Color features are extracted by color moments, and LPB, GLCM, and GLDM extract texture features.

A total of 638 features are combined from these extractions, with the distribution as follows: 12 color moments features, 512 histogram HSV features, 18 LBP features, 64 GLCM features, and 32 GLDM features. The combination aims to achieve robust features that provide optimal accuracy in classification, and it involves extracting informative values from a set of measured data to create a vector collection of features. A classification system is then trained using this feature vector.

6.1 Colour Features

Color features were calculated by color moment and histogram. Where Extraction Features by color moments from three-channel RGB color space (red, green, and blue) provide a compact representation of color information Extract the mean, standard division, skewness, and root mean square (RMS). For each channel, 4 features were extracted, and the total extracted was 12 features in three channels. In color histogram from histograms of HSV values (hue, saturation, and value) are extracted features. The histogram function counts the number of times each pixel value occurs in each image channel. Pixel values are grouped into 8 bins according to each channel, resulting in three channels [8, 8, 8] array dimensions of their value, and the range defines the channel of parameter values (0, 180, 0, 250, 0, 250). The total features extracted from histogram HSV channels were 512 features. After that, normalized values fall into the standard range.

6.2 Texture features

Texture features were calculated by LBP, GLCM, and GLDM. The local binary pattern (LBP) used 16 neighbor pixel points (P=16) and a radius of 2. The values are converted to a binary pattern in a clockwise direction. The center pixel was converted from binary to decimal, followed by normalization of histogram computation, resulting in 18 features. (GLCM) grey level co-occurrence matrices were used to extract second-order statistics for texture feature extraction calculated with four directions (0, 45, 90, and 135). For each image, 16 features were extracted per direction, totaling 64 features. The key features include entropy, ASM, contrast, dissimilarity, homogeneity, energy, correlation, mean value, standard deviation, ratio, clustering prominence, clustering tendency, symmetry, maximum value, minimum value, and RMS. The grey level difference method(GLDM) was computed in four directions(0, 45, 90, 135). This method calculates the difference between each pixel and its neighbor. Key features extracted include (contrast, dissimilarity, homogeneity, energy, correlation, ASM, entropy, and mean), resulting in 8 features per direction and a total of 32 features.

7. Feature Selection

In this paper, Salp Swarm Algorithm (SSA) optimization was used, and a metaheuristic algorithm inspired by the natural behaviors and characteristics of the Salp Swarm was employed for the feature selection method. The feature selection process is a binary vector mechanism representation to identify the optimal subset from features. In this mechanism, each feature was represented by binary value: a feature was selected if its value was 1 and not selected if its value was 0. After that, the selected features were classified using the XGBoost classifier, and the performance was performed using cross-validation. The mean of the cross-validation was converted into negative values to compute the objective function. This allowed the optimization process to minimize the objective function.

The SSA optimization process began with initializing the agents positions and identifying the leader salp. Then, Update agents positions iteratively. During each iteration, the objective function was evaluated for each agent. If an agent score is better than the current leader score, then update the leader position and score. If the leader score remains unchanged for 15 iterations, then meet the condition terminates early and returns the best score and position. If this condition was not met, the process continued until a maximum of 50 iterations was reached.

8. Classification and Evaluation

The primary objective of classification is to organize new, unlabelled samples into predefined classes. Initially, the classifier was trained to identify the features of the data and the relationship between attribute values and the class label. These classifiers are helpful in various classification jobs since they offer unique approaches, attributes, and performances. In this paper, three types of supervised machine learning classifier models were used: Random forced (RF), Extreme gradient boosting (XGBoost), and categorical boosting (CatBoost). The performance was evaluated using the following metrics: accuracy, precision, recall, and F-score.

9. Result and Discussion

Classification focuses on diagnosing diseases in three types of Fruit Leaf Plants. Table 1 demonstrates the feature selection using SSA has proven to be beneficial for all classifiers by improving accuracy, reducing processing time, and increasing the number of correctly classified labels. This demonstrates the effectiveness of feature selection in optimizing model performance and efficiency. It enhances the performance of the classifiers; the Random Forest RF classifier improved the accuracy from 95.58% to 96.49% after feature selection, the processing time decreased from 25.18 seconds to 13.23 seconds, and The number of correctly classified labels increased from 736 to 743. In the XGBoost classifier, the accuracy increased from 96.36% to 96.62% after feature selection, the processing time reduced from 31.53 seconds to 15.58 seconds, and the number of correctly classified labels increased from 742 to 744. In the CatBoost classifier improved the accuracy from 97.79% to 98.05% after feature selection; it provided the highest accuracy, the processing time fell from 74.47 seconds to 42.51 seconds, and The number of correctly classified labels increased from 753 to 755.

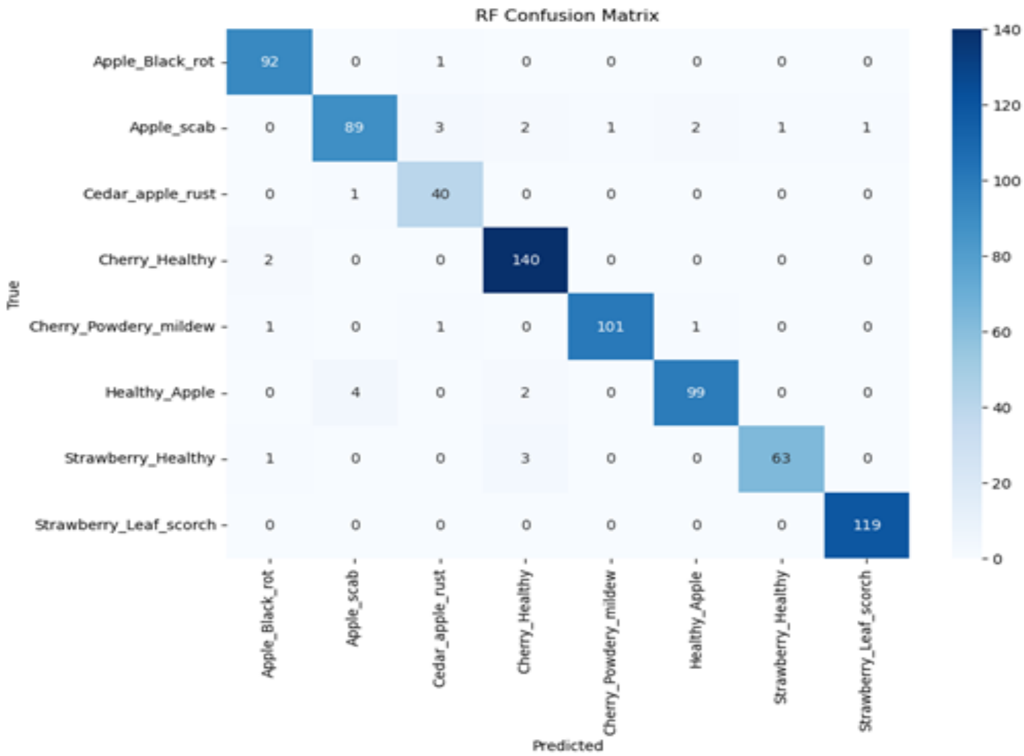
Table 1
Comparative Performance before and after feature selection of SSA algorithm in different diseases of Fruit Leaf Plant

Classification	Accuracy before feature selection	Accuracy after feature selection	Number of testing	No. of correctly classified labels before feature selection	No. of correctly classified labels after feature selection	Time testing before feature selection in the second	Time testing after feature selection in the second
RF	95.58%	96.49%	770	736	743	25.18	13.23
XGBoost	96.36%	96.62%	770	742	744	31.53	15.58
CatBoost	97.79%	98.05%	770	753	755	74.47	42.51

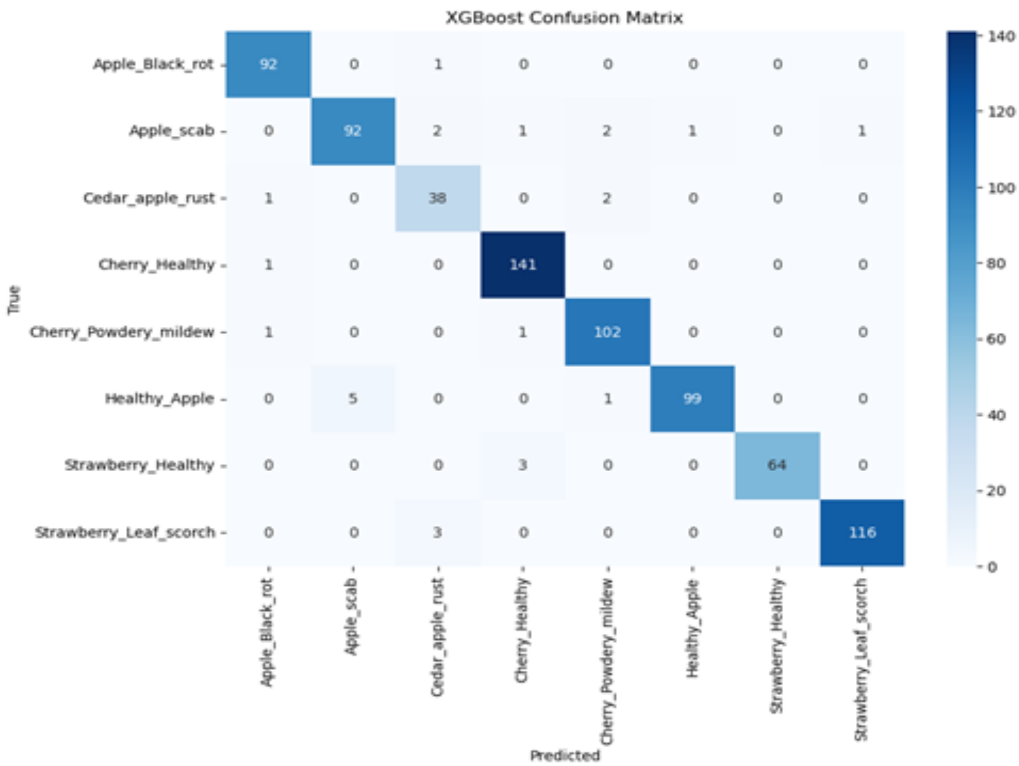
Table 2 compares three classifiers based on accuracy, precision, recall, f1-score, and AUC metrics applied to feature selection from SSA optimization. CatBoost provided the highest accuracy compared to RF and XGBoost. Figure 3 (a), (b), and (c) demonstrated the confusion matrix over all the classifiers models RF, XGBoost, and CatBoost.

Table 2
Comparative of the performance Precision, Recall, and F1-Score over RF, XGBoost, and CatBoost for different diseases of Fruit Leaf Plant

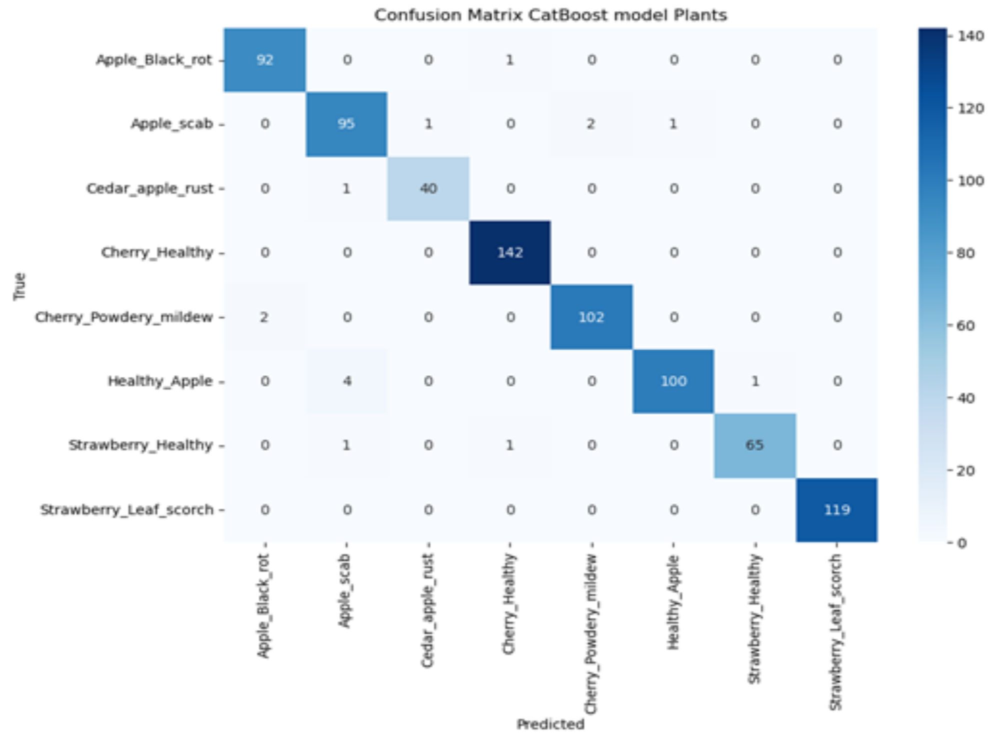
Classification	Accuracy	Precision	Recall	F1-Score
RF	96.49%	0.9654	0.9649	0.9648
XGBoost	96.62%	0.9669	0.9662	0.9663
CatBoost	98.05%	0.9806	0.9805	0.9805



(a) RF Confusion matrix



(b) XGBoost Confusion matrix



(c) CatBoost Confusion matrix

Fig. 3. (a), (b), and (c) Demonstrated the confusion matrix over all the classifier models RF, XGBoost, and CatBoost

Table 3
Presents the accuracy performance of various classifiers, RF, XGBoost, and CatBoost, on Fruit Leaf Plant before and after applying feature selection (fs) by the SSA algorithm

Type of fruit	Label of Disease in Fruit Leaf Plant	Random forest (RF)		XGBoost		CatBoost	
		Accuracy before (fs)	Accuracy after (fs)	Accuracy before (fs)	Accuracy after (fs)	Accuracy before (fs)	Accuracy after (fs)
Apple	Apple Scab	0.86	0.90	0.92	0.90	0.92	0.95
	Black Rot	0.98	0.99	0.99	0.99	0.99	0.97
	Cedar Rust	0.98	0.98	0.93	0.98	0.93	0.98
	Healthy	0.95	0.96	0.93	0.94	0.93	0.95
Cherry	Powdery Mildew	0.96	0.97	0.97	0.97	0.97	0.98
	Healthy	0.99	0.99	0.99	0.99	0.99	1.00
Strawberry	Leaf Scorch	1.00	1.00	0.98	1.00	0.98	1.00
	Healthy	0.94	0.94	0.96	0.94	0.96	1.00

Table 3 presents the accuracy performance of various classifiers RF, XGBoost, and CatBoost on the disease of the Fruit Leaf Plant before and after applying feature selection by the SSA algorithm. The results improved the accuracy of the disease detection label for each one after feature selection.

The range of accrues after feature selection is from 90% to 100%, with a minimum accuracy of 90% in testing of the Apple Scab dataset, while the maximum accuracy of 100% represented in three categories: Healthy Cherry, Leaf Scorch Strawberry, and Healthy Strawberry.

Additional three types of vegetable datasets taken from the Kaggle website [15] were used to experiment with the proposed model to determine its performance, generalizability, and robustness. 2000 images were taken and distributed over 500 images for each dataset. Vegetable datasets consist of Potato (Early Blight, Late Blight) diseases, Pepper Bell (Bacterial Spot) diseases, and Squash (Powdery Mildew) diseases. Table 4 presents the accuracy performance of various classifiers RF, XGBoost, and CatBoost on the disease of vegetable leaf Plants before and after applying feature selection by the SSA algorithm.

The performance of the Totally classifiers: the Random Forest RF classifier improved the accuracy from 97.97% to 98.73% after feature selection, the processing of time decreased from 13.01 seconds to 5.20 seconds, and The number of correctly classified labels increased from 387 to 390. The XGBoost classifier improved accuracy from 97.94% to 99.24% after feature selection, the processing time reduced from 15.81 seconds to 6.25 seconds, and the number of correctly classified labels increased from 385 to 392. The CatBoost classifier improved the accuracy from 98.97% to 99.24% after feature selection, the processing time reduced from 39.14 seconds to 16.13 seconds, and the number of correctly classified labels increased from 388 to 392.

Table 4
Presents the accuracy performance of various classifiers, RF, XGBoost, and CatBoost, on vegetable leaf Plants before and after applying feature selection (fs) by the SSA algorithm

Type of vegetables	Label of Disease in vegetables	Random forest (RF)		XGBoost		CatBoost	
		Accuracy before (fs)	Accuracy after (fs)	Accuracy before (fs)	Accuracy after (fs)	Accuracy before (fs)	Accuracy after (fs)
Potato	Early Blight	0.96	0.96	0.96	0.99	0.96	0.99
	Late Blight	0.99	0.99	0.97	1.00	0.97	1.00
Pepper Bell	Bacterial Spot	0.97	1.00	0.99	0.98	0.99	0.98
Squash	Powdery Mildew	0.99	1.00	0.98	1.00	1.00	1.00
Totally Accuracy		97.97%	98.73%	97.94%	99.24%	98.97%	99.24%
Totally Time in second		13.01	5.20	15.81	6.25	39.14	16.13
Totally corrected test from overall image test 395		387	390	385	392	388	392

Table 5 illustrates the information on the feature selection of the Fruit Leaf Plant. Such as the condition to find the best feature and the model, which used classification with cross-validation to evaluate, as well as the number of agents, lower and upper bounds, and the number of iterations. The optimal scores obtained from iteration 35 in pest position -0.9696103896103896 and the feature selection by the SSA algorithm reduced features from 638 to 347. Figure 4. Illustrates the history of Best Score and Position SSA of Fruit Leaf Plant.

Table 5
Information on SSA feature selection in Fruit Leaf plants

Condition to find best feature	x>0.5	No. of iteration	50 stop at 35
Classification model and evaluated by cross-validation score	XGBoost Cv= 5	Condition to stop the search for the best position	After 15 iterations, do not change the position, then get the best position
Objective function get	Negative mean scores	The best position of Salp	-0.9696103896103896
Lower bound	0	Total no. of feature	638
Upper bound	1	Total no. of feature after selection	347
No. of agents	15		

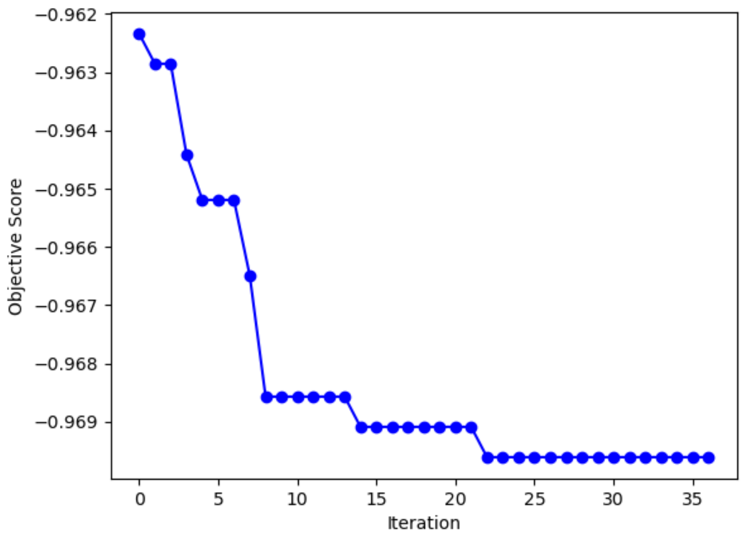


Fig. 4. History of Best Score and Position SSA of Fruit Leaf Plant

Table 6 demonstrates that the proposed model outperforms a set of previous works that used the leaf plant diseases of image datasets.

Table 6
The proposed model outperforms a set of previous works that used the leaf plant diseases of image datasets

	REF. WITH YEAR	FEATURE EXTRACTION AND FEATURE SELECTION	DATASET	CLASSIFIERS	ACCURACY
1	2021 [10]	Colour feature, GLCM, And MSSOA	maize, rice, and grape consist of 9-disease datasets	SVM	Mize 93.96%, Rice 79.17%, Grape 95%
2	2021 [4]	GLCM and colour moments	PlantVillage dataset 38 classes, 11 different plants, 26 diseases, and 12 healthy plant	SVM	classify healthy and unhealthy 91.40% identify diseases 82.47%

3	2023 [11]	5-convolution layer, 5-pooling layers from 14-layer CNN	The Kaggle website, Plant-Village dataset tomato leaf diseases	1- dense, 1-flatten layer	96%
4	2024 [16]	Shape feature, Colour feature, Texture feature, and Principal Component Analysis (PCA)	mango leaf diseases consist of 6-datasets diseases, each one having 500 images	VGG-16, MobileNet, Googlenet, YoloV8, and EfficientNet	94.5%
5	2024 Proposed model	Feature Extraction Colour moments, Colour Texture Feature selection SSA	The Kaggle website, Plant-Village dataset three types of fruit (Apple, Cherry, and Strawberry) of 5 datasets of diseases and three datasets of health; each set has 500 images	RF, XGBoost and CatBoost	98.05%

10. Conclusion and Future work

This paper demonstrated that preprocessing images by removable background masking and GrupCut, as well as combining features LPB, GLCM, GLDM, color moments, and color histograms hsv and using multiple feature extraction techniques yields the best accuracy of 98.05% in 42.51 seconds. Also, when the SSA algorithm applies the feature selection method, it helps to reduce the features, which leads to a reduction of time to 42.51 seconds of execution and gives a maximum accuracy of 98.05%. This reduction in execution time is most beneficial when using the system as an application in real-time, such as mobile devices or computers. Finally, the CatBoost Classifier gets the optimal solution for accuracy. When the proposed model is used as a real-world application in the future, it will help preserve the agricultural environment and thus contribute to maintaining a sustainable environment. In future work, this proposed model can be applied to different types of plants to diagnose the disease and can also used with real-life categories, take images of infected plants on farms to verify the accuracy of the used model and the potential benefits and convert it into a real-time application program for mobile phones or computers. Also, the system model can focus on optimizing by using a hybrid of SSA (Salp Swarm Algorithm) with other swarm intelligence algorithms such as GWO (Grey Wolf Optimizer)[17] or Harris Hawks [18]. Additionally, the SSA swarm can be replaced with other algorithms, such as GWO optimization [19] or Fox algorithm [20].

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