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Hybrid Particle Swarm and Chicken Swarm Optimization for Plant Disease Diagnosis using Leaf Images

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Abstract

Background: Plants play a vital role in sustaining life on Earth, particularly in maintaining ecological balance. They also contribute significantly to the economies of many countries and provide other valuable benefits. These plants are susceptible to many different diseases. Traditionally, trained specialists diagnose plant diseases based on their experience. However, this approach leads to problems, as diagnoses can vary from person to person. Objective: This work aims to present a novel approach to reduce errors and eliminate guesswork using a hybrid method. Methodology: We have developed a novel hybrid method combining Particle Swarm Optimization (PSO) and Chicken Swarm Optimization (CSO) algorithms to diagnose plant diseases in a group of ten species based on images of their leaves. Therefore, images of leaves from ten different plant species were collected and processed to improve contrast and remove noise. Using a statistical method incorporating hybrid classification, features were extracted. The method was applied to leaf images of ten different plant species, such as guava, jamun, mango, grape, apple, tomato, argon, and cherry, using a MATLAB simulation program. Results: The results for the hybrid method (PSO-CSO) achieved a diagnostic accuracy of 98.9%. Conclusions: The results indicate that the proposed model is an effective tool for the automated diagnosis of plant diseases. Future efforts may include expanding the database to include new crops and integrating the model into mobile applications for immediate field use.

Keywords: chicken swarm optimization (CSO), image processing, MATLAB, particle swarm optimization (PSO), plant disease diagnosis.

1 Introduction

Agricultural cultivation is an industry that is a pillar of the foundation for global food security and sustainable ecological system for all living things, because they produce oxygen. Most commonly, the leaves are used to visually identify or classify the plant based on characteristics such as color, texture, shape, and size. in contemporary agriculture, the identification of plant diseases is crucial for enhancing crop yield. Plants are very important to all living organisms because they produce oxygen, which is essential for life [1]. The leaves are classified according to their features such as color, texture, size and shape. [2]. In agriculture, diagnosing plant diseases is extremely important. To boost output on a big scale, it is vital to detect illness onset and provide farmers with advice. Previous approaches for detecting plant diseases required manual feature extraction, which is more expensive than modern methods. [3]. However, because of the visual similarities between them, this method is time-consuming, expensive, and prone to human mistakes. For instance, in agricultural areas, weeds grow alongside crops when they are cultivated. The weeds and the crop frequently share characteristics, making it impossible for the unaided eye to distinguish between the two. They deplete the soil's nutrient supply [4], which negatively affects crop productivity and quality.

Due to its straightforward nomenclature, as shown in Figure (1), computer vision concepts, image processing, and algorithms for machine learning are primarily employed in a variety of applications [5], such as pattern recognition, classification, segmentation, etc. In recent years, numerous researchers from various fields have become interested in the autonomous detection of plants [6]. Learning has always been a common occurrence from the beginning of time. Living things have evolved over generations, and learning is no exception [7]. These days, machines learn in the same manner as people. The term "machine learning" also refers to the process of teaching a machine to become intelligent [8]. Because these algorithms can interpret the displayed data, they open the door to the possibility of creating intelligent devices. Pattern recognition and categorization are two key techniques that the machine uses to do this [9].

Diseases that affect plant leaves halt the growth of their leaf. Early plant leaf analysis may reduce the likelihood that the plant will be harmed [10]. Because of their extensive history, leaves have contributed significantly to the construction of automatic systems [11]. The shape, color, and texture of a leaf define it. Computer vision concepts aim to replace traditional approaches and propose new techniques for plant segmentation. These days, plant segmentation methods and techniques that are automatic or computer-aided are quite important. There are primarily two stages to automatic detection systems [12]. Using handheld cameras or drones, plant leaf images are first taken. The plants are then segmented and classified using a variety of techniques, including obtaining the area of interest, locating images from the database that represent common features, and categorizing those images with other images that have unique features [13].

Today, artificial intelligence has become commonly used in machine learning systems and improving performance based on the data it uses [14]. It is considered an advanced technology that uses neural networks to provide high performance, as in algorithms used in medical diagnostics, trait detection, learning automation, pattern recognition in plants, and others. For this reason, artificial intelligence offers many advantages, including Deep Learning, the science of discrimination, such as distinguishing the hand and the eye, performing mathematical and logical operations, and the ability to absorb a large number of data [15]. Therefore, it is considered the main driver of emerging technologies and others.

This research aims to apply some artificial intelligence techniques (Swarm Algorithms) such as the Chicken Swarm Optimization (CSO) algorithm and the Particle Swarm Optimization (PSO) algorithm to discover and diagnose some diseases that affect plant leaves and are caused by insects or bacteria. By designing the application based on a hybrid algorithm using the Matlab language, based on the combination of the CSO and PSO algorithms, and applying it to 10 different types of plant species. Traditional algorithms often face the significant challenge of handling complex visual data from the real world. For example, the PSO algorithm exhibits a predictive tendency towards early convergence and stagnation at local optimums during intensive feature extraction. However, the CSO algorithm is considered effective for exploring living space. The mathematical coupling achieves an ideal balance, where the PSO framework focuses on boundary accuracy, while the CSO framework prevents premature entanglement in the network. This results in improved classification accuracy for the leaves of different plants, and therefore, the proposed hybrid PSO-CSO methodology represents an ideal computational solution. The proposed system consists of several stages: the first is the data collection stage, and the second is the image pre-processing stage, which involves resizing the images, enhancing their contrast, and removing image noise. Next, the Lab* color space is used to extract features based on color and texture. The PSO and CSO algorithms are then used for segmentation in the next stage. Finally, the performance of the proposed method is evaluated using test data. Figure 1 show the Flowchart illustrating the steps of the proposed system for classifying and diagnosing plant leaves.

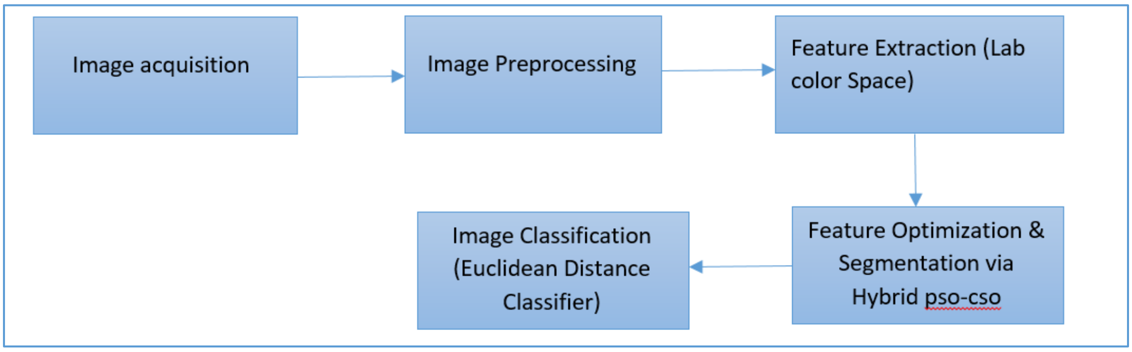

Figure 1 A flowchart illustrating the steps of the proposed model used in classifying and diagnosing plant leaves.

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2 Literature Review

Disease diagnosis and classification using computers are complex. Therefore, AI methods and techniques have been employed to address these challenges. Particle Swarm Optimization (PSO) and Chicken Swarm Optimization (CSO) algorithms have proven effective in diagnosing diseases in several plant species, such as Guava, Jamun, Mango, Grapes, Apple, Tomato, Arjun, and Cherry [16]. Some recent studies have achieved 98% accuracy when color feature discrimination using the (SOS) algorithm for Supporting Vector Machine (SVM) classification. [17]. other studies have achieved an accuracy of 91.85% when using local binary patterns and SVM optimization techniques. [18], similarly, the detection rate for harmful diseases using morphology factors and Fourier coefficients also reached 90%. [19]. Accuracy reached 98% when using more sophisticated models incorporating neutral approaches and random forests. [20]. Also, paper shape features and dimensionality reduction techniques demonstrated an accuracy rate of 96%. [21]. Despite all the progress made, hybrid models are still needed to reduce diagnostic errors and increase the accuracy of plant disease diagnosis [22]. One of the problems we deal with in plant diseases is the variation in leaf texture. Therefore, combining the PSO-CSO algorithms is an optimal way to balance local and global search capabilities. The PSO algorithm is able to simulate complex plant leaf patterns because it is known for its multidimensional optimization capabilities stemming from its behavior, mimicking group behavior. By adding the CSO algorithm and its hierarchical structure (roosters, hens, and chicks), the early convergence problem was solved, and performance improved due to its social hierarchy. Thanks to these two algorithms, we reached local minimums, especially with high-resolution images [23] [24].

Table 1 shows the results of the comparative analysis of the methodologies used in previous research, focusing on differences in algorithms, datasets and accuracy.

Table 1 Comparison of previous studies in plant disease diagnosis

Accuracy	Main Dataset	Algorithm	Reference
86%	Maize leaves	SOS & SVM	[17]
91.85%	BCCR/SEGSET	LBP & SVM	[18]
90%	Weed images	ANN & SVM	[19]
98%	400 images	Neutrosophic & Decision Tree	[20]
96%	625 images	Geometrical & KNN	[21]
98.9%	1000 images	Hybrid PSO-CSO	Proposed

To further enhance the optimization process, the (CSO) is integrated. The movement of the chicks towards their mothers is governed by Equation (1), which defines their search behavior based on a follow-factor

$$X(i,j)t+1 = X(i,j)t + S1 * r1 * (Xr1,j - Xi,j) + S2 * r2 * (Xr2,j - Xi,j) \quad (1)$$

Where:
X(i,j)t+1: is the new position of the particle.
X(i,j)t: is the current position.

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S1, S2: are learning factors that control the search step.
r1, r2: are random numbers between 0 and 1.
Xr1, Xr2: represent the positions of the rooster and a random chicken in the swarm.

3 Research Method

3.1 MATERIALS AND METHODS

The proposed methodology consists of seven main stages: image acquisition, preprocessing, feature extraction, feature selection, segmentation, classification, and performance evaluation subsequently, a comprehensive explanation of the proposed system's general architecture is detailed as follows:

Particle Swarm Optimization

Due to its ability to solve multi-dimensional problems and increase the likelihood of reaching an optimal solution, swarm algorithms are considered among the most advanced artificial intelligence techniques with a wide range of applications. In PSO, a random initialization process is used to generate a set of candidate solutions, and the particles' positions and velocities are updated iteratively to search for the optimal solution [22].

Chicken Swarm Optimization

The swarm of chickens will be split up into several smaller groups, each headed by a rooster that will have several chicks and some of its chickens. The location of the rooster will also be dictated by the other roosters in the group [23]. Chicks depend on hens within the group hens' mothers. Within a flock of chickens, the hierarchy plays a crucial role since individual fitness values determine the relative importance of each member and their function within the group; roosters have the greatest fitness levels, followed by hens. Then make the females among them weaker. In this case, we will suppose that the number of hens (H), the number of roosters (R), and the number of chicks (C.M.) reflect the mother hens. The basis of the hierarchical structure is (G), which represents a specific time interval. Every few time intervals, only these (G) states are updated. [24].

Building on the mathematical foundation and the hybrid logic discussed in Section 2, the following equations represent the specific computational implementation of the proposed model. The following equations are used to combine the velocity (Vi) and position (Xi) equations in the PSO algorithm, resulting in a hybrid algorithm created by combining PSO and CSO. This combines the search capabilities of both PSO and CSO to achieve optimal segmentation and classification results.

$$V_{i,j}^{k+1} = w \times V_{i,j}^{k} + c1 \times r1 \times (P\,\mathrm{best}_{i,j}^{k} - X_{i,j}^{k}) + c2 \times r2 \times (Gbest_{i,j}^{k} - X_{i,j}^{k}) \qquad (2)$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + X_{i,j}^{k+1} \qquad (3)$$

So, it will be replaced by the rooster position motion equations in the CSO algorithm exposed under:

$$X_{i,j}\,(t+1) = X_{i,j}\,(t)_{\times}\,(1 + \mathrm{Rand}(0,\sigma^2)) \qquad (4)$$

$$\sigma 2 = \begin{cases} \exp^{(fk - fi)}, & \text{else} \quad k \epsilon [1, CN], k \neq i \\ |\,fi\,| + \varepsilon & \end{cases} \qquad (5)$$

For Equation 2 Where:
$V_{i,j}^{k+1}$ represents the updated velocity vector of the i-th particle in the j-th dimension during iteration k+1.

$V_{i,j}^{k}$: denotes the particle's current velocity at iteration k.

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W: controls the inertia weight, which regulates the impact of previous velocities on the current movement.

$c1$, $c2$: signify the cognitive and social acceleration factors, respectively, designed to pull the particle toward its individual best memory and the swarm's global best position.

$r1$, $r2$: are independent random numeric values uniformly generated within the interval to introduce stochastic behavior into the search process.
($P\ best_{i,j}^{k}$- $X_{i,j}^{k}$) : identifies the personal best coordinates achieved by the specific particle.

($Gbest_{i,j}^{k}$- $X_{i,j}^{k}$) **:** represents the global best spatial position discovered by the entire swarm population up to iteration K .

For Equation 3, 4 and 5 where:

$X_{i,j}^{k+1}$: represents the newly computed spatial coordinates of the i-th agent in the j-th dimension, derived by adding the current location vector $X_{i,j}^{k}$ to the optimized velocity component $X_{i,j}^{k+1}$.
For individuals operating as rooster within the hierarchy, Equation (4) describes their specific stochastic motion sequence.

Where:

$X_{i,j}\ (t+1)$and $X_{i,j}\ (t)$ signify the rooster's location coordinates at the next and current time steps, respectively.

Rand$(0,\sigma^2)$: generates a normally distributed random numeric value with a mean of zero and a variance of σ^2.

in Equation (5):

σ^2: establishes the step size dynamic based on the relative fitness values.

fk: represents the fitness evaluation score of the chosen rooster.

fi : The current agent's individual fitness score. To avoid computational runtime errors caused by a zero denominator.

ε: A variable, which added to the fraction to ensuring absolute mathematical stability throughout optimization cycles.

3.2 Database Collection

The database was divided into three groups: three groups of infected leaves and one group of healthy leaves. Each group contained 250 samples, totaling 1000 images. Each group was further divided into two parts at an 80/20 ratio, with 80% used for training and 20% for testing. To obtain reliable statistical results and enhance the system's ability to efficiently process plant leaves, a 10-fold cross-validation protocol was incorporated into the calculation process.

3.3 Pre-processing Phase

Based on the aforementioned, the suggested method will combine the PSO and CSO algorithms to improve results by striking a balance and making improvements. Thus, when taken, the pictures have varying sizes. In certain photos, the intriguing region is either visible or not. This problem calls into question how well any model or strategy performs. For that, the acquired images are only partially preprocessed, separating the paper from the backdrop according to color values. A binary filter image

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is then produced using Matlab's Color Threshold program. The image has been converted from RGB to grayscale and then adjusted using a histogram filter. It improves the clarity and ease of use of the image pre-treatment.

3.4 Feature Extraction

Noise is an unwanted signal that affects image quality by altering pixel intensity and color distribution. change the intended or actual information. Noise introduces a reasonable fluctuation in color and brightness in photographs. It modifies the image's real color and pixel distribution or looks [22]. There are various sorts of noise in images, such as Gaussian noise, shot noise, quantification noise, pepper and salt noise, etc., depending on the nature of the image and the method used to collect it. Depending on the type of noise, different filters are used to eliminate it. To eliminate the disruptive noise in color photographs, several filters are used, including hybrid filters, vector median filters, and Gaussian filters. [25]. Therefore, the foundation of any image processing system is the extraction of properties. Under the objectives of the intended system, this procedure explains how an image is fed into the system with a set of values corresponding to a specific feature, or an assortment of features that will determine the image processing method—clustering, diagnosis, classification, or perhaps something else entirely. The properties of the paper that was segmented from the backdrop are extracted using the Statistical Feature Extraction method in the suggested method. From there, the following: Contrast, Correlation, Homogeneity, RMS, Mean, Skewness, Standard Deviation, Variance, and Smoothness. Figure (3), shows image segmentation.
The process for defining and allocating the coefficients that are needed for individual algorithms varies depending on the kind of work being done and the problem the researcher is trying to answer. The particular coefficients used in an algorithm may also vary depending on the kind of problem that has to be solved. The numbers given for each coefficient of the algorithms employed in the present research were decided upon as the best course of action for us to take after the experiment. For the population of 1000, the (PSO) method has (C1, C2) set to (2), (W) set to (0.4), and (300) iterations. The (CSO) approach yielded the following results: the population size (1000), and the coefficients R=0.35, H=0.55, and C=0.5, the value of G=3. Figure 2, shows the PSO flowchart, and figure 3 shows image segmentation. In addition, Figures (4–9) show segmentation results for different plant species.

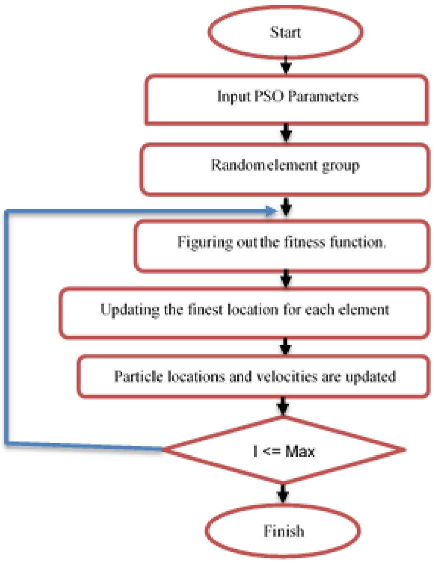

Figure 2 Unified procedural flowchart of the particle swarm optimization (PSO) computational phase

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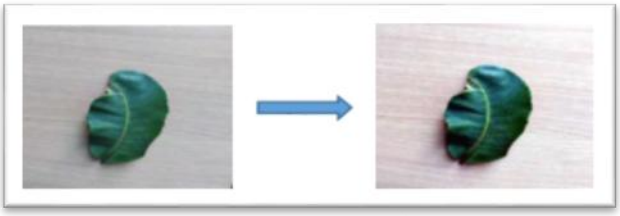

Figure 3 Visual comparison demonstrating (a) the original baseline RGB histogram characteristics and (b) the enhanced feature distribution outcomes.

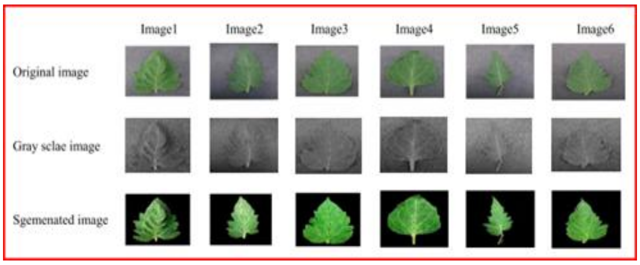

Figure 4 Visual assessment of the proposed segmentation framework using six different tomato leaf samples under varying natural lighting conditions and size constraints.

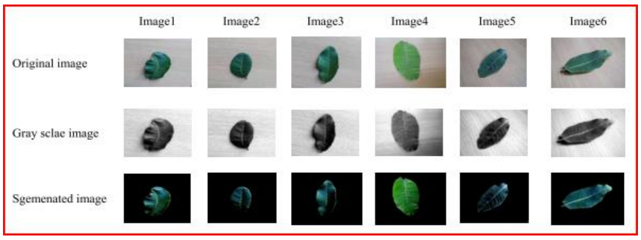

Figure. 5 Visual assessment of the proposed segmentation framework using six different Arjun leaf samples under varying natural lighting conditions and size constraints.

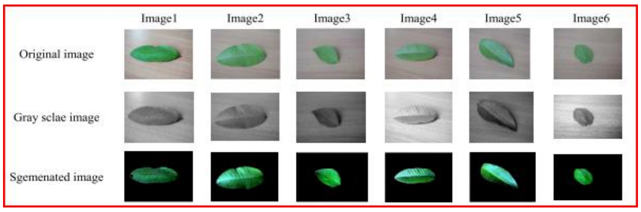

Figure 6 Visual assessment of the proposed segmentation framework using six different Guava leaf samples under varying natural lighting conditions and size constraints.

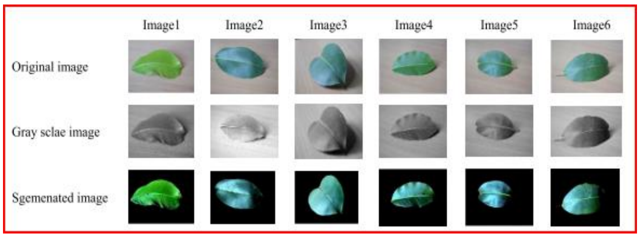

Figure 7 Visual assessment of the proposed segmentation framework using six different Jamun leaf samples under varying natural lighting conditions and size constraints.

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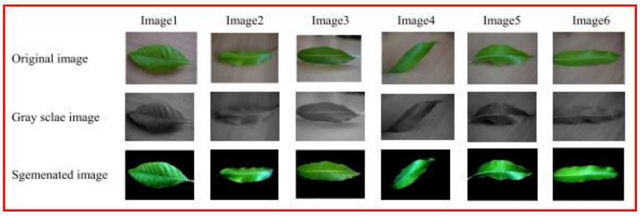

Figure 8 Visual assessment of the proposed segmentation framework using six different Mango leaf samples under varying natural lighting conditions and size constraints..

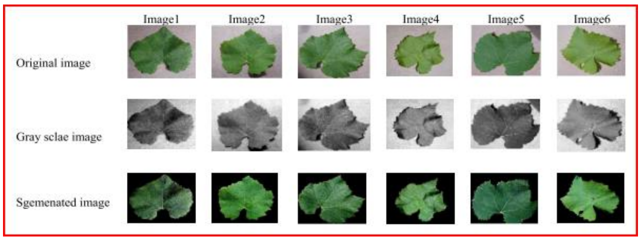

Figure 9 Visual assessment of the proposed segmentation framework using six different Grapes leaf samples under varying natural lighting conditions and size constraints.

3.5 Training and Classification

The PSO-CSO hybrid algorithm functions as an advanced feature selection and dimensionality optimization algorithm. First, the system extracts a high-dimensional matrix of color and texture characteristics from leaf samples. The proposed hybrid system manipulates the feature space by isolating the most useful feature vectors and removing redundant descriptors. After extracting the optimal features, the system moves to the classification stage. Here, the spatial convergence (similarity) between the test and training image vectors is measured using Euclidean distance criteria. Based on this convergence within the input data range, leaf diseases are classified.

The proposed hybrid system integrates two algorithms (PSO and CSO) for accurate leaf disease detection. Initially, it analyzes images and extracts texture and color features as a statistically rich matrix, rather than dealing with raw and complex data. The system relies on optimal feature vectors as the primary input to accelerate processing and reduce computation time.

To leverage the advantages of both algorithms, the Particle Swarm (PSO) and Chicken Swarm (CSO) algorithms are optimized. PSO provides fast and accurate local searches and precise parameter adjustments. Conversely, the CSO algorithm's organizational structure prevents localized solutions by expanding the solution space. The algorithm operates through successive optimization cycles to update the positions and speeds of swarm members based on an evaluation of the efficiency and quality of available solutions. To ensure the highest levels of efficiency and accuracy in the calculations, the control parameters for both algorithms were carefully adjusted. In the Particle Swarm Optimization (PSO) algorithm, the total number of search elements was set at 50. This test aimed to achieve an optimal balance between cognitive and social learning. The values for the cognitive (C1) and social (C2) learning coefficients were set at 0.2. The inefficiency weight (W) was also adjusted to decrease linearly from 0.9 to 0.4 during execution, contributing to a smooth and systematic transition from the exploration phase to the exploitation phase.

In the Chicken Swarm Optimization (CSO) algorithm, the population was hierarchically divided into specific ratios: 15% roosters, 70% hens, and 15% chicks, representing the least efficient solutions. This arrangement was updated periodically every 10 iterations. Ultimately, the practical application of this method depends on two criteria: either reaching the maximum number of repetitions, which is exactly 200 repetitions, or when the value of the general fitness function remains stable and no significant improvement is recorded.

4 Results and Analysis

The experimental results clearly demonstrated the superiority of the proposed hybrid model (PSO-CSO), achieving the highest classification accuracy of 98.9%, surpassing both the PSO algorithm alone (96.4%) and the CSO algorithm alone (94.7%). These results confirm the high

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effectiveness of hybrid integration in improving classification quality, enhancing diagnostic capabilities, and reducing data noise. This is clearly demonstrated in the comprehensive statistical comparison shown in Table 2 of the overall performance criteria (such as overall accuracy, recall, F1 score, and precision) for ten different plant species.

The accurate classification of plant leaves was based on the definition of enhanced features using the minimum Euclidean distance after the training phase was completed. For evaluation, images were collected from a dual source: direct collection from real plants and reliance on the open-source CrowdAI data repository. In conclusion, this entire computational framework was developed and run environmentally using MATLAB R2018b software, on a computer powered by an Intel Core i7 processor, 8 GB of RAM, and a 1 TB hard drive to ensure operational power and computational robustness.

Table 2. Performance evaluation and comparative analysis of hybrid PSO-CSO against standard methods

Methods	Number of images used for analysis	Accuracy	Precision	Recall	F1-score
Hybrid method (PSO-CSO)	1000	98.9	98.2	98.0	98.1
PSO	1000	96.4	95.8	95.5	95.6
CSO	1000	94.7	93.9	93.1	94.0

The confusion matrix (Figure 10) provides a detailed evaluation of the classification.

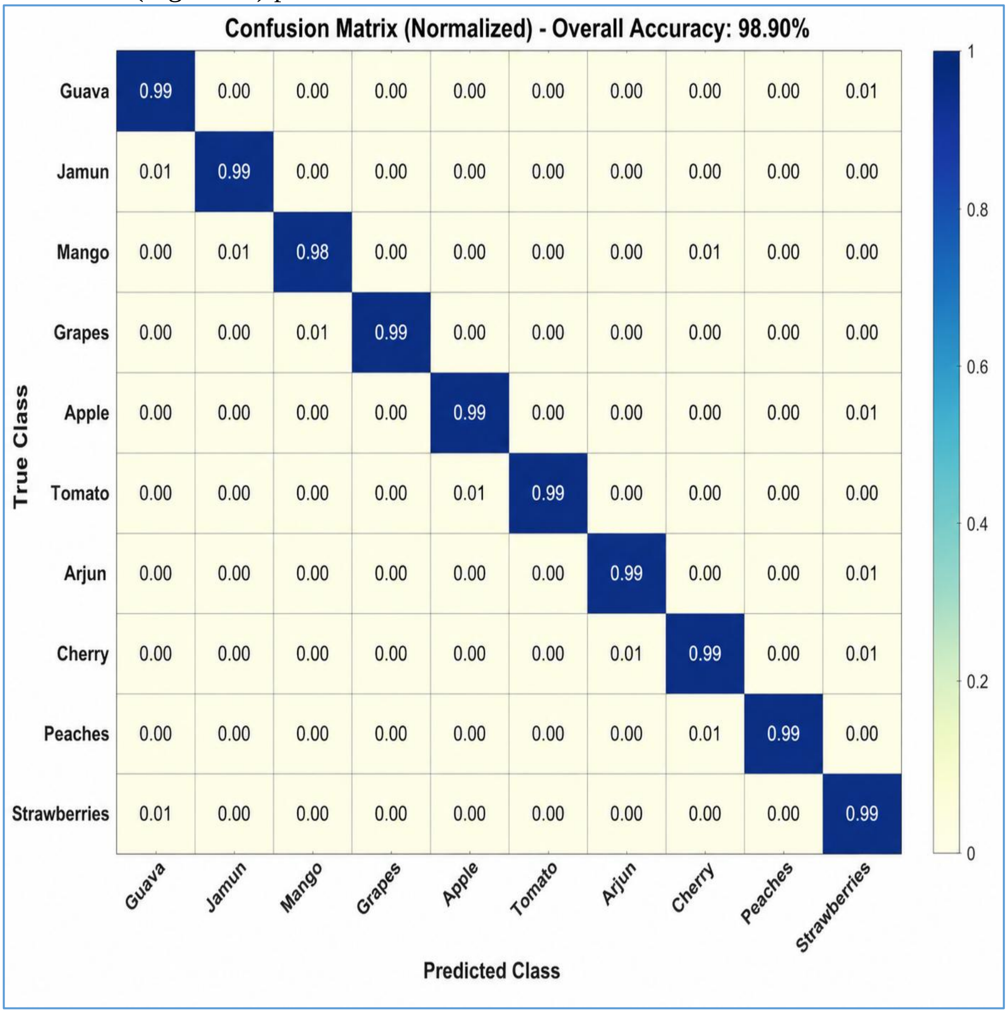

Figure 10 Confusion matrix of the proposed PSO-CSO model

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To understand the classification of the proposed system, the confusion matrix showed an accuracy of 0.99 for the first nine categories, while the strawberry category was the only one with lower accuracy. This error is attributed to the high histological similarity among the early stage fungal spots on the leaves. Consequently, the distance-based classifier misclassified a small percentage (0.01) of (guava, peach, apple, and argon) samples as strawberries, resulting in false positives. However, the proposed PSO-CSO system minimized this boundary ambiguity, ensuring high overall classification tracking.

The results indicate that the proposed PSO-CSO effectively addresses the limitations of individual optimization. While PSO excels in overall search efficiency, it suffers from early convergence. By combining it with the hierarchical structure of CSO, a better balance between exploration and exploitation is maintained. This is clearly demonstrated by the 98.9% accuracy rate, which surpasses the methods mentioned earlier in Section 2, such as the SOS-SVM [17] and LBP-SVM [18] methods. The high diagnostic accuracy achieved across ten different plant species indicates that the proposed hybrid model possesses superior adaptability to various leaf tissues and diverse diseases. To evaluate these results, a statistically significant paired t-test (p-value < 0.05) was performed on all comparisons. This mathematical verification confirms the significant improvements in the hybrid model's accuracy, improvements that are reliable and not due to variance or chance.

Furthermore, visual analysis of Figures 4-9 confirms that the proposed PSO-CSO hybrid method effectively and efficiently isolates diseased areas from the complex leaf background. Despite the varying levels of light and noise in the original images, the algorithm was able to identify and define disease boundaries with exceptional precision.

5 Conclusion

This study presented a novel hybrid approach combining Particle Swarm (PSO) and Chicken Swarm (CSO) algorithms, resulting in a significant increase in accuracy to 98.9%. This represents a promising solution for agriculture, enabling the early and accurate detection and treatment of plant diseases. In the future, several other varieties could be added to the hybrid system, utilizing the Internet of Things (IoT) and sensors to obtain real-time images and provide rapid diagnosis.

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