InfoTech Spectrum: Iraqi Journal of Data Science (IJDS)
ISSN: 3007-5467, Vol 3(No.1), 1-13 (2026)
DOI: https://doi.org/10.51173/ijds.v3i1.38
https://ijds.mtu.edu.iq

ENHANCING OPTICAL COHERENCE TOMOGRAPHY IMAGE CLASSIFICATION VIA SWARM OPTIMIZATION-BASED FEATURE SELECTION AND MACHINE LEARNING MODELS

Zaid Al-Jubouri [1*], Sarah Saadoon Jasim [1]

[1] *Technical College of Management – Baghdad, Middle Technical University, Baghdad, Iraq*

** Corresponding author E-mail: dac2014@mtu.edu.iq (Zaid Al-Jubouri)*

RESEARCH ARTICLE

ARTICLE INFORMATION

SUBMISSION HISTORY:
Received: 27 June 2025
Revised: 21 July 2025
Accepted: 15 August 2025
Published: 30 January 2026

KEYWORDS:
Swarm Intelligence;
Feature Selection;
Convolutional neural networks;
Optical coherence tomography;
Classification;

ABSTRACT

Optical Coherence Tomography (OCT) greatly facilitates the diagnosis of retinal diseases. However, traditional models based on Convolutional Neural Networks (CNNs) suffer from challenges, most notably high computational cost, sensitivity to noise, and data imbalance. This study aims to compare three hybrid deep learning frameworks, all of which rely on feature extraction using a pre-trained CNN model and then selecting the most important features using intelligent swarm algorithms: the Dolphin Swarm Optimization (DSO), the Particle Swarm Optimization (PSO), and the Ant Swarm Optimization (ACO). The selected features were evaluated using four classifiers: SVM, random forest, XGBoost, and k-NN. Experiments were conducted on a standard dataset from the University of California, San Diego (UCSD) and a local dataset. The comparison results showed that the hybrid framework, which combines the dolphin swarm algorithm and SVM, outperformed the other combinations, achieving a classification accuracy of 93% on local data and 95% on standard data, while also outperforming them in terms of accuracy and computational efficiency.

1. INTRODUCTION

Retinal disorders such as drusen, Choroidal Neovascularization (CNV), and Diabetic Macular Oedema (DME) are mostly responsible for vision impairment worldwide. Therefore, OCT is crucial for the early detection and diagnosis of various illnesses. The intricacy of OCT images, the variation in disease characteristics, and noise make accurate categorization difficult. Another issue is that some Deep Learning (DL) models are biased towards the majority classes due to unbalanced class distributions in medical datasets, which reduces their ability to identify rare conditions. In the end, the slow learning process, overfitting issues, and heavy computational demands mainly stem from the high dimensionality of OCT data and poor hyperparameter tuning, which together make real-time implementation practically impossible [1]. However, deep learning methods, especially CNNs, have proven highly effective in medical image analysis. Still, their performance largely relies on how well the model can extract meaningful features from the data [2]. Swarm intelligence and other evolutionary optimization techniques are therefore crucial, as they offer practical ways to improve model performance and identify the most critical elements [3]. The study [4] also highlighted the importance of feature extraction as a crucial step in enhancing the performance of classifiers, particularly in image- or biosignal-based systems, which supports the trend towards integrating intelligent processing techniques into modern classification models.

In this study, we seek to assess hybrid frameworks, which exploit a Convolutional Neural Network (CNN) architecture populated with different intelligent swarm algorithms to increase classification accuracy and steer clear of artificial overextraction of feature vectors in classic models. Conventional CNN approaches generally suffer from the problems of feature redundancy and parameter tuning. On the other hand, swarm optimization techniques like Dolphin Swarm, PSO, and ACO explore the extracted feature space dynamically to seek a subset of features that are discriminative and useful. For each hybrid framework, we apply various classifiers over the provided features to evaluate its performance. This provides a complete accuracy vs computing efficiency comparison. The main contributions of this study can be summarized as follows:

- Conducting a systematic evaluation of 12 hybrid models combining CNN-based feature extraction with individual swarm intelligence algorithms (Dolphin Swarm, PSO, ACO) and traditional classifiers (SVM, KNN, Random Forest, XGBoost), across both local and a public OCT dataset (UCSD)
- Addressing the challenge of feature redundancy by applying intelligent feature selection strategies to reduce dimensionality and computational cost.
- Emphasizing the Dolphin Swarm Algorithm's consistent and competitive performance when combined with SVM, which earned the maximum classification accuracy and computing efficiency in most evaluation settings, with only minor variations noted in specific instances.

The paper starts with a brief review of swarm intelligence algorithms and OCT image classification. Then, the datasets, swarm optimization techniques, hybrid methodology, experimental setup (including feature extraction), evaluation metrics, and implementation details are described. After that, the findings of the hybrid model are examined. The following report includes major conclusions, recommendations for further research, and references.

2. BACKGROUND AND RELATED WORK

Recent deep learning architectures have emerged as robust methodologies for OCT image classification, producing clinically significant results in corneal and retinal diseases. The features that are spatial in nature can be directly read from high-resolution OCT images by a CNN to enable early detection of diseases like CNV and DME. Developed in the 1980s, swarm intelligence algorithms represented a new paradigm in AI and have since blossomed into a major area of research. Of course, these algorithms have gotten a lot of buzz given their promise of being able to solve complicated problems. Most practical optimization tasks are high-dimensional, which are called large-scale optimization problems. Problems of this form arise in several scientific and engineering disciplines, such as high-dimensional function optimization, large-scale electronic system design, resource scheduling, large-scale traffic management, and bioinformatics, in which gene identification is involved.

Over the past few decades, numerous meta-heuristic algorithms have been proposed to enhance the accuracy and efficiency of solving these large-scale problems. However, as the number of variables increases, the search area expands considerably, leading to much higher computational demands, especially in high-dimensional optimization processes. Therefore, developing improved heuristic algorithms based on existing technologies is essential to effectively address these complex, large-scale challenges [5]. In this context, extensive research has yielded a wide range of effective solutions, including traditional feature selection techniques such as relevance-based selection and information gain, as well as population-based intelligence optimization algorithms, as summarized in Table 1.

A significant gap, however, is that while swarm intelligence algorithms have been successfully adapted for feature selection in many domains, evaluations in the context of medical OCT datasets are limited. In particular, none of the previous research has managed to compare multiple swarm techniques (DSO, ACO, PSO) across various classifiers. Effective feature selection is highly important for classification accuracy and real-time application in intelligent healthcare systems because of the high dimensionality of the features and the diagnostic importance of OCT images. Therefore, to overcome this problem, this work critically examines various hybrid models on local (OCT-HRF) and benchmark (OCT) datasets.

Table 1. Summary of prior research

Year	Source	Dataset	Proposed Model	Model Improvement Strategy	Accuracy%
2025	[3]	UCSD	CNN+ DWT+ACO	(ACO)(Hyperparameters)	93.20
2020	[6]	OCT	GP&SVM	Determine the optimum feature extraction method combination (Gabor, LBP, GLCM, Histogram, SURF)	90.65
2021	[7]	COVID-19 chest X-ray collection	CNN	GA (Hyperparameters)	94.93
2022	[8]	DIARETDB0 DIARETDB1	SAE+ CTSA	The CTSA swarm algorithm was used to adjust the weights in SAE.	95.90 95.48
2022	[9]	NTHU-DDD	ANN+GWO	GWO (Weights & Bias Optimization)	97.60
2022	[10]	Voice dataset (16 participants)	ANN+GWO	GWO (Weights & Bias Optimization	90.05
2023	[11]	HAM10000 ISIC 2017 ISIC 2018 ISIC 2019	CNN+GA	GA (Hyperparameters)	98.66 92.66 95.96 93.57
2023	[12]	Soonchunhyang University Bucheon Hospital	ResNet-50, InceptionV3, DenseNet-201	ACO (Feature Selection)	99.10
2024	[13]	Iris images	AG + Wavelet + PSO	(Feature Selection)	82.70
2024	[14]	APTOS 2019 Blindness Detection Dataset	CNN+AG	GA (Hyperparameters)	97.45
2024	[15]	OCTID	GLCM+AG+RF	GA (Feature Selection)	100
2024	[16]	(ECG) MIT-BIH, Arrhythmia.	CNN+ PSO	PSO (Hyperparameters)	99.58
2024	[17]	Images of skin diseases	DLSTM	(TSA) (Parameter optimization)	95

3. METHODOLOGY

This work employs a hybrid extensive framework for the classification of retinal images using deep learning approaches and smart evolutionary algorithms. Our methodology represents a systematic arrangement of three correlated stages: starting with the extraction of deep features from a pre-trained CNN model, followed by the selection of optimal features using a swarm algorithm as a representative of swarm intelligence methods, and finally a set of classical classifiers to evaluate the classification performance based on the selected features system, which will be described in detail below. Each stage outlines a specific phase with respect to the study focus, beginning with the data, swarm algorithms, classifiers, hybridization mechanism, comparison conditions, metrics used, and testing the effectiveness of the results on various classifiers. This method attempts to reduce the number of features used without compromising accuracy. This helps build a model that works well and is easy to use, as shown in Fig. 1.

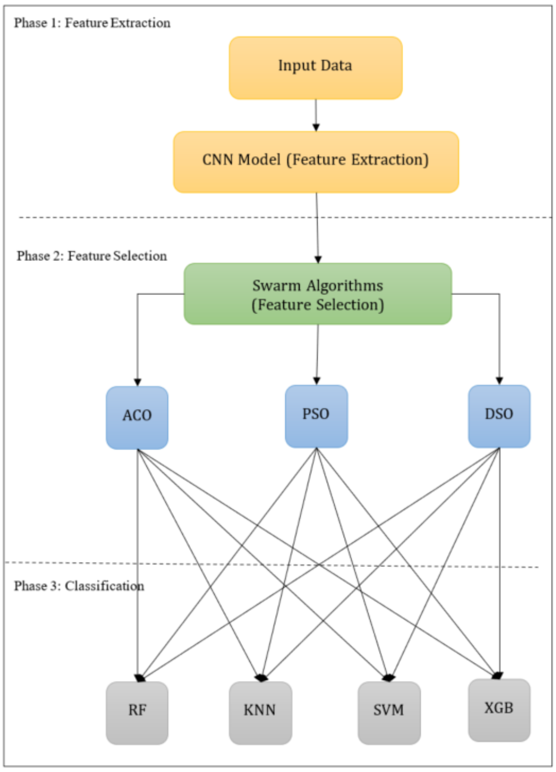

Figure 1. Methodology for comparing and integrating swarm algorithms with classifiers

3.1 Dataset

We used two datasets: the UCSD OCT dataset [18], which is one of the most popular databases for classifying retinal diseases and has optical coherence tomography (OCT) images of the retina. There are 84,484 pictures in the dataset, divided into four groups: CNV, DME, DRUSEN, and NORMAL. Fig.2. shows how many pictures are in each group. In addition, a local dataset was collected from Al-Karama Hospital in Baghdad, consisting of 4,558 images of three classes (DME, CRVO, and OTHER), and the size of each class is shown in Fig. 2. The dataset was divided into 70% training, 15% testing, and 15% validation sets.

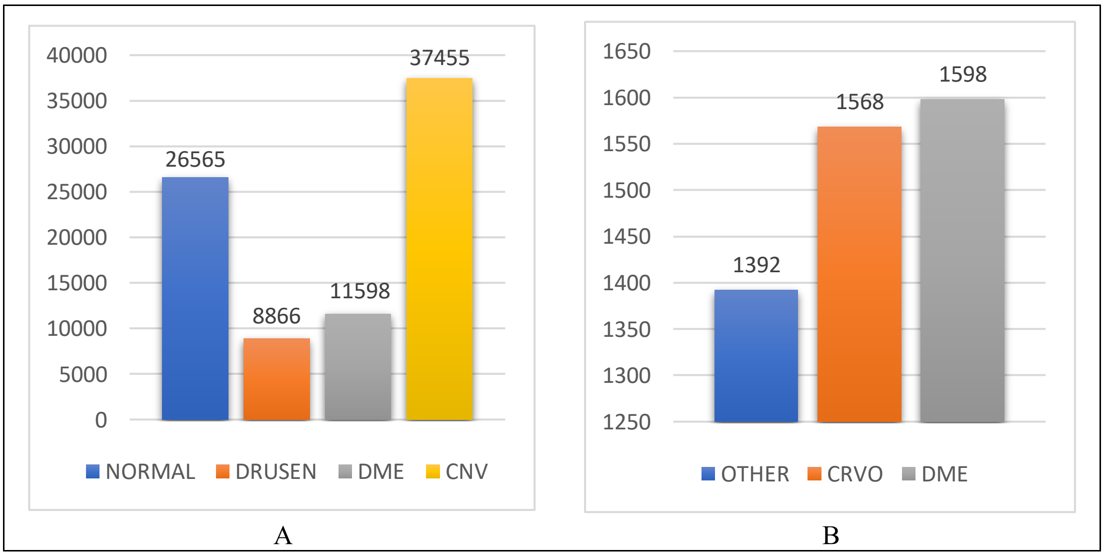

Figure 2. Data size (a) for the UCSD OCT dataset and (b) for the local dataset

3.2 Swarm Optimization

In this section, we talk about the swarm algorithms used in this study, how they work, the main factors that affect their performance, and how they can be used to choose features.

3.2.1 Dolphin Swarm Optimization (DSO)

The features are selected using the DSO, and a specific classifier is then trained on the selected features. The algorithm begins by generating random binary masks representing the dolphin locations in the search space. For each mask, the accuracy of the validation is calculated as a fitness function. The search, call-receive, and prey phases are then repeated for a fixed number of iterations. Finally, the best global mask is used to filter the datasets, and all performance metrics, such as accuracy, log-loss, execution time, and so on, are calculated for comparison between classifiers. The special transactions are listed in Table 2.

Table 2. Dolphin swarm Optimization parameters

Variable	Value	Description
M	8	Number of directions searched per dolphin
T1	10	Maximum number of searches
speed	2	Signal propagation speed
A	5	Acceleration coefficient for signal transmission
e	5	Siege radius reduction factor

3.2.2 Particle Swarm Optimization (PSO)

The feature selection process is performed using the PSO algorithm, followed by training a classifier on the selected subset. Initially, a population of binary masks is randomly generated to represent feature selection states, and each individual is assigned a small random velocity. For each generation, the algorithm updates the velocities and positions using inertia and both cognitive and social learning components. The sigmoid function is applied to convert velocities into selection probabilities. Personal and global best solutions are updated based on fitness, which is calculated using the validation accuracy. After the final iteration, the best global mask is used to select features, train the classifier, and calculate performance metrics such as accuracy, record loss, and runtime. Table 3 shows the special parameters.

Table 3. Particle Swarm Optimization parameters

Variable	Value	Description
W	0.7	Inertia weight controlling momentum
C1	1.5	Cognitive learning factor
C2	1.5	Social learning factor

3.2.3 Ant Colony Optimization (ACO)

Feature selection is based on an ant colony optimization (ACO) algorithm. Each ant builds its feature subset, where features are chosen stochastically according to a pheromone matrix, which is updated in each iteration. The pheromone evaporates, and the attributes identified in the best solution of the current iteration are strengthened. Once the algorithm has converged, it remembers the best solution found up to that point during all iterations until the end of its lifespan. Ultimately, the classifier is applied to the newly identified features for training, verification, and testing of the resulting model. The special transactions are shown in Table 4.

Table 4. Ant Colony Optimization parameters

Variable	Value	Description
P	0.05	Pheromone evaporation rate
α	0.8	Influence of pheromone strength on selection
Q	2.0	Pheromone update factor

3.3 Hybridization Mechanism

Our mechanism is based on three-layer hybridization, which incorporates deep learning, crowdsourcing algorithms, and traditional classifiers in a single approach. It starts with the deep feature extraction process. OCT images are fed into a model that has already been trained, and the vectors from the dense layer just before the output are obtained. Thus, each tissue structure in the images can be represented by an extensive, high-dimensional vector. Then, feature selection is performed using a feature selection swarm algorithm (DSO, PSO, ACO). Binary masks with the same length as the features are generated by the swarm algorithm. A mask has features activated (1) and deactivated (0) to define a subset of variables. Each mask is evaluated using a measure of the validation accuracy achieved with a particular classifier, known as the fitness function.

The rules of the algorithm (such as pheromone in ACO or velocity in PSO) indicate that the search and update processes are repeated until the global mask with the highest accuracy is determined. Finally, in the classification stage, the best-found mask is applied to the filtered feature vectors, which are divided into training, validation, and test sets. One of four classifiers (SVM, Random Forest, XGBoost, or KNN) is trained on the selected features. Performance metrics are then calculated, including training, validation, and test accuracy; log loss to measure the quality of probabilistic predictions; the number of selected features and execution time to assess computational efficiency; and graphs to compare the best performance among different groups. In this sequence, the CNN is responsible for extracting representations. At the same time, the swarm algorithm is assigned to the task of dimensionality reduction and discrimination improvement, and the conventional classifier then evaluates the final performance. This hybridization results in a less complex and more accurate model than using a single component alone.

3.4 Experimental Setup

To make sure that each combination of swarm algorithms and classifiers could be fairly compared, all experiments were done under the same controlled conditions. We used the following settings for all of the experiments:

3.4.1 Feature Extraction

Deep features were extracted using a pre-trained CNN model. Features were taken from the last dense layer immediately preceding the output layer. To ensure reproducibility, random seeds were set to 42 across all libraries used, including Python, NumPy, and TensorFlow.

3.4.2 Swarm Algorithm Settings

A fixed configuration swarm algorithm was used, as follows: For the UCSD OCT data, the number of individuals was 10 and the number of iterations was 5. For the local data, we set the number of agents and iterations to 30 and 50, respectively. We then randomly generated binary feature masks so that each mask had at least one active feature. SVM with a linear kernel, Random Forest with 50 trees (UCSD OCT data and local data with 100 trees), XGBoost classifier performing multiclass log loss, and KNN with k = 5 were used. Validation accuracy was used to assess the suitability. The best mask was applied to the test data. The performance measures were classification accuracy, log loss, number of selected features, and runtime.

3.5 Evaluation Metrics

In this study, a set of quantitative performance metrics was utilized to evaluate the efficiency of each combination of swarm algorithms and classifiers. These metrics are:

Accuracy: is the percentage of samples that are correctly classified. It is used to show how well the model is learning [20].

$$\text{Accuracy} = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \quad \dots (1)[19].$$

Where:

- **True Positive - TP:** Correctly predicted positive data.
- **True Negative - TN:** Correctly predicted negative data.
- **False Positive - FP**: Correctly predicted negative data.
- **False Negative - FN**: Correctly predicted positive data.
- **Log-Loss**: This metric compares the model's predictions to the actual classifications. A lower loss indicates that the model's predictions are closer to the true values, meaning the classification is more accurate and the results are more reliable.

$$\log loss = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m} y_{i.j}\log\left(p_{i,j}\right) \text{ ... (2)[21].}$$

- **Runtime**: It is the time taken to run the swarm algorithm and test the classifier. It is measured in seconds and helps to gauge the speed and resource efficiency of the model. We computed all these metrics by separately considering all data experiments, which allowed us to perform a comprehensive assessment based on both accuracy and computational efficiency.

3.6 IMPLEMENTATION DETAILS

All experiments were conducted on a personal computer with the following specs.

- Hardware: AMD Ryzen 7 3700X (8 cores, 16 threads, 3.6 GHz), 64 GB DDR4 RAM, and NVIDIA RTX 3080 GPU (12 GB, CUDA 11.0).
- Software: Python 3.9.10, Jupyter Notebook, and Visual Studio Code.
- Libraries:(TensorFlow, Scikit-learn, NumPy, Pandas, OpenCV, and PIL).

4. RESULTS AND PERFORMANCE ANALYSIS

Combining slightly modified swarm algorithms with four commonly used classification methods and features from a CNN model to investigate the effectiveness of classification models. In each experiment, the swarm-based algorithm selected the optimal features from the feature set, which were then given to the classifier to test its accuracy. We measured the results according to training accuracy, validation accuracy, test accuracy, log loss, number of selected features, and total execution time. This part introduces the datasets used in the experiments: the local dataset and the UCSD OCT dataset. In this paper, twelve hybrid configurations based on swarm intelligence algorithms and classifiers are explored. The experiments were divided into two parts:

4.1 Results on Local OCT Dataset

We conducted twelve tests on the local dataset. For each of the three swarm algorithms (DSO, PSO, ACO), we analyzed their performance when combined with four classical classifiers (SVM, KNN, RF, XGB). In Tables (5, 6, 7) and Figures (3, 4, 5), we present the results of these combinations in terms of classification accuracy, number of selected features, and execution time.

Table 5. Performance of the DSO algorithm with the four classifiers on the local data.

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
SVM	31	1.0	0.9371	**0.9298**	0.0017	0.2268	0.2610	86.88
KNN	36	1.0	0.9356	0.9210	0.0001	2.0332	2.1499	856.26
RF	27	1.0	0.9415	0.9152	0.0034	0.3713	0.3507	30068.88
XGB	39	1.0	0.9312	0.9137	0.0004	0.3231	0.3415	1884.59

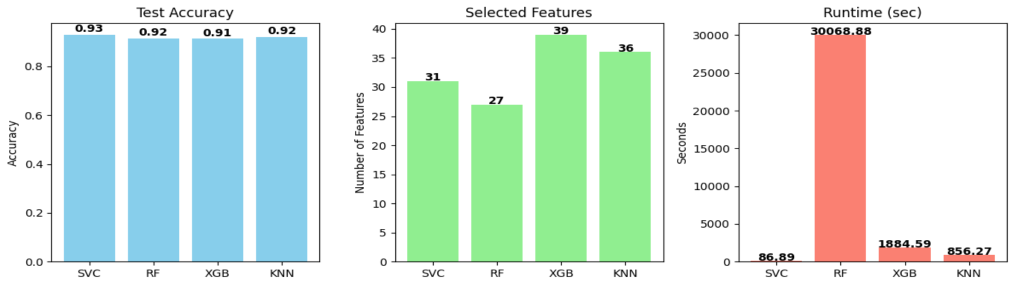

Figure 3. The performance of the DSO algorithm with the four classifiers on local data, specifically in terms of feature selection, test accuracy, and processing speed.

Table 6. Performance of the PSO algorithm with the four classifiers on the local data

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
SVM	25	1.0	0.9356	**0.9254**	0.0021	0.2423	0.2774	46.56
RF	27	1.0	0.9400	0.9254	0.0034	0.3682	0.3851	402.08
KNN	25	1.0	0.9371	0.9210	0.0001	2.0344	2.1993	98.09
XGB	41	1.0	0.9239	0.9152	0.00043	0.3906	0.3554	219.14

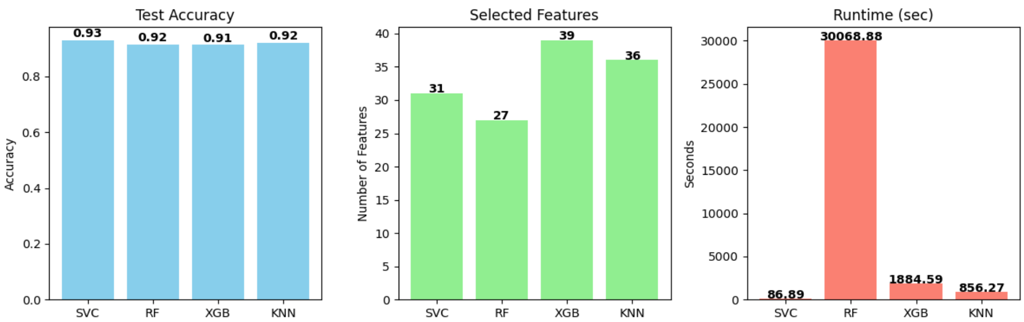

Figure 4. The performance of the PSO algorithm with the four classifiers on local data in terms of feature selection, test accuracy, and processing speed.

Table 7. Performance of the ACO algorithm with the four classifiers on local data.

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
SVM	4	0.9990	0.9122	**0.9108**	0.0049	0.3575	0.3836	508.15
XGB	5	0.9996	0.9078	0.9078	0.0023	0.5425	0.5655	336.98
RF	4	1.0	0.9093	0.8976	0.0039	1.7493	1.7000	267.01
KNN	5	0.9921	0.9078	0.8932	0.0378	2.229	2.3016	46.86

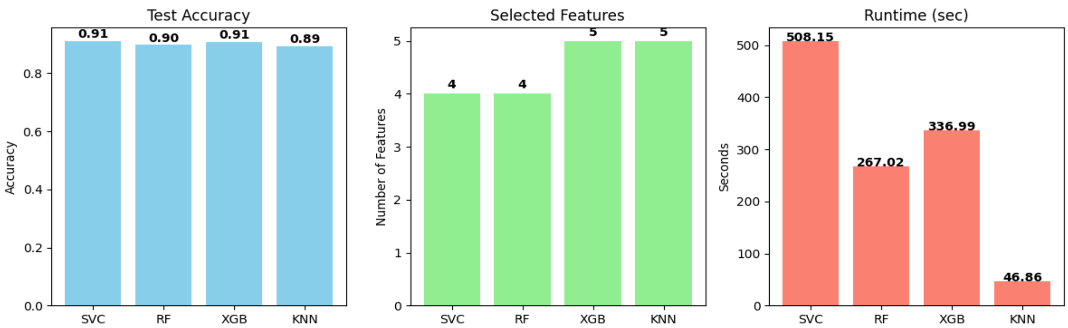

Figure 5. The performance of the ACO algorithm with the four classifiers on local data in terms of feature selection, test accuracy, and processing speed.

Table 8 and Fig. 6 show a comparison of the performance of three swarm algorithms (DSO, PSO, and ACO), along with the best classifier for each algorithm in terms of classification accuracy on local data.

Table 8. Comparison of the performance of the three algorithms on local data

swarm	Classifier	Selected Features	Test Accuracy%	Runtime sec
DSO	**SVM**	**31**	**92.98**	**86.88**
PSO	SVM	25	92.54	46.56
ACO	SVM	4	91.08	508.15

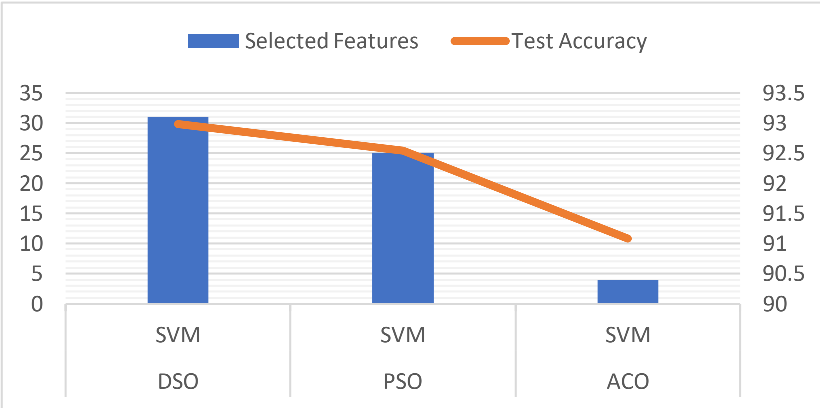

Figure 6. A comparison between the number of selected features and the test accuracy for DSO, PSO and ACO on local data.

4.2 Results on UCSD OCT Dataset

Twelve experiments were conducted on the UCSD OCT dataset, where the performance of each of the three algorithms (DSO, PSO, ACO) was evaluated separately when combined with four legacy classifiers (SVM, KNN, RF, XGB). For budget usage Tables (9, 10, 11) and Figures (7, 8, 9), the results of these combinations were presented in terms of classification discrimination, number of choices, and execution time.

Table 9. Performance of the DSO algorithm with four classifiers on UCSD OCT data

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
SVM	26	0.9963	0.9514	**0.9511**	0.0111	0.3234	0.3273	775.88
RF	31	0.9981	0.9520	0.9508	0.0049	0.8098	0.8892	2823.29
KNN	36	0.9960	0.9509	0.9506	0.0073	1.3593	1.3346	6396.44
XGB	42	0.9981	0.9513	0.9495	0.0028	0.4117	0.4172	3552.85

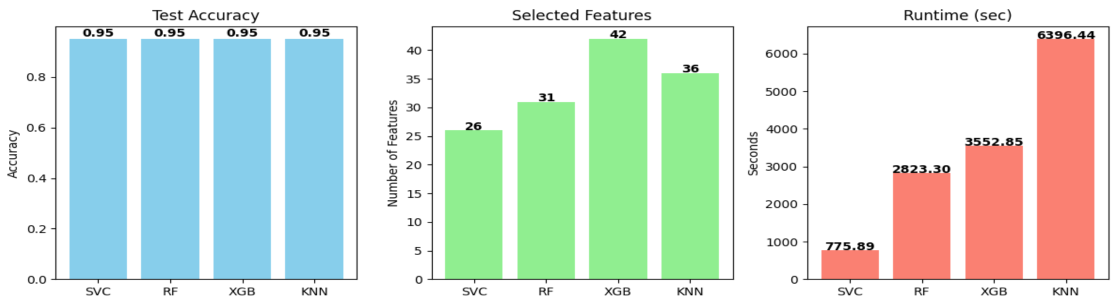

Figure 7. The performance of the DSO algorithm with the four classifiers on UCSD OCT data in terms of feature selection, test accuracy, and processing speed

Table 10. Performance of the PSO algorithm with the four classifiers on UCSD OCT data.

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
RF	35	0.9981	0.9509	**0.9507**	0.0049	0.8088	0.8615	367.60
KNN	41	0.9962	0.9511	0.9506	0.0078	1.2794	1.2770	836.98
SVM	22	0.9959	0.9509	0.9502	0.0116	0.3397	0.3468	92.32
XGB	33	0.9981	0.9507	0.9494	0.0028	0.4113	0.4141	457.88

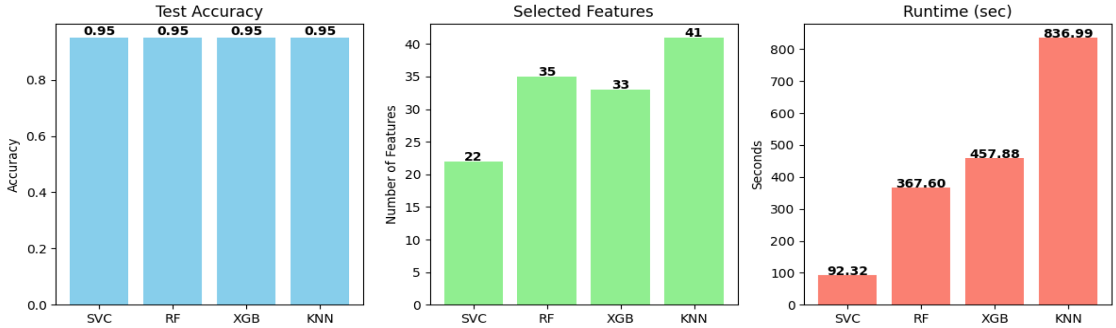

Figure 8. The performance of the PSO algorithm with the four classifiers on UCSD OCT data in terms of feature selection, test accuracy, and processing speed

Table 11. Performance of the ACO algorithm with the four classifiers on UCSD OCT data.

Classifier	Selected Features	Train Accuracy	Val Accuracy	Test Accuracy	Train Log Loss	Val Log Loss	Test Log Loss	Runtime sec
SVM	3	0.9940	0.9482	**0.9491**	0.0208	0.3351	0.3311	1144.17
XGB	5	0.9928	0.9440	0.9447	0.0211	0.3268	0.3378	198.88
RF	3	0.9979	0.9453	0.9441	0.0087	0.9172	0.9562	144.67
KNN	4	0.9881	0.9407	0.9416	0.029	1.3943	1.4303	49.28

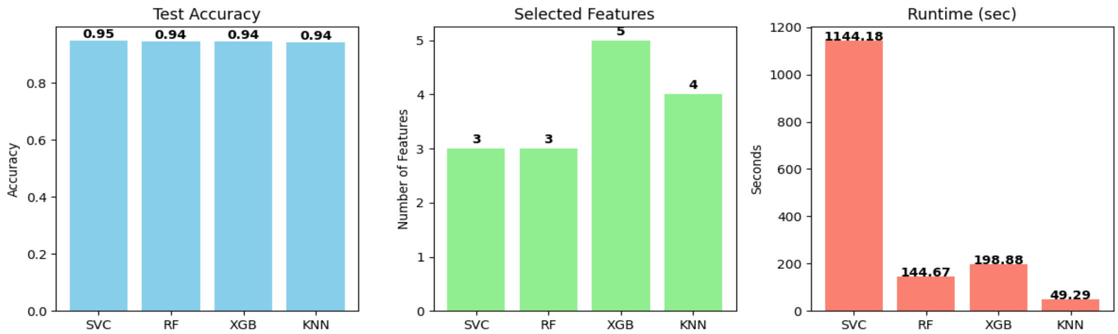

Figure 9. The performance of the ACO algorithm with the four classifiers on UCSD OCT data in terms of feature selection, test accuracy, and processing speed

Table 12 and Fig. 10 present a comparison of the performance of three swarm algorithms (DSO, PSO, ACO) in conjunction with the best classifier for each algorithm, in terms of classification accuracy on UCSD OCT data.

Table 12. Comparison of the performance of the three algorithms on UCSD OCT data.

swarm	Classifier	Selected Features	Test Accuracy%	Runtime sec
DSO	**SVM**	**26**	**95.11**	**775.88**
PSO	RF	35	95.06	367.60
ACO	SVM	3	94.91	1144.17

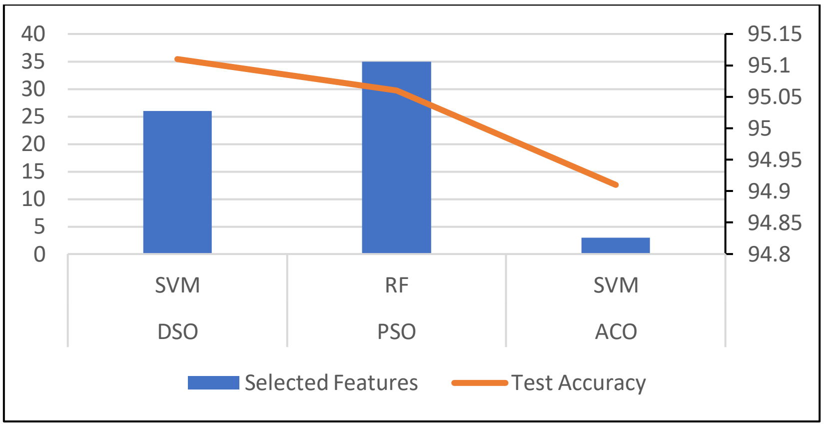

Figure 10. Comparison between the number of selected features and the test accuracy for DSO, PSO, and ACO on UCSD OCT data.

4.3 Performance analysis

On comparing the performances in both of these two sets, the DSO + SVM combination resulted in the highest accuracy, 92.98% on the local data (Table 5) and 95.11% on the UCSD (Table 9), while keeping a good trade-off between the number of features and time. Finally, PSO showed equal performance for SVM locally (92.54%) and RF globally (95.06%) whilst requiring shorter run time (Tables 6 and Table 10). At the same time, ACO did well in feature optimization (3–4) with a resulting lower accuracy (Tables 7 and Table 11). These results are summarized in Tables 8 and 12, and confirm DSO is most accurate, PSO is a balanced performer, and ACO is the optimal choice for dimensionality reduction.

5. CONCLUSION AND RECOMMENDATIONS

The best performance on local and global datasets was shown by the SVM classifier and DSO algorithm, where the test accuracy for each study result is verified in all situations. The ACO algorithm excelled in feature selection since it selected a relatively smaller number of features as expected, but it performed poorly in terms of classification accuracy. Likewise, the trade-off between accuracy and execution speed for PSO + SVM was appropriate, also highlighting how selecting the appropriate algorithm is strongly based on the application needs. This study contributes to providing a systematic comparison between several hybrid combinations of swarm algorithms and traditional classifiers. The study offers empirical proof of the DSO algorithm's efficacy in striking a balance between accuracy and execution time, a goal that hasn't been adequately addressed in earlier research in this area.

The hybrid model (DSO + SVM) is therefore proposed to demonstrate its applicability in medical practices that require highly accurate diagnoses within a reasonable time frame (e.g., smart doctor assistance systems). However, there are also some limitations. Swarm algorithms are both computationally time-consuming and require high processing power due to the exponential increase in computational time with the increase of data size (at least up to October 2023). The model might also perform based on the hyperparameters chosen for this model setup. Additionally, the number of datasets in which the study was replicated is only two; thus, the conclusions cannot be completely extended to other applications and domains. As plans, it is suggested to test the hybrid algorithm on multi-modal data (such as combined medical images and text), or experiment with different swarm algorithms or multiple hybrid methods. It is also possible to combine features extracted from various CNN models to enhance the diversity of feature representation and achieve higher accuracy and better generalization.

CONFLICT OF INTEREST

The authors declare that there is *no conflict* of interest regarding the publication of this paper.

REFERENCES

[1] M. Kulyabin *et al.*, "OCTDL: Optical Coherence Tomography Dataset for Image-Based Deep Learning Methods," *Sci Data*, vol. 11, no. 1, Dec. 2024, doi: 10.1038/s41597-024-03182-7.

[2] Shahad A. Salih, Sadik Kamel Gharghan, Jinan F. Mahdi, and Inas Jawad Kadhim, "Lung Diseases Diagnosis-Based Deep Learning Methods: A Review," *Journal of Techniques*, vol. 5, no. 3, pp. 158–173, Sep. 2023, doi: 10.51173/jt.v5i3.1469.

[3] S. Agarwal, A. K. Dohare, P. Saxena, J. Singh, I. Singh, and U. K. Sahu, "HDL-ACO hybrid deep learning and ant colony optimization for ocular optical coherence tomography image classification," *Sci Rep*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-89961-7.

[4] S. S. Jasim and A. K. A. Hassan, "Modern drowsiness detection techniques: a review," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 3, pp. 2986–2995, 2022, doi: 10.11591/ijece.v12i3.pp2986-2995.

[5] W. Qiao and Z. Yang, "An Improved Dolphin Swarm Algorithm Based on Kernel Fuzzy C-Means in the Application of Solving the Optimal Problems of Large-Scale Function," *IEEE Access*, vol. 8, pp. 2073–2089, 2020, doi: 10.1109/ACCESS.2019.2958456.

[6] H. Abdulrahman and M. Khatib, "Classification of Retina Diseases from OCT using Genetic Programming," *Int J Comput Appl*, vol. 177, no. 45, pp. 41–46, Mar. 2020, doi: 10.5120/ijca2020919973.

[7] P. K. Shukla, J. K. Sandhu, A. Ahirwar, D. Ghai, P. Maheshwary, and P. K. Shukla, "Multiobjective genetic algorithm and convolutional neural network based COVID-19 identification in chest X-Ray images," Mathematical Problems in Engineering, vol. 2021, pp. 1–9, Feb. 2021, doi: 10.1155/2021/7804540.

[8] A. M. Dayana and W. R. S. Emmanuel, "An enhanced swarm optimization-based deep neural network for diabetic retinopathy classification in fundus images," *Multimed Tools Appl*, vol. 81, no. 15, pp. 20611–20642, Jun. 2022, doi: 10.1007/s11042-022-12492-0.

[9] S. S. Jasim, A. K. Abdul Hassan, and S. Turner, "Driver Drowsiness Detection Using Gray Wolf Optimizer Based on Face and Eye Tracking," *ARO-The Scientific Journal of Koya University*, vol. 10, no. 1, pp. 49–56, Jun. 2022, doi: 10.14500/aro.10928.

[10] S. S. Jasim, A. K. Abdul Hassan, and S. Turner, "Driver Drowsiness Detection Using Gray Wolf Optimizer Based on Voice Recognition," *ARO-The Scientific Journal of Koya University*, vol. 10, no. 2, pp. 142–151, Dec. 2022, doi: 10.14500/aro.11000.

[11] O. Salih and K. J. Duffy, "Optimization Convolutional Neural Network for Automatic Skin Lesion Diagnosis Using a Genetic Algorithm," *Applied Sciences (Switzerland)*, vol. 13, no. 5, Mar. 2023, doi: 10.3390/app13053248.

[12] A. Khan, K. Pin, A. Aziz, J. W. Han, and Y. Nam, "Optical Coherence Tomography Image Classification Using Hybrid Deep Learning and Ant Colony Optimization," *Sensors*, vol. 23, no. 15, Aug. 2023, doi: 10.3390/s23156706.

[13] A. Pujianto, R. Andriani, A. Sa'di, and R. Wardhana, "Cholesterol Detection Through Iris Using Genetic Algorithm, Wavelet and Particle Swarm Optimization," in *2024 International Conference on Smart Computing, IoT and Machine Learning, SIML 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 31–34. doi: 10.1109/SIML61815.2024.10578188.

[14] A. A. Nilatika, S. H. Pramono, and Rahmadwati, "Early Diagnosis of Diabetic Retinopathy through Optimization of Convolutional Neural Network Hyperparameters using Genetic Algorithm," in *ICSINTESA 2024 - 2024 4th International Conference of Science and Information Technology in Smart Administration: The Collaboration of Smart Technology and Good Governance for Sustainable Development Goals*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 384–389. doi: 10.1109/ICSINTESA62455.2024.10747887.

[15] R. Loganathan and S. Latha, "Age-related macular degeneration diagnosis in optical coherence tomography images with gray level co-occurrence matrix features, genetic algorithms, and random forest classifier," *Technol Health Care*, vol. 33, no. 3, pp. 1509–1521, May 2025, doi: 10.1177/09287329241301649.

[16] C. Venkatesh, B. V. V. S. Prasad, M. Khan, J. C. Babu, and M. V. Dasu, "An automatic diagnostic model for the detection and classification of cardiovascular diseases based on swarm intelligence technique," *Heliyon*, vol. 10, no. 3, Feb. 2024, doi: 10.1016/j.heliyon.2024.e25574.

[17] R. A. Krishnamaneni Jurypicks *et al.*, "Deep Long and Short Term Memory with Tunicate Swarm Algorithm for Skin Disease Detection and Classification," 2024. [Online]. Available: https://www.researchgate.net/publication/381266979

[18] D. S. Kermany *et al.*, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell*, vol. 172, no. 5, pp. 1122-1131.e9, Feb. 2018, doi: 10.1016/j.cell.2018.02.010.

[19] H. S. Gill, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Fruit Image Classification Using Deep Learning," *Computers, Materials and Continua*, vol. 71, no. 2, pp. 5135–5150, 2022, doi: 10.32604/cmc.2022.022809.

[20] H. Alshammary, M. F. Ibrahim, and H. A. Hussein, "Evaluating The Impact of Feature Extraction Techniques on Arabic Reviews Classification," *InfoTech Spectrum: Iraqi Journal of Data Science*, vol. 1, no. 1, pp. 42–54, Jun. 2024, doi: 10.51173/ijds.v1i1.10.

[21] M. O. Ayemowa, R. Ibrahim, and Y. A. Bena, "A systematic review of the literature on deep learning approaches for cross-domain recommender systems," 01 December, 2024, *Elsevier Inc.* doi: 10.1016/j.dajour.2024.100518.