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Research Article

Enhanced Face Recognition Using Dolphin Swarm Optimization with Euclidean Classification and PCA

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Abstract: Face recognition (FR) is a widely used biometric technology. Nevertheless, achieving efficient and robust FR is still challenging due to variations in illumination, pose, and facial expression. A vital step in any FR system is to select the most informative features and eliminate the redundant ones. In this study, a hybrid approach combining Principal Component Analysis (PCA) and the Dolphin Swarm Algorithm (DSA) with Euclidean Distance as a lightweight classifier is proposed. Experiments were made by using the ORL dataset, which consists of 400 grayscale images. With a 98% recognition rate for this hybrid approach against a recognition rate of 90–92% that can be achieved by PCA only, the proposed PCA+DSA outperformed standalone PCA while still being computationally economical. The metrics of Recognition Rate, Receiver Operating Characteristic (ROC), Cumulative Match Curve (CMC), and Expected Performance Curve (EPC) provided numerous confirmations for this Hybrid model. Additionally, the convergence analysis corroborated DSA's efficacy in feature selection as the fitness was nearly 92% after nine iterations. Without requiring sophisticated classifiers or deep learning models, our findings show that the identification rate can be improved by combining a bio-inspired optimization technique and the classical PCA method. However, the current study is limited to the ORL dataset in a controlled environment. Future research will focus on implementing and evaluating the system in real-time scenarios on larger and more diverse datasets to enhance its scalability and robustness in practical applications.

Keywords: Biometric authentication; Dolphin swarm optimization; Euclidean distance; Face recognition; Feature selection; Principal component analysis; Swarm intelligence.

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1. Introduction

Face recognition (FR) is a primary problem in appearance-based pattern recognition. It has become an attractive option to meet multiple needs in identity verification and identification. It has become a widely used feature in modern video surveillance systems. For many years, FR has been extensively studied by practitioners and researchers due to its wide variety of uses. Law enforcement, Surveillance, national security, and public safety are some of the main areas where the FR technology is implemented [1]. Nevertheless, facial expressions, lighting, body positioning, and the background, either obscured or complex, can be indicated as factors that can affect the performance of FR [2]–[4].

Beyond security, facial recognition has also been used in healthcare settings to identify and track patients, which improves the quality of medical care, especially during emergencies. It is also valuable for disaster response and rescue operations, where finding and identifying the victims is critical. More broadly, human identification and detection systems help maintain order by preventing unauthorized access to restricted areas and aiding law enforcement in apprehending criminals [3]. In addition, FR technology is increasingly adopted in commercial and industrial sectors. Recent advances have produced high-performance systems with multimodal detection capabilities, able to identify faces even when partially obstructed [5].

Generally, FR systems can be divided into two categories: verification and identification. Face verification makes a matching of one-to-one between a query image and a reference template, whereas face identification involves a 1:N comparison against an entire database [6]. Several biometric recognition methods exist, such as iris or fingerprint scanning, but they require the user to interact with the system. By contrast, FR provides a practical and non-intrusive way of capturing and monitoring people. Due to the varying sources, databases in FR systems can differ significantly, ranging from controlled still images to uncontrolled video footage.

Typically, an FR system is composed of the following three modules: preprocessing, feature selection, and classification [7]. These modules are vital in ensuring that the system can extract the discriminative features and achieve stable performance. However, issues still exist for the feature selection optimization because unnecessary or superfluous features can decrease the accuracy and elevate the computational cost. This gap triggers the exploration of hybrid methods combining classical statistical and AI techniques, and bio-inspired optimization algorithms to attain both accuracy and efficiency in FR tasks.

2. Literature Review

A lot of studies have been done to detect faces using different techniques. For example, in [8], a practical approach was used to reduce the complexity and database size in FR methods. As a result, the discrimination speed was increased by relying on half of the face. The face was first divided into two halves according to facial symmetry. The PCA algorithm was then applied to the left half and compared with the results obtained using Euclidean distance.

In [9], the feature selection technique employed the PCA method, which is capable of diminishing dimensionality by its nature. Particle Swarm Optimization (PSO) was employed to refine the features further, and the results obtained from implementations of the Genetic Algorithm and Artificial Bee Colony for performance comparison, using Euclidean distance and K-Nearest Neighbor. In [10], the neurons of the Self-Organizing Map (SOM) network were clustered through an agglomerative hierarchical method, which was applied to facial datasets. Prior to this, the dimensionality of the data was reduced via PCA, and the initial state of the SOM neurons was determined by the well-known ORL database, which indicates the success of the proposed model.

In [11], the nature-inspired Cuckoo Search method was proposed and found to be effective for face detection. In [12], the authors implemented and evaluated the proposed approach on the databases of YALE and ORL using MATLAB 2020a. PSO was also applied as a feature selection strategy in the same experiments. The use of Gabor filters showed that wavelet-based feature extraction with large numbers of training samples is more effective than alternative approaches. In [13] and [14], Swarm-based PCA, Ant Colony, and Grey Wolf algorithms were employed, while studies [15]–[18] used other techniques for face detection.

In this study, PCA and DSA are employed to improve FR performance compared with the aforementioned methods. This is achieved by utilizing a simpler classifier and a practical dimensionality reduction technique that incorporates a new optimization algorithm. The main objective is to integrate PCA and DSA in a way that leverages Euclidean distance to enhance both the reliability and accuracy of FR. Here, PCA simplifies the data representation by selecting the most relevant features, while DSA further refines these features by eliminating noise and redundancy. With statistically optimized features, Euclidean distance provides a straightforward and effective method for face comparison.

The combination of PCA and DSA is expected to perform better than PCA alone, as well as other simple methods. Compared to hybrid and deep learning-based approaches discussed in [8]–[12], [14]–[17], [19], the proposed PCA+DSA framework with Euclidean distance is anticipated to achieve higher recognition accuracy (~98%) on the ORL dataset, while requiring significantly lower computational cost, offering simpler implementation, and avoiding the complexity of deep learning.

The following is a summary of this study's main contributions:

- We propose a hybrid FR approach that integrates PCA (for feature extraction and dimensionality reduction) with the Dolphin Swarm Algorithm (DSA) for optimal feature selection.

- Unlike conventional PCA, the proposed integration retains more discriminative and relevant features while reducing redundancy, thereby addressing the main limitation of PCA.
- Euclidean distance is employed as a simple and efficient classifier in the reduced feature space, demonstrating that high recognition accuracy can be achieved without complex classifiers.
- This work provides new evidence that bio-inspired optimization (DSA) can effectively enhance a classical PCA-based FR pipeline.

This paper's remaining sections are arranged as follows: the third section explains the data and proposed methods, the fourth section presents the results and discussion, and the fifth section concludes the study.

3. Proposed Method

This section presents the suggested methods along with the dataset used in the experiments.

3.1. Data and Methods

In this research, an FR system is implemented using two approaches, both evaluated on the ORL Face database. This dataset is widely used in FR studies because it is simple, well-structured, and historically meaningful as a benchmark. The ORL dataset includes 400 grayscale images (10 images per subject for 40 individuals, totaling 400 images) with minor variations in facial expression, pose, and illumination, thus providing controlled conditions for evaluating recognition algorithms. Its relatively small size (92 × 112 pixels per image) makes it computationally efficient, particularly for classical methods such as PCA, LDA (Linear Discriminant Analysis), KNN (K-Nearest Neighbors), and SVM (Support Vector Machines). Figure 1 illustrates some sample images from the ORL dataset.

Figure 1.The ORL database's samples

The first approach applies PCA for extracting features from the ORL dataset and uses Euclidean distance as the metric for comparing feature vectors. The second approach combines PCA with the DSA to enhance feature selection, aiming to improve classification accuracy. Euclidean distance is again employed as the classifier. The steps of these two methods are outlined below, and the parameters for PCA and DSA are presented in Tables 1 and 2, respectively.

Table 1. Parameters of DSA.

Parameters	Values	Purposes
Size of the population	20	Dolphins number
Maximum number of Iterations	10	Optimization steps number
Search Area	5-100	Range of PCA feature lengths
Fitness Function	Computed according to Eq. (10)	Measure of recognition accuracy

Table 2. Configuration of PCA.

Component	Configuration
Input Data	Face images in grayscale, flattened into vectors
Size of the image	32 × 32 (resized from the original)
Length of the feature vector	Adjustable (e.g., 10, 25, or DSA-optimized)
Dimensionality Reduction	Performed by applying eigen decomposition of the covariance matrix
Mean Centering	Subtracting the mean from each training sample to normalize the data
Covariance Matrix	Computed from zero-centered data
Eigen Decomposition	Eigenvectors ordered according to eigenvalues in descending magnitude

Fig. 2 illustrates the steps of using PCA. In the first step, the system begins with the ORL dataset, where the facial images are processed, resized, converted to grayscale, and flattened into 1D vectors. The dataset in the second step is divided into three groups: training (280 images, 70%), testing (80 images, 20%), and evaluation (40 images, used to build the PCA model, validate performance during development, and assess unseen cases after final testing). The third step involves extracting principal components (eigenvalues) from the training images using PCA. In the fourth step, each image is projected onto a lower-dimensional eigenspace, capturing important facial features while removing redundancy and noise. Finally, the training images are compared with the test and evaluation images.

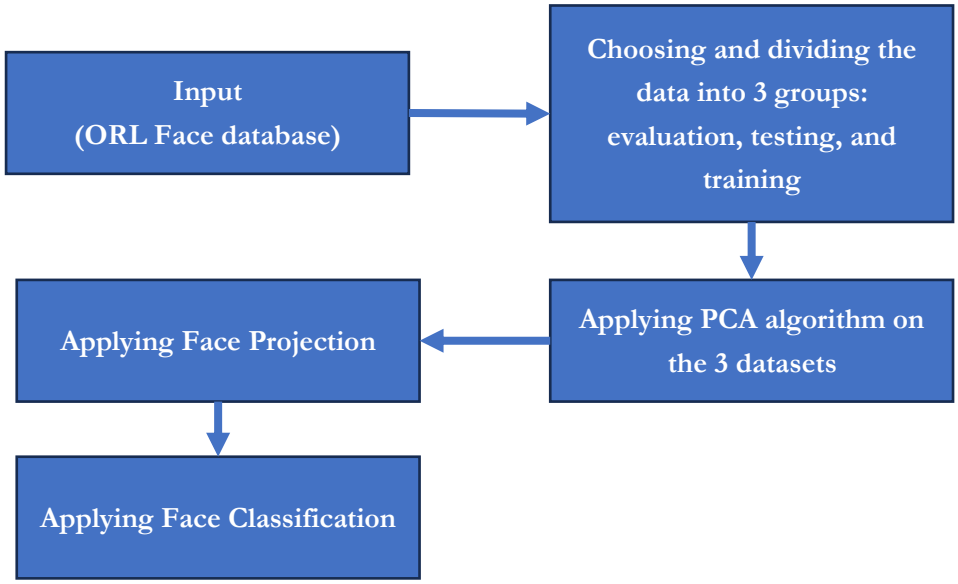


Figure 2. The workflow of PCA algorithm

Fig. 3 illustrates the steps of the PCA-DSA FR system, which aims to improve recognition accuracy. Images are first preprocessed by normalizing, reshaping, and converting them to grayscale before representing them as vectors. PCA is then applied, including the computation of the mean face, image normalization, covariance matrix calculation, and the selection of the top eigenvectors to project the images into a lower-dimensional space. For feature

selection, the DSA is employed by initializing candidate subgroups, evaluating their fitness based on recognition accuracy, and iteratively improving these subsets through swarm behaviors. Finally, test images are classified with training samples using Euclidean distance, and the system's accuracy is assessed accordingly.

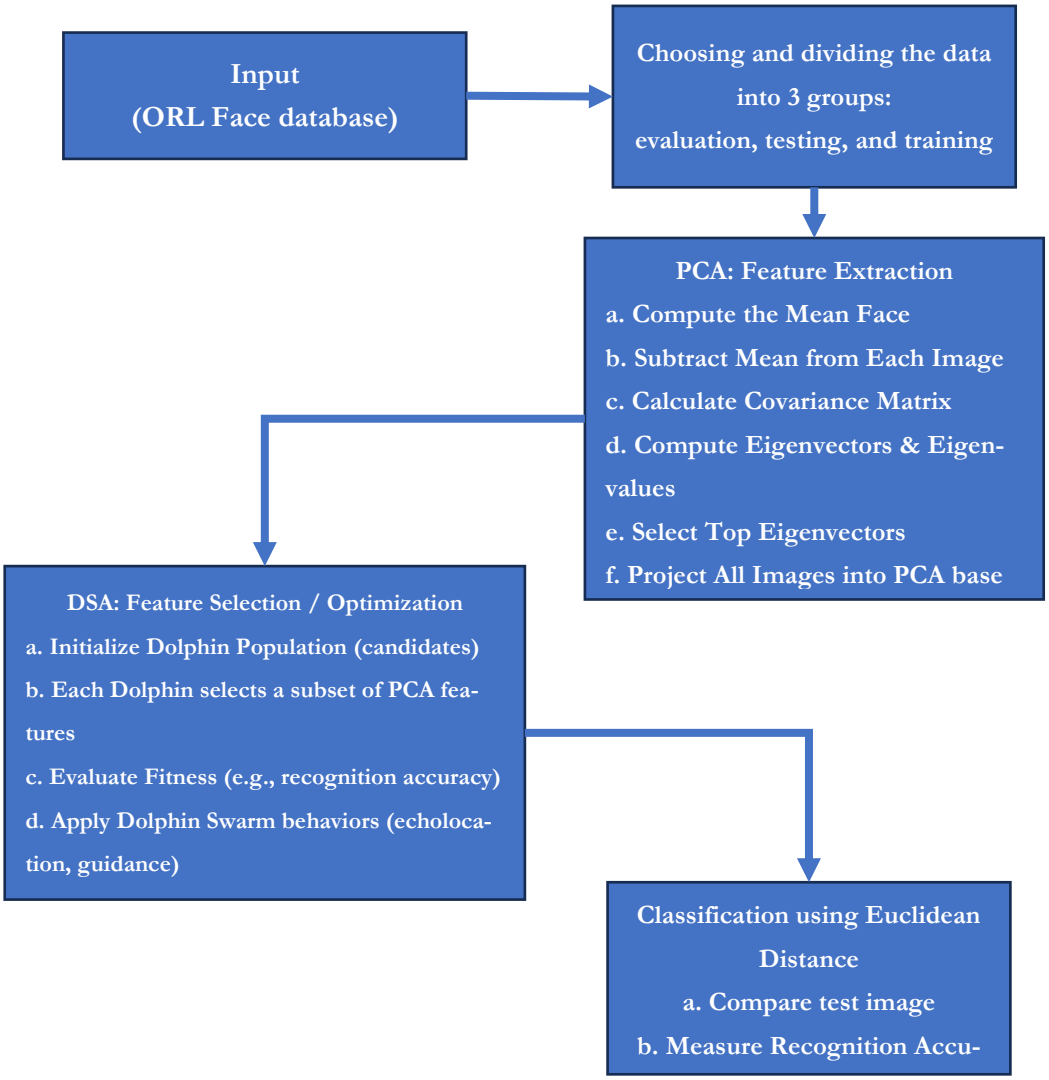


Figure 3. The workflow of the (PCA+ DSA)

3.2. Principal Component Analysis (PCA) Algorithm

The PCA is applied to extract global features from high-dimensional datasets. This technique discovers data patterns and represents them to highlight similarities and dissimilarities. As a dimensionality-reduction method, PCA preserves the most informative structure of the data while removing redundancy. It constructs a linear least-squares subspace for the training set[19], [20].

Given an s-dimensional vector representation of each face image in a training set of N images, PCA finds a t-dimensional subspace $(t \ll s)$ whose basis vectors correspond to the directions of highest variance in the original space. After projecting all training images onto this subspace, a set of weights W_{train} describing each vector's contribution is computed. For a test image, a weight vector W_{test} is obtained by projecting it onto the same subspace. Identification is then performed by computing distances between W_{test} and all W_{train}; the identity corresponds to the nearest W_{train}.

$$S_T = \sum_{j=1}^{N} (X_j - \mu)(X_j - \mu)^T \quad (1)$$

Eigenvectors of the scatter matrix S_T define the PCA basis vectors, where X_j denotes the j_{th} training image and μ represents the mean image of the training set[21], [22].

3.3. Euclidean Distance

The database includes both training and testing images with various expressions (e.g., neutral, happy, sad, angry, fearful, disgusted, surprised). For each image, facial feature points are detected and stored (e.g., as relative (x, y) coordinates). The system computes the Euclidean distance between corresponding points of a training image and a test image provided as input. If the coordinates on the testing and training images are (x_1, y_1) and (x_2, y_2) respectively, the distance is in Equation (2) [2], [23].

$$ED = \sqrt{(x_1, y_1)^2 + (x_2, y_2)^2} \quad (2)$$

3.4. Dolphin Swarm Algorithm (DSA)

This algorithm is a population-based metaheuristic inspired by dolphins' cooperative hunting behavior. DSA models four essential phases—search, call, reception, and predation—and iteratively updates candidate solutions to approach the optimum [24], [25].

3.4.1 Search Stage

To model a dolphin searching for prey, let the sound (search) vector be $VV_i = (vv_1, vv_2, \dots, vv_D)$for $i = 1, 2, \dots, M_i$, where each vv_j is a component in dimension j. M_1 is the number/direction of sounds. The sound satisfies $\|VV_i\| = \text{speed}$. A maximum search time TT_1 is set to avoid remaining in the search phase. For $t \in [0, TT_1]$, the sound VV_i emitted by dolphin Dol_i yields a new solution:

$$XX_{ijt} = Dol_i + VV_{jt} \quad (3)$$

Its fitness is

$$EE_{ijt} = \text{Fitness}(XX_{ijt}) \quad (4)$$

Let

$$LL_i = XX_{iab} \quad (5)$$

If

$$\text{Fitness}(LL_i) < \text{Fitness}(KK_i) \quad (6)$$

then LL_i replaces KK_i remains unchanged. After all dolphins update LL_i and KK_i, the algorithm proceeds to the calling phase.

3.4.2. Call Stage

For KK_i, KK_j and TS_{ji}, if

$$\text{Fitness}(KK_i) > \text{Fitness}(KK_j) \quad (7)$$

$$TS_{ji} > \frac{DD_{ji}}{A \cdot SS'} \quad (8)$$

Where A denotes acceleration.

3.4.3. Reception Stage

This stage follows the calling stage:

$$TS_{1ji} = 0 \quad (9)$$

If the fitness condition in Eq. (7) still holds, then KK_i is updated to KK_j; otherwise, KK_i remains unchanged. After TS_{1ji} is completely updated, the algorithm proceeds to the predation stage (described in [26], [27]).

3.4.4. Fitness Function and Evaluation Metrics

The fitness function $FF_{(x)}$ is defined as the recognition rate, i.e., the percentage of correctly recognized images:

$$FF_{(x)} = RR_{(x)} = \frac{N_{co}(x)}{N_T} \times 100 \tag{10}$$

Here, x is the candidate parameter (e.g., number of features selected by DSA), N_{co} represents the number of correct recognitions, and N_T represents the total number of images. Equivalently,

$$RR = \frac{N_{co}}{N_T} \tag{11}$$

Recognition rate is a direct and widely comparable measure in closed-set FR. Additional evaluation metrics include the Cumulative Match Curve (CMC), the Receiver Operating Characteristic (ROC), and the Expected Performance Curve (EPC).

- The CMC curve evaluates how often the correct identity appears within the top-k ranked matches in the candidate list.
- The ROC curve measures the system's ability to distinguish between genuine and impostor matches by plotting the False Acceptance Rate (FAR) against the Face Verification Rate (FVR).
- The EPC curve summarizes the expected overall error across application contexts, representing trade-offs between FAR and the False Rejection Rate (FRR).

The supporting equations are as follows:

- The FAR is the ratio of impostor attempts wrongly accepted, defined in Equation (12).

$$FAR = \frac{N_{Fa}}{N_t} \tag{12}$$

where N_{Fa} represents the number of false acceptances and N_t represents the total number of impostor attempts.

- The FRR is the ratio of genuine attempts incorrectly rejected, defined in Equation (13).

$$FRR = \frac{N_{Fr}}{N_g} \tag{13}$$

where N_{Fr} represents the number of false rejection and N_g represents the total number of genuine attempts[19], [28].

- The FVR is complementary to FRR and is given in Equation (14).

$$FVR = 1 - FRR \tag{14}$$

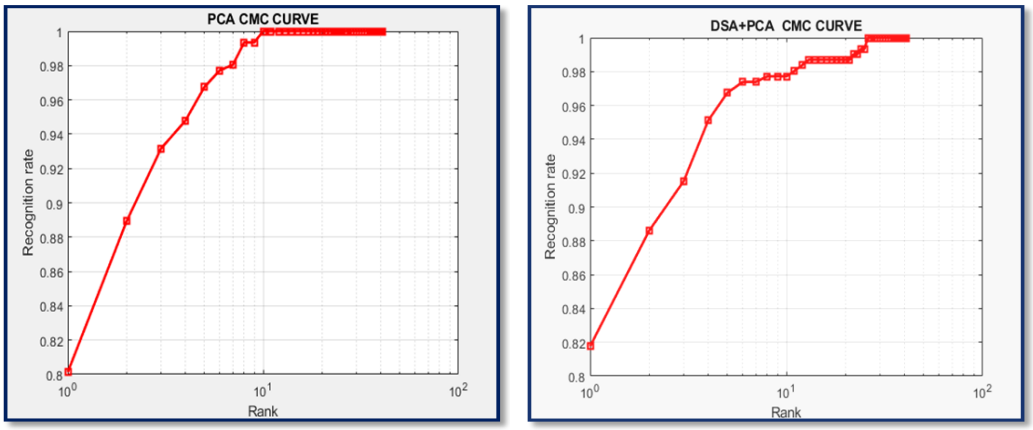
- The Half Total Error Rate (ER_h) used in EPC analysis, is the average of FAR and FRR, as shown in Equation (15).

$$ER_h = \frac{FAR + FRR}{2} \tag{15}$$

4. Results and Discussion

The performance of the proposed FR system was evaluated using recognition rate, CMC, ROC, EPC, and fitness curves. These results are summarized in Figures 4–7. A comparative analysis with previous studies is also presented in Table 4. The recognition rate was determined from the classification results. The system achieved a high recognition rate of approximately 98% when PCA was combined with DSA, which outperformed conventional PCA-only methods (~90%). This improvement demonstrates the benefit of integrating an optimization-based feature selection strategy.

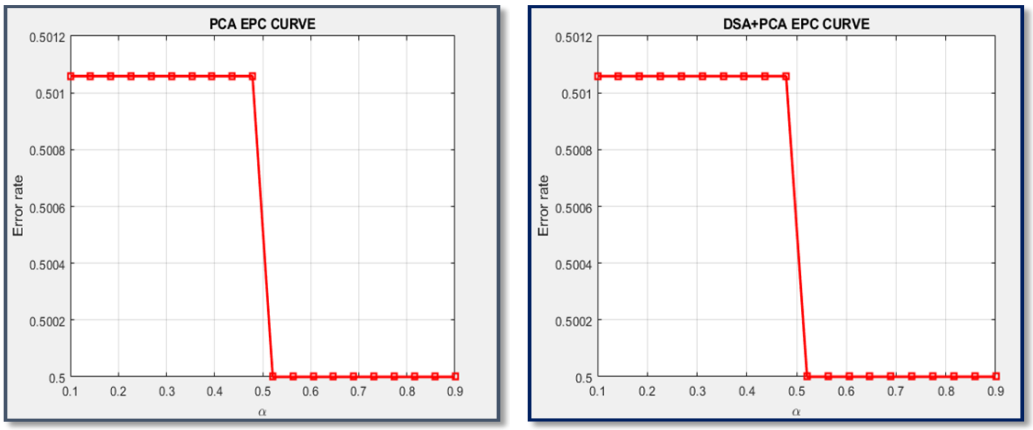
The CMC, presented in Figure 4, measures the accuracy of the recognition system in the closed set by ranking gallery images against probe images. The X-axis shows the rank order, while the Y-axis shows the cumulative match score. As shown in Figure 4, the proposed PCA+DSA method achieved better ranking performance compared to PCA alone, indicating higher robustness and accuracy.



(a) (b)

Figure 4. The CMC's curve for FR using (**a**) PCA; (**b**) DSA+PCA.

The EPC, shown in Figure 5, evaluates the trade-off between the false acceptance and false rejection under varying application contexts. The X-axis shows the weighting parameter α, and the Y-axis shows the corresponding error rates. The EPC curves indicate that PCA+DSA provides a lower and more stable error rate compared to PCA-only. The sharp drop observed in the EPC curve highlights the optimal threshold where the system achieves the best balance between FAR and FRR.

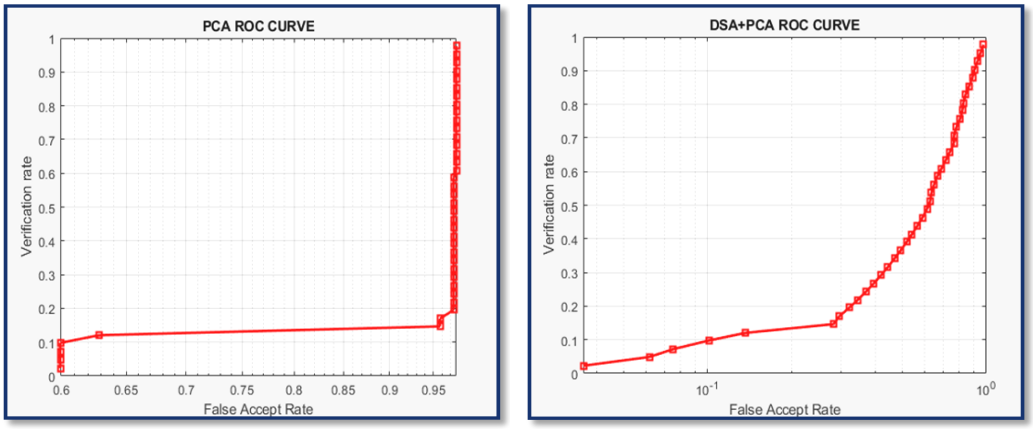


(a) (b)

Figure 5. The EPC's curve for FR using (**a**) PCA; (**b**) DSA+PCA.

The ROC curves, illustrated in Figure 6, assess the verification capability of the system by plotting the False Acceptance Rate (FAR) on the X-axis against the Face Verification Rate (FVR) on the Y-axis. The ROC curve for PCA+DSA is consistently above the PCA-only curve, indicating superior discriminative ability. This also corresponds to a higher Area Under the Curve (AUC), confirming the improved classification performance achieved by the hybrid approach.

The fitness curve of DSA, shown in Figure 7, demonstrates the optimization process across iterations. The fitness value increased from approximately 90.5% to 92% during iterations 1–10. Convergence was achieved around the 9th iteration, after which further improvement was negligible. This confirms the stability of the DSA in selecting optimal feature subsets without overfitting.



(a) (b)

Figure 6. The curve of ROC for FR using (**a**) PCA; (**b**) DSA+PCA.

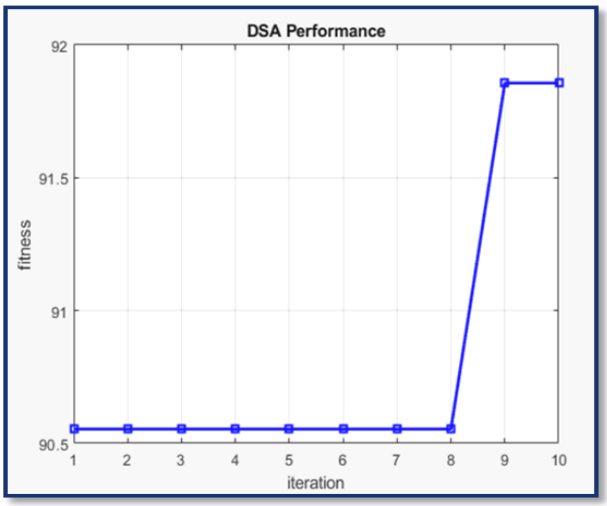
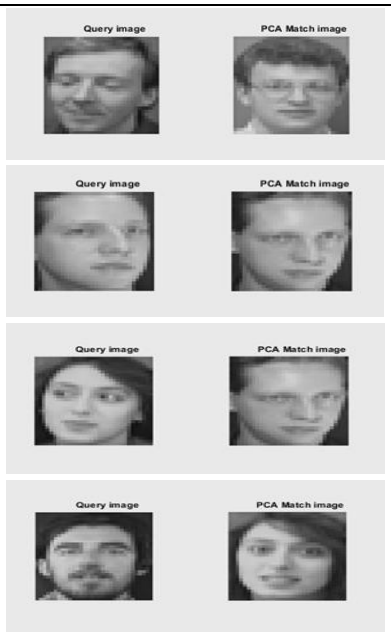
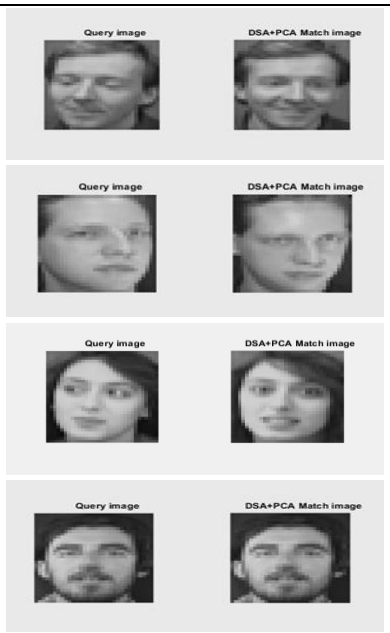


Figure 7. Fitness of DSA vs iteration

Table 3. Sample FR results using PCA and DSA technique.

PCA only	PCA + DSA
	

Depending on these results, the proposed system can be used efficiently to recognize faces in daily life. In Table 3, the pictures of four persons were selected to demonstrate the application of the proposed system, which combines PCA and DSA, achieving very accurate results in person detection compared to using PCA alone. A comparative analysis with previous studies is provided in Table 4. The table lists recognition rates, classifiers, and key weaknesses of earlier methods. It is evident that while some approaches, such as PCA+ACO [13] and Gabor wavelet-based methods [12], reported competitive accuracies (~96–98%), they often suffered from higher computational complexity, sensitivity to noise, or longer training times. In contrast, the proposed PCA+DSA approach achieved a comparable recognition rate (~98%) while maintaining lower computational cost, simpler implementation, and no need for deep learning models. This balance of efficiency and accuracy represents a practical advantage, particularly for real-time or resource-limited environments.

Table 4. Comparison with the most advanced.

Ref.	Algorithms	Classifier	Recognition Rate (Accuracy, %)	Weakness	Advantages of the Proposed Method over this work
[8]	PCA	Euclidean	~96.0	Sensitive to pose variations; limited feature information	Higher robustness and accuracy through DSA-based feature optimization
[9]	PCA + GA/ABC	KNN / Euclidean	~93.7	Increased complexity; slower convergence	Simpler and faster with competitive accuracy
[10]	PCA + SOM	SOM	~94.7	High memory usage; requires tuning	Lower computational load with comparable performance
[11]	PCA + DCT + CS	Euclidean	~96.5	Slow convergence; sensitive to parameter settings	More stable optimization, faster convergence
[12]	Gabor Wavelet + PSO + CNN/DNN	Softmax / DNN	~96.2	High computational cost; requires deep learning and preprocessing	Comparable accuracy without deep learning; simpler implementation
[13]	PCA + ACO	Euclidean	~98.0	Risk of local minima; slower with large datasets	Avoids local optima; stable convergence
[14]	GWO + PCA	R-CNN / ResNet50	~94.0	Limited generalization; requires deep learning	Optimized the full pipeline without deep learning
[15]	PCA + GA (Optimized Eigenfaces)	Euclidean	~97.5	Complexity of GA; convergence depends on parameters	Simpler optimization; avoids GA issues; yields higher recognition
[16]	PCA + ANN	ANN	~87.5	Long training; overfitting with small datasets	Faster classification; avoids overfitting
[17]	Patch-Based PCA	Nearest Neighbor	~93.0	Sensitive to patch size; parameter tuning required	Preserves local features with lower cost and robust accuracy
Ours	PCA + DSA	Euclidean	~98.0	—	High recognition rate; low computational cost; no deep learning

Overall, the experimental results clearly demonstrate that integrating PCA with DSA yields better recognition accuracy and error trade-offs than PCA alone or many other hybrid methods, while keeping the system lightweight and efficient.

5. Conclusions

This study proposed a hybrid FR method that integrates PCA for dimensionality reduction with the DSA for feature optimization, using Euclidean distance as a classifier. The approach achieved a recognition accuracy of approximately 98% on the ORL dataset, outperforming conventional PCA-only methods (~90%). These findings demonstrate that optimization-based feature selection can effectively enhance a classical PCA pipeline, offering higher recognition accuracy while maintaining lower computational complexity and avoiding the need for deep learning. The obtained results confirm that the combination of PCA with DSA improves both the robustness and the overall quality of recognition, particularly in controlled environments. However, the study has certain limitations. The evaluation was conducted only

on the ORL dataset, which represents relatively simple and constrained conditions, and the system has not yet been tested in real-time scenarios or under challenging conditions such as occlusion, pose variation, or changing illumination. Future work will extend the evaluation to larger and more diverse datasets such as Yale, FERET, and LFW, and investigate the practical deployment of the suggested method in real-time applications. Further research will also focus on enhancing robustness and scalability in unconstrained environments, including variations in occlusion, posture, and illumination.

Author Contributions: This project was carried out with cooperation from all participants. Methodology: R.M.A and W.M.R.S; Validation: all; Software: I.A.A; Formal analysis: all; Investigation: all; Resources and Data: R.M.A. The authors, R.M.A, I.A.A., and W.M.R.S revised and proofread the manuscript after analyzing the results. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The ORL dataset is available for download. via URL

https://www.kaggle.com/datasets/kasikrit/att-database-of-faces.

Conflicts of Interest: The authors declare no conflict of interest.

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