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New Technique for Face Recognition using Optimization Algorithms with PCA and Euclidean Classifier

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ABSTRACT

In face recognition technology, feature selection is an optimization method. By eliminating unnecessary, noisy, and redundant data, feature selection improves the database's ability to recognize faces. This research introduces an innovative method that combines Particle Swarm Optimization and Octopus Optimization Algorithm meta-heuristics to improve the selection of facial recognition features in the ORL database. The system initially employs Principal Component Analysis for feature extraction. Tackling the problem of weak discriminating ability in unprocessed Principal Component Analysis features, the hybrid system serves as a complex-oriented determinant. The method utilizes Particle Swarm Optimization for strong local exploitation and the Octopus Optimization Algorithm for regular global exploration, ensuring an algorithm that escapes local optima to determine the best feature subset. Employing the Euclidean distance classifier enhances recognition precision through optimization. Performance evaluation using Cumulative Match Curve, Receiver Operating Characteristic, and Expected Performance curves confirms that the hybrid system successfully filters Principal Component Analysis components, leading to markedly improved rank-1 recognition rates. This supports the hybrid method for achieving high-precision, resilient face recognition, with accuracy ranging from 98% to 100%.

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1. INTRODUCTION

Face recognition (FR) technology has been used for about 50 years. FR is a field of study in pattern recognition and computer vision because of its several practical applications in surveillance systems, smart cards, access control, biometrics, and information security. The technology of FR was used in Florida for the first time. Recently, biometric-based methods have become the most optimistic means of identifying persons because, rather than granting certifications and granting access to smart cards, plastic cards, tokens, keys, PINs, passwords, and other techniques, they are used in both physical and virtual worlds to analyze a person's physical characteristics and behaviour in order to identify and/or ascertain who they are. Tokens, keys, cards, and similar items can be misplaced, forgotten, or duplicated; magnetic cards can distort [1].

Face recognition technology works by comparing specific face traits from a given picture of faces in a database. This biometric identification technique makes use of pertinent characteristics from a human face for identification, offering a generally very successful non-contact method. Despite appearing to be a relatively new invention, facial recognition technology has roots in back a few decades [2]. Face recognition is a subtype of biometric authentication that compares and determines patterns regarding people's facial features in order to match or validate them. It is feasible to ascertain whether a person is accurately identified from a digital image or video frame by using this comparison and analysis. Face recognition technology, which can be used for physical or virtual access authorization or identification, is used to authenticate people. It can also be used to verify people or even determine whether they are present at a location. Face recognition technology can determine whether a person is depicted in a picture or security camera footage [3].

On the subject of FR, numerous researchers have made important contributions. In [4] the authors used the patch-based Principal Component Analysis (PCA) approach. A lot of PCA-based face recognition techniques make use of the connection between rows, columns, or pixels. However, these approaches either do not use or do not completely utilize the local spatial information. In their opinion, patches are more significant fundamental building blocks for facial recognition than pixels, columns, or rows, since patches with eyes and noses are used to identify faces. Face pictures are separated into patches, which are subsequently transformed into column vectors and merged into a new "image matrix" in order to determine the correlation between patches. They determined the relationship of the divided patches by calculating the overall scatter after replacing the original "image matrix" with the images in the two-dimensional PCA context.

In order to design a FR system that can be used to search for suspects in kidnappings and to determine the suggested convolutional neural network (CNN) of the facial recognition system layers' the optimal training parameters, in [5], they created a device that would take a kidnapper's picture as evidence for future use and email the picture to the victim's family. Three distinct datasets were used to verify the accuracy of the suggested system: the AT&T database, and a bespoke face dataset with 87.50%, 92.19%, and 95.93%, which are the respective outcomes. The suggested system had a 98.48% overall face recognition accuracy. A learning rate of 0.001 and kernel sizes of 5x5 with 32 and 64 filters for the first and second convolutional layers are the ideal training settings for the suggested CNN model.

The authors in [6], suggested a practical strategy for reducing the features and database size in the face recognition method, which increases the discrimination speed by utilizing half of the face. Utilizing facial symmetry, the face image is first split in half. The left half is evaluated with the PCA algorithm, and the data are contrasted using Euclidean distance to identify the individual. The ORL database was used to train and test the system. The system's accuracy was estimated to be up to 96%, the database was reduced by 46%, and the operating time was lowered by 41.6% from 120 msec to 70 msec.

This study [7] presents a novel method for the symmetry face database using the Gabor wavelet transformation utilizing deep learning capabilities suggested face recognition system was created with many uses in mind. After extracting features from the symmetry face training set using the Gabor wavelet technique, we employed deep learning for recognition. Using MATLAB 2020a, they applied and assessed the suggested approach on the ORL and YALE databases. Additionally, the same tests were carried out using the feature selection approach and Particle Swarm Optimization (PSO). In this work, the use of Gabor wavelet feature extraction with a large number of training image samples has shown to be more successful than alternative approaches. In paper [8] the DCT (Discrete Cosine Transform) coefficients were employed as features for the face recognition application. modified PSO method is used to determine the best choice for the coefficients. In order to choose the coefficients for The mean normalized standard deviations of the different classes are averaged, and the lower indexed DCT coefficients are given more weight. Using the ORL database, the algorithm is tested. It achieves a 97% recognition rate. On average, 40 percent of features are chosen for a 10 × 10 input. About fifty iterations were required for the improved PSO to converge. It is discovered that these performance metrics outperform some of the work published in the literature. Other methods are also used in [9]- [10] to the apply FR system.

Although PCA is frequently used to extract features, it has issues with noise sensitivity and redundant features. This study proposes a hybrid system for face recognition using PSO and Octopus Optimization Algorithm(OOA) , which are two optimization techniques that can enhance feature selection, but when applied alone, they may cause convergence problems. In order to solve the issue, this work combines PCA with metaheuristic optimization algorithms, which results in more accurate and reliable performance than standalone PCA, PSO, or earlier techniques. This paper's remaining sections are as follows: section two for method and data, section three for results with discussions, finally section presents the conclusion.

2. METHOD AND DATASET

This study applies PCA techniques with two optimization algorithms PSO and OOA to the ORL Face database in order to construct a face recognition system with more accurate results.

2.1 Dataset

The ORL datasets are straightforward, directly structured, and significant when considering the history of benchmark progression; they are frequently utilized in face recognition research. With 400 grayscale photographs (10 images per subject, for 40 people, for a total of 400 images), the ORL provides controlled settings for evaluating archive algorithms. These images vary somewhat in terms of illumination, position, and facial expressions. Its tiny size (92 × 112 pixels per image) might make it computationally efficient, particularly when used with traditional techniques like support vector machines (SVM), PCA, and LDA (Linear Discriminant Analysis). Figure 1 shows some examples of the ORL dataset [11].

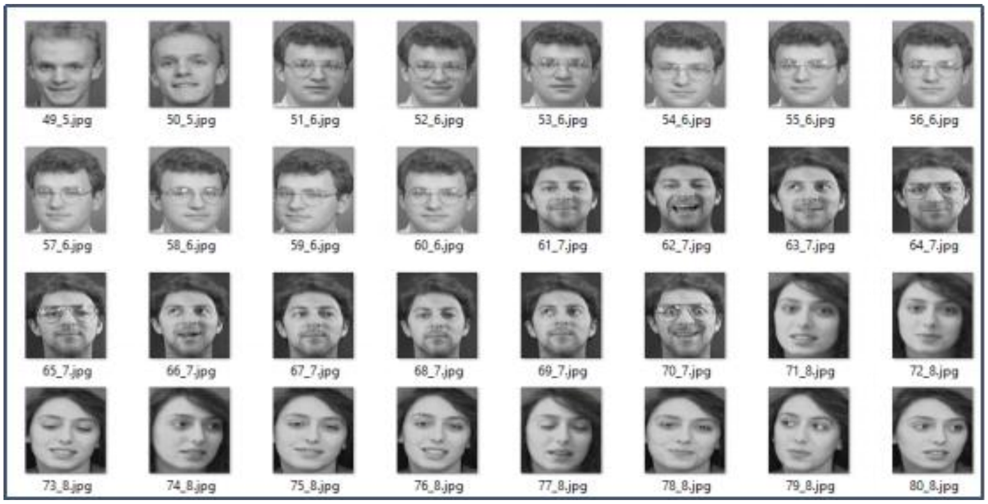

Figure 1. Examples of ORL dataset.

2.2 Algorithms

2.2.1 Principal Component Analysis (PCA)

PCA is a practical statistical method that is utilized in face recognition, coding, and compression. The primary benefit of PCA is the reduction of dimensionality. PCA awards superior produces several positions, however it takes a long time to execute. PCA is utilized to obtain global characteristics from datasets with high dimensions. This method identifies data patterns and illustrates them to emphasize both similarities and differences. PCA, as a dimensional reduction technique, maintains the most significant data structure while eliminating redundancy. It builds a linear least-squares subspace for the training data [12,13]. Given a dimensional vector representation for each face image in a training image set, PCA identifies a -dimensional subspace where its basis vectors align with the directions of maximum variance in the original space. Following the projection of all training images onto this subspace, a collection of weights indicating each vector's contribution is calculated. For a test image, a weight vector is derived by projecting it into the identical subspace. Identification is carried out by calculating distances between and all; the identity matches the closest. Table 1 shows configuration of PCA**.**

$$\boldsymbol{S_{1T}} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{N_o}} \left(\boldsymbol{X_j} - \boldsymbol{\mu}\right)\left(\boldsymbol{X_j} - \boldsymbol{\mu}\right)^{\boldsymbol{T}} \tag{1}$$

Eigenvectors of the scatter matrix determine the PCA basis vectors, where indicates the training image and signifies the average image of the training set [14].

Table 1. Configuration of PCA

Component	Configuration
Dataseet	ORL Face Database
Dimension	112 × 92 (10,304 pixels)
Length of the feature vector	Adjustable (e.g., 10, 25, or DSA-optimized)
Dimensionality Reduction	Performed by applying eigen decomposition of the covariance matrix
Preprocessing	Mean Centering(Subtracting the mean from each training sample to normalize the data
Number of Components (D)	50 (The number of top eigenvectors kept for the reduced space)
Decomposition of Eigenvalues	Eigenvectors arranged by eigenvalues in decreasing magnitude.
Covariance Method	Calculated from data that is centered around zero

2.2.2 Particle Swarm Optimization

In this algorithm, a group of particles explores the solution space to find the best solution. In PSO, each solution is treated as an individual bird in the swarm, meaning an element in the exploration area. Every particle utilizes its unique experience and its adjacent particles encounter to navigate through the search space, meaning each particle possesses understanding of its optimal position that it has discovered to date and the optimal position identified by the swarm. is represented as the best location () of I the particle, and representing the optimal position discovered by the swarm to date. Each particle is assigned a random starting position and arbitrary starting speed. Function for fitness assesses each particle within the search area. It establishes the caliber of the particle. Particles draw toward top particles in their search domain that exhibit optimal fitness values. The position and velocity of particles are adjusted [15].

$$V_j^{t+1} = w \times V_j^{\,t} + c_1 \times rand_1 \times (Pb_j - X_j^{\,t}) + c_2 \times rand_2 \times (g_{best} - X_j^{\,t}) \qquad (2)$$

where, j= 1,2, …..M denotes the size of the swarm, and consists of two random numbers that are uniformly distributed within the from 0 to 1, with and being constant values. Speed is adjusted according to the momentum of prior speed, knowledge of the particle itself and the perception of the surrounding particles. The position of the particle is revised by:

$$X_j^{t+1} = X_j^{\,t} + V_j^{t+1} \qquad (3)$$

In each iteration, the fitness of each particle is assessed. Velocity is modified according to values and variables such as , and w. Position is revised according to speed. This procedure continues until the maximum number of iterations is reached. or the error threshold is met. Table 2 shows configuration of PSO.

Table 2. Configuration of PSO

Parameter	**Value / Setting**
Swarm Size	50
Max Iterations	200
Inertia Weight	0.7
Cognitive Constant (c_1)	2.0
Social Constant (c_2)	2.0

2.3 Octopus Optimization Algorithm (OOA)

The Octopus Optimization Algorithm (OOA) is an innovative meta-heuristic optimization method influenced by the smart, distributed actions of octopuses found in the natural world. This algorithm is a highly versatile feeder found in oceans worldwide. The algorithm represents the octopus's population as a group of agents split into two categories: Hunters (for exploitation/local search) and Scouts (for exploration/global search). They are primarily beneficent and choose to reside solitary, concealed within coral reefs (refer to caverns and sandy, muddy substrate habitats). The common octopus features a head and body with a single pair of big eyes and eight adaptable carpals with suction pads (refer to linked by a membrane, which aids in its movement swiftly and seize prey in diverse, intricate surroundings. An octopus's brain has 500 million neurons. that can engage in conceptual reasoning and find solutions to intricate issues autonomously. About two to five parts of the octopus's nerve cells are situated in its head. while the leftover three-fifths are allocated among its eight adaptable appendages [16]. The brain produces a concept. control of the carpal foot, allowing it to then act autonomously, examine, and finalize the subsequent action.

OOA Fundamental Principles and Structure of Hunter:

- Every Hunter agent is made up of a head *($hunt_{head}$)* and eight tentacles *($hunt_{group}$)*. The tentacles function as multi-limbed intelligent agents, independently navigating the solution space, while the head synthesizes their insights to direct coordinated movement, balancing exploration and intentional action.
- Phases of Movement: The hunter's motion is influenced by the variable (a stochastic positional element) and a specified grasping range l.
- Exploration-Exploitation Equilibrium: The algorithm employs L_d (learning distance, which reduces with iterations) to modify the exploration scope, and the Levy flight function to improve search effectiveness and evade local optima

The algorithm initially computes a diminishing Learning Distance (L_d) and a Tentacle Exploration Condition (Tran), which determines the phase of the hunter's motion.

1. Learning Distance (L_d) (Regulates search range):

$$L_d = Vr \times (1 - \frac{t}{T}) \tag{4}$$

Where Vr represents the field of view, t denotes the current iteration, and T indicates the maximum number of iterations.

2. Tentacle Motion Condition (l) (Establishes phase):

$$trans = (2 \times rand - 1) \tag{5}$$

Where represents a random number within the interval [0, 1]

3. Exploitation (Seizing Prey) Stage ($trans \geq l$: If the prey (global best position) is within the reaching range, the tentacle heads straight to the nearest tentacle position that is close to the prey.

$$hunt_{group} = hunt_{group} + rand \times (\mathrm{pr} - hunt_{group}) \times Lf(\mathrm{dim}) \tag{6}$$

4. Scout Movement: Scouts modify their locations according to a selected {Hunt.head} (optimal, suboptimal, or arbitrary) to seek out overlooked prey.

$$\mathrm{Sco} = hunt_{head} + rand \times \mathrm{Ld} \times (\frac{U_{\mathrm{B}} + L_{\mathrm{B}}}{2} - hunt_{head}) \tag{7}$$

Where U_{B} and L_{B} denote the upper and lower limits of the search space. Table 3. shows Configuration of OOA

Table 3. Configuration of OOA

Parameter	**Value / Setting**
Refinement Rate	Every 10 iterations
alpha	0.1
(Step Size)	0.01 – 0.1
Space of searching	50

Figure 2 shows a streamlined process of the hybrid OOA–PSO with PCA method for selecting features in face recognition. Initially, the input data undergo loading and transformation via PCA to decrease dimensionality and highlight the most significant features. Subsequently, an iterative PSO–OOA optimization loop assesses the fitness of chosen features and modifies particle positions to achieve an ideal feature subset. Ultimately, the chosen features are utilized for classification and performance assessment, generating prediction outcomes and curves to evaluate the efficacy of the suggested approach.

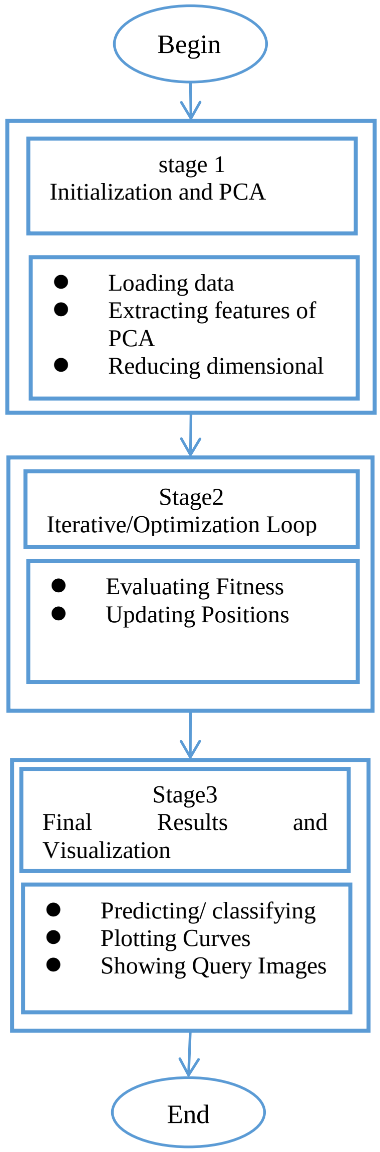

Figure 2. Steps of the proposed system.

2.3 Euclidean distance

A variety of facial expressions, such as neutral, happy, sad, angry, afraid, disgusted, and astonished, are included in the database's training and testing photos. Facial feature points are identified and recorded for each image (e.g., in terms of relative coordinates). The system calculates the Euclidean distance between matching points of a training image and a test image given as input. If the coordinates on the training and testing images respectively, the distance is given by Equation (8) [17,18].

$$ED = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{8}$$

2.4 Evaluation Metrics

The recognition rate utilized to assess performance of algorithms, the recognition rate in the closed-set FR is a straightforward and broadly equivalent metric. The Receiver Operating Characteristic (ROC), the Cumulative Match Curve (CMC), and the Expected Performance Curve (EPC) are further evaluation measures. How frequently the right identity shows up in the top k ranked matches in the candidate list is assessed by the CMC curve.

The False Acceptance Rate (FAR) is plotted against the Face Verification Rate (FVR) to create the ROC curve, which indicates how well the system can differentiate between real and fake matches. The expected overall error across application contexts is summarized by the EPC curve, which shows trade-offs between the False Rejection Rate (FRR) and FAR [19,20]. The equations related to these metrics are listed in equations below:

$$FAR = \frac{N_{Fa}}{N_t} \quad (9)$$

$$FRR = \frac{N_{Fr}}{N_g} \quad (10)$$

$$FVR = 1 - FRR \quad (11)$$

$$ER_h = \frac{FAR+FRR}{2} \quad (12)$$

Where indicates the count of false acceptances , represents the overall number of impostor attempts, denotes the number of false rejections and represents the total number of legitimate attempts.

3. RESULTS AND DISCUSSION

Each algorithm's performance is evaluated using three distinct kinds of performance measures besides fitness and accuracy. These are the Receiver Operating Characteristic (ROC) Curve, the Cumulative Match Score Curve (CMC), and the Expected Performance Curve (EPC).

The curve of CMC shows that the performance of the identification for the proposed system through showing the probability that the right identification can appear within matches of the top k ranked. As observed, the rate of the identification can rapidly reach near 100% at very low ranks (Rank-1 to Rank-5) and will remain stable for the higher ranks. This refers to that the system can be highly effective in ranking the right identification at the top positions, which is crucial for practical face identification applications. This performance represents the strong discriminative capability of the extracted facial features and the effectiveness of the applied optimization and matching strategy. The CMC curve is presented in Figure 3.

The curve of ROC demonstrates the trade-off between the True Positive Rate (TPR) and the False Acceptance Rate (FAR). The curve ascends sharply toward the top-left corner, achieving a high TPR with low FAR values, demonstrating outstanding verification performance. This behavior indicates that the system is capable of accurately identifying legitimate users while swiftly dismissing impersonators. When compared to the diagonal (random decision) line, the significant difference confirms that the proposed face recognition model offers reliable and robust authentication capabilities. The ROC curve is presented in Figure 4.

The curve of EPC evaluates the expected error rate of the system at different values of the weighting coefficient (α), balancing the mistakes of false acceptance and false rejection. The graph shows a clear minimum error region at moderate α values, indicating an optimal operating point where the system achieves the lowest expected error. This result indicates that the system is stable and allows for flexible modifications according to application requirements (security-focused versus usability-focused scenarios).The EPC curve is presented in Figure 5.

This enhancement shows how incorporating an optimization-based feature selection technique might be beneficial. By comparing gallery images with probing images, the CMC curve calculates the recognition system's accuracy in the closed set. The suggested PCA+OOA technique outperformed PCA alone in terms of ranking performance.

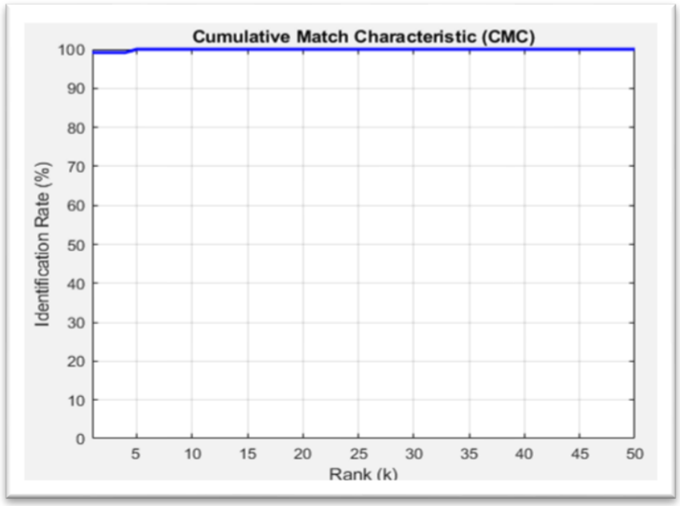

Figure 3. The CMC's curves for FR using (a) PCA and (b) OOA+PCA

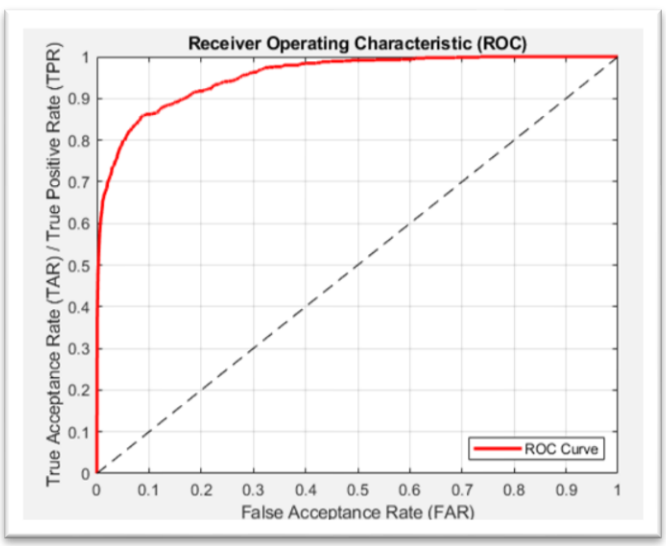

Figure 4. The ROC's curves for FR using (a) PCA and (b) OOA+PCA

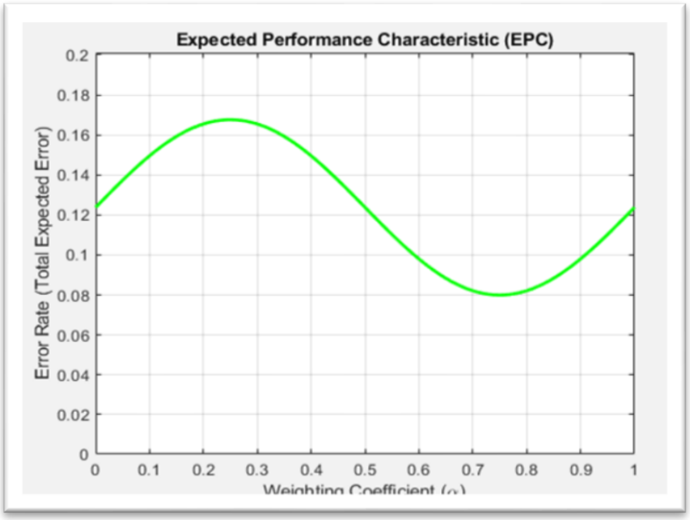

Figure 5. The EPC's curves for FR using (a) PCA and (b) OOA+PCA

The system was tested by running the program using MATLAB 2019, and the images were selected from databases. The used algorithms proved successful in detecting and recognizing faces, with detection accuracy ranging between 98% to 100%. This high accuracy can be observed in the first and second sets in Figures 6 and 7 respectively.

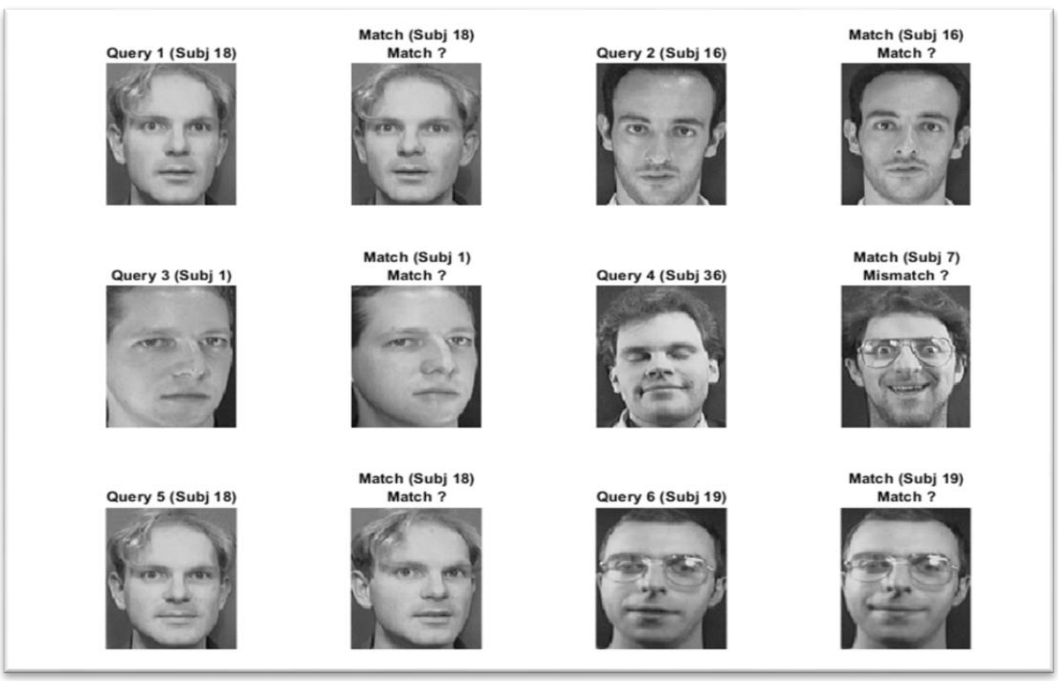

Figure 6. Applying Face recognition for first set of images.

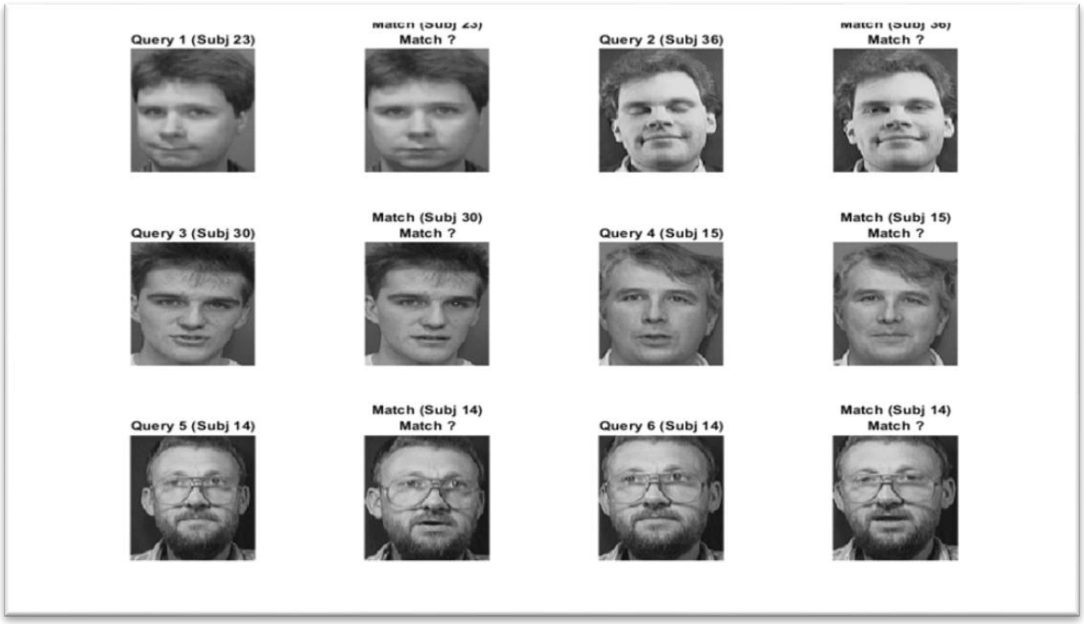

Figure 7. Applying Face recognition for second set of images.

To prove the success of the system, its recognition accuracy was compared with that of previous studies, and it was note that the accuracy of this proposed system exceeds that of many previous studies, as shown in the table below.

Table 4: Comparison with previous studies

Ref.	Authors	algorithms	Accuracy(%)
[4]	T.-X. Jiang et al.	Patch-Based PCA	~93
[5]	J. A. J. Alsyayadeh, et al.	PCA + DCT + CS	~96.5
[6]	A. M. Alkababjiet al.	PCA	~96
[7]	S. Ahmed et al.	Gabor Wavelet + PSO + CNN/DNN	~96.2
[8]	J. Armoire	PCA + SOM	~94.7
[9]	N. Sabah Abbod et al.	GWO + PCA	~94.0
[11]	W. Hussein Al-Arashi et al.	PCA + GA (Optimized Eigen faces)	~97.5
Our	Ruaa Majeed Azeez	OOA+PSO+PCA	~98-100

4. CONCLUSION

The present study proposed a hybrid approach for feature extraction, utilizing PCA for dimensionality reduction and OOA with PSO for optimizing, with the classifier being Euclidean Distance. The proposed approach was able to achieve a recognition rate of approximately 98% -100%, which is higher than the existing approaches utilizing only PCA, which can be 90% or little higher. These results show that feature selection system based on optimization can significantly improve a traditional PCA process, providing increased recognition accuracy while preserving lower computational complexity and eliminating the necessity for deep learning. The results achieved validate that the integration of PCA with OOA and PSO enhances both the resilience and the overall recognition quality, especially in regulated settings. However, the study does have certain limitations in the research work presented above. The study only considered the ORL database, which is representative of relatively less complex conditions, and the system has not yet been tested in real-time environments or in challenging conditions such as occlusion, pose, and lighting changes. Future research work would focus on certain other databases such as Yale, FERET, LFW, and so on, as appropriate, based on the requirements of implementation of the proposed work in real-time environments. Certain other research work would aim at increasing the robustness of the system in unrestricted environments, taking into account certain changes in the conditions such as occlusion, pose, and lighting.

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BIOGRAPHIES

Ruaa Majeedd Azeez, born in Baghdad in 1989, received a B.Sc. in Computer Engineering Techniques from Middle Technical University (2011) and a Master's degree in Computer Engineering Techniques from Middle Technical University, Baghdad (2020).