# Evaluation Study for the Performance of PSO and AOPSO Algorithms in Optimizing the SVM Classifier

Asaad Noori Hashim [1], Safaa Jasim Mosa [2], Abbas F. H. Alharan [2], and Ahmed J. Obaid [1,*]

[1] Faculty of Computer Science and Mathematics, University of Kufa, Kufa, Iraq
[2] Faculty of Education for Girls, Department of Computer Science, University of Kufa, Kufa, Iraq
Email: asaad.alshareefi@uokufa.edu.iq (A.N.H.); safaaj.aljuburi@uokufa.edu.iq (S.J.M.); abbasf.abood@uokufa.edu.iq (A.F.H.A.); ahmedj.aljanaby@uokufa.edu.iq (A.J.O.)
*Corresponding author

*Abstract*—**Face recognition plays a crucial role in our daily lives by identifying and authenticating individuals. One of the most widely used methods in this domain is the Support Vector Machine (SVM), a supervised machine learning classifier. However, optimizing SVM parameters is a key challenge. This study proposes a comparative evaluation of two optimization algorithms—Particle Swarm Optimization (PSO) and Adaptive-Opposition PSO (AOPSO)—for enhancing SVM performance in face recognition tasks. The proposed methods, PSO-SVM and AOPSO-SVM, were implemented and tested on two benchmark face datasets: CASIA V5 and FEI. Using 10-fold cross-validation, the models were evaluated based on classification accuracy, computational time, and optimization performance. The experimental results show that AOPSO-SVM consistently outperforms the standard PSO-SVM model. Specifically, AOPSO-SVM achieved an accuracy of up to 91.4% on the CASIA V5 dataset and 80.1% on the FEI dataset, while also reducing computational time and improving convergence behavior. These results demonstrate the effectiveness of AOPSO in optimizing SVM parameters for robust and efficient face recognition.**

*Keywords*—**optimization, support vector machine, particle swarm optimization, face recognition**

## I. Introduction

Face recognition is a way to identify or verify the identity of an individual using their face. It is used in several areas such as at homes for protection by identifying people at the front door and in ATMs by integrating it with a smart card for inspecting and verifying people from security tapes recorded on video [1–3]. Face Recognition is classified into two methods according to the scenario of face recognition: face verification and face identification. Support Vector Machines (SVMs) are often reported as a new classifier for pattern recognition tasks, and many papers have used SVM to classify images of human faces [4–8]. However, defining the best training parameters in SVM is a significant challenge. Recently, the Particle Swarm Optimization (PSO) method was introduced by Kennedy and Eberhart in 1995 [9], has been employed in combination with Support Vector Machines (SVM) to find the optimal parameters for the SVM. Wei *et al.* [10] recently proposed a new method for combining particle swarm optimization with support vector machines. They utilized Particle Swarm Optimization to enhance Support Vector Machine training parameters. The trials used the FERET face database and demonstrated promising recognition accuracy. The authors of [11] gave another method of face recognition called OPSO-SVM, which used OPSO for optimizing the SVM. They also employed random number generation and opposing numbers. The experiment comprises two categories of facial databases: FERET and YALE. This method outperformed PSO-SVM in terms of accuracy. Author [12] tried to enhance the performance of OP-SVM as follows. Author [13] introduced a novel method in AAPSO-SVM. The YALE and CASIA datasets are used in their tests.

One of the central challenges in face recognition using Support Vector Machines (SVM) is the selection of optimal hyperparameters, which directly affect the classifier's accuracy and generalization ability. Traditional optimization techniques like Particle Swarm Optimization (PSO) often suffer from premature convergence and lack the diversity required to escape local minima. These limitations lead to suboptimal parameter tuning, particularly in high-dimensional spaces like facial recognition. Moreover, balancing classification accuracy with computational efficiency remains a persistent issue, especially when deploying such models in real-time or resource-constrained environments. This study addresses these challenges by evaluating an improved optimization strategy—Adaptive-Opposition PSO (AOPSO)—which aims to enhance convergence, maintain diversity, and improve SVM performance across multiple evaluation metrics.

Optimizing the parameters of Support Vector Machines (SVMs) is a critical yet challenging task in improving the

Manuscript received March 14, 2025; revised April 17, 2025; accepted June 16, 2025; published October 17, 2025.

doi: 10.18178/joig.13.5.521-527 

accuracy and efficiency of face recognition systems. Traditional optimization algorithms like Particle Swarm Optimization (PSO) often face issues such as premature convergence and limited exploration of the search space. Although advanced methods like Opposition-based PSO (OPSO) and Adaptive Acceleration PSO (AAPSO) have been introduced to address these limitations, further enhancement is required for more consistent and accurate performance. To address this gap, a newly improved AOPSO-SVM algorithm has been developed by combining the strengths of OPSO and AAPSO to better determine optimal SVM parameters. The primary objectives of this study are:

1 To present an improved AOPSO-SVM algorithm that integrates features of OPSO and AAPSO for superior parameter optimization in SVMs.
2 To compare the performance of the proposed AOPSO-SVM model with the traditional PSO-SVM approach in terms of accuracy, computational time, and optimization quality.
3 To evaluate both models on standard benchmark datasets (CASIA V5 and FEI) using a structured experimental design and statistical validation.

The rest of this paper is organized as follows: Section I, Introduction, breaks down the research methodologies; Section III explains the proposed evaluation technique; Section IV focuses on the implementation of the proposed methods; Section V explains the results, discussion, and conclusion. The definitions of the symbols used in this study are summarized in Table A1: Nomenclatures.

### A. Objectives and Motivations

The support Vector Machines (SVM) are widely employed in face recognition tasks, optimizing their training parameters remains a significant challenge, impacting classification accuracy and computational efficiency. Traditional optimization methods like PSO have shown promise but suffer from issues such as premature convergence and limited diversity in the search space. Recent approaches like OPSO, AAPSO, and AOPSO attempt to overcome these challenges by incorporating advanced strategies such as opposition-based learning and adaptive mechanisms. The main objectives of this study are:

1 To enhance the accuracy and efficiency of face recognition by optimizing SVM parameters using advanced PSO variants.
2 To compare the performance of standard PSO and Adaptive-Opposition PSO (AOPSO) in optimizing SVM classifiers across benchmark datasets.
3 To address the research gap by evaluating AOPSO-SVM's effectiveness over PSO-SVM in terms of classification accuracy, computational time, and optimization quality.

### B. Research Questions

This study is showed by the following research questions:

1 How does the performance of AOPSO-SVM compare to that of the standard PSO-SVM in terms of face recognition accuracy across different datasets?
2 Does AOPSO offer advantages in computational efficiency and optimization capability over the standard PSO when used to train SVM classifiers?
3 Can AOPSO-SVM be considered a more robust alternative for face recognition tasks in practical biometric applications?

## II. Related Work

Author [11] study investigates the combination of the Rain Optimization Algorithm (ROA) with Support Vector Machines (SVM) to boost the accuracy of face recognition. The proposed ROA-SVM approach demonstrates improved classification performance over conventional PSO-SVM techniques. Author [14] evaluates various metaheuristic algorithms for optimizing the architecture of Convolutional Neural Networks (CNNs) in face recognition tasks, incorporating Support Vector Machines (SVM) for multi-class classification. Author [15] proposes an enhanced facial recognition method by employing Dragonfly and Grasshopper Optimization algorithms, showing improved classification accuracy when integrated with Support Vector Machines (SVM) [16]. Author [17] proposes an innovative few-shot transfer learning framework for sentiment analysis using facial expressions. The method utilizes deep learning models pre-trained on extensive datasets and refines them through few-shot learning strategies to enhance the accuracy of sentiment classification. Table I shows the Comparative Analysis with Recent Works (2023–2024) which can be found in the following research works of [18–21].

Author [22] presents an innovative real-time Facial Expression Recognition (FER) framework based on Convolutional Neural Networks (CNNs), specifically designed for online learning environments. The framework integrates dynamic region attention and self-attention mechanisms, enabling the model to prioritize facial areas that hold varying significance based on emotional context. Leveraging transfer learning, the proposed system improves its effectiveness in recognizing facial expressions across a wide range of scenarios. Author [23] shows the impact of deep learning on image processing and computer vision, with a focus on dog breed classification. Earlier approaches depended on manually engineered features and traditional machine learning algorithms, which often performed poorly due to the high visual similarity among different breeds. The emergence of Convolutional Neural Networks (CNNs) has enhanced recognition accuracy by enabling automatic feature extraction from images. The research particularly underscores the advantages of MobileNetV2, a lightweight CNN model that delivers efficient breed identification while maintaining low computational demands. Additionally, the authors examine multiple deep learning models and highlight the significance of deploying these systems on cloud platforms to support real-time use cases.

TABLE I. PRESENTS A COMPARISON OF THE PROPOSED AOPSO-SVM MODEL WITH RECENT WORKS

| **Study** | **Optimization Method** | **Classifier** | **Dataset(s)** | **Key Contributions** |
|---|---|---|---|---|
| Zhang *et al.* [18] | Improved PSO | SVM | ORL, YALE, MU_PIE Face dataset | Introduced an improved PSO algorithm into a face recognition system based on image feature compensation techniques, enhancing recognition efficiency and accuracy. |
| Zhang, Hongliang *et al.* [19] | Biogeographic Optimization | - | IEEE CEC2020 | Proposed a threshold segmentation technique based on particle swarm optimization to improve image segmentation efficiency. |
| Kumar *et al.* [20] | Hybrid PSO-BFO | SVM | YALE Face database | Presented a novel approach for facial feature selection using a hybrid PSO and Bacterial Foraging Optimization algorithm, enhancing identification accuracy. |
| Shelar, A., & Kulkarni, R. [21] | Hybrid Cuckoo Search + Self-Adaptive PSO | Deep Neural Network | - | Developed an optimal deep neural network model for image recognition using hybrid cuckoo search with self-adaptive PSO, achieving high accuracy. |
| Proposed Study | AOPSO | SVM | CASIA V5, FEI | Adaptive-opposition strategy improves convergence, accuracy, and time efficiency. |

## III. RESEARCH METHODS

All the research methodologies utilized in the study have been explained in the following sections. SVM and PSO played an important role in several applications such as security, biometrics, big data, etc. [24].

### *A. Support Vector Machine*

The support vector machine is a type of method in machine learning. This strategy is commonly used in classification problems. For the classification problem, it tries to find the best hyperplane that can separate two distinct classes with the maximum proper margin. The support vectors determine the hyperplane [12, 25]. The process of the SVM classifier is shown in the Fig. 1 below:

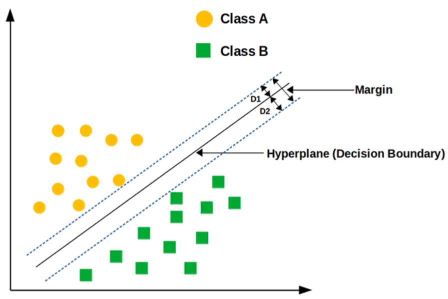



Fig. 1. The SVM classification procedure.

For the simplification and the nonlinear decision surface, the optimization task is represented as in Eq. (1):

$$\min_{Z,\zeta} \frac{1}{2}\|Z\|^2 + O\sum_{i=1}^{n} \zeta_i\, y_i(z.x_i + \text{bias}) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1,2,\ldots \tag{1}$$

where, $O$ is a regularization constant that signifies the “penalty parameter”. Besides, the classification decision function is represented as mentioned in Eq. (2):

$$f(x) = \sin\left(\sum_{i=1}^{n} f_i\, y_i \mathrm{ke}(x_i, x_j) + \text{bias}\right) \tag{2}$$

In the preceding equation, $f_i$ is a “lagrange multiplier” and $\mathrm{ke}(x_i, x_j) = \phi x_i, \phi x_j$ “kernel function” is the term. In order to construct the Support Vector Machine (SVM), we made use of the “Radial Basis Function” (RBF), which has been utilized extensively in previous studies. The formula for RBF kernel function is exp $(-\|x_i - x_j\|/2\sigma^2)$, $\sigma$ is a real number (positive).

### *B. Particle Swarm Optimization*

This method is an artificial intelligence-based optimization algorithm known as the Particle Swarm Optimization (PSO), first developed by Eberhart and Kennedy in 1995. It mimics how birds and fish aggregate. The PSO method develops particles randomly to explore the optimal solution in the “solution space” [9]. Updating particle velocity and location in the algorithm according to Eqs. (3) and (4):

$$\text{Velocity}_i^{t+1} = E \times V_i^{t} + w_1 \times ra_1 \times (\text{pee}_{\text{ibest}} - N_i^{t}) + w_2 \times ra_2 \times (\text{ge}_{\text{best}} - N_i^{t}) \tag{3}$$

$$N_i^{t+1} = N_i^{t} + \text{Velocity}_i^{t+1} \tag{4}$$

The size of the swarm is denoted by K, and i= 1,2,…,K. The velocity of the current particle is $\text{Velocity}_i$, and the new particle speed is $\text{Velocity}_i^{t+1}$. $E$ represents the “inertia weight” and $w_1$ and $w_2$ are velocity coefficients. The $ra_1$ and $ra_2$ are two random numbers with the range [0, 1], and $N_i^{t+1}$ is the particle’s location in the swarm. $\text{pee}_{\text{i\_best}}$ signifies the best-acquired solution of the certain particle while $\text{ge}_{\text{best}}$ denotes the finest “particle’s solution” in the entire swarm.

### *C. Hyperparameter Fine-Tuning*

In this paper, we used Particle Swarm Optimization (PSO) and Adaptive-Opposition Particle Swarm Optimization (AOPSO) algorithms to fine-tune the hyperparameters of the Support Vector Machine (SVM) classifier. There are two primary hyperparameters were tuned:

$C$ (Penalty parameter): Controls the trade-off between maximizing the margin and minimizing the classification error.

$\gamma$ (Gamma): A parameter for the RBF kernel function that defines the influence of a single training example.

The goal of fine-tuning was to identify the optimal $(C, \gamma)$ pair that yields the highest classification accuracy on the validation data. The following steps were carried out for the fine-tuning process where, $C$ have the value [0.1, 1000] and $\gamma$ is [0.0001, 10].

### *D. Evaluation Procedure*

Fig. 2 describes the evaluation procedure for conducting an evaluation study for the suggested methods:

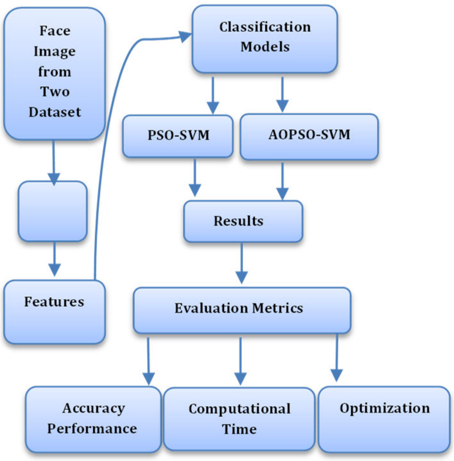



Fig. 2. Evaluation procedure.

The steps describing the proposed study are summarized in Fig. 2.

- Retrieving the facial image from the database.
- After getting the extracted facial features, we apply the PCA algorithm to them. Principal Component Analysis (PCA) was used as the primary embedding technique to reduce the dimensionality of facial feature data prior to classification. PCA transforms the original high-dimensional facial images into a lower-dimensional feature space while preserving the most significant variance in the data. This process helps improve the performance and efficiency of the SVM classifier by reducing computational complexity and minimizing noise.
- Training and testing scheme for each classification methods (PSO-SVMA and AOPSO-SVM).

After applying all proposed classification methods, we will compare all proposed classification methods in terms of contribution, accuracy, computational time and optimization function.

### *E. Implementation of the Suggested Methods*

The suggested facial authentication techniques in this study have been executed on the MATLAB platform, CASIA V5 [26], and FEI [27]. Face datasets have been used in the experiments. These include variations in illumination and pose, limited samples per subject, and lack of demographic and environmental diversity. These factors contribute to the complexity of face recognition and further justify the need for robust optimization techniques like AOPSO-SVM. The performance of the investigated methods in this study has been examined by utilizing n-fold cross-validation for every dataset since n = 10. The common measures are statistically determined for the evaluation. Ten folds of training and testing samples were created using the folding operation from the datasets to cross-validate them. Ten images for fifty persons were chosen from each database for the experiment. There were five hundred images for every dataset and the images were equally divided—50% for training and 50% for testing. The features were extracted using the PCA algorithm and the recognition process was performed using both PSO-SVM and AOPSO-SVM models.

#### *1) CASIA V5 face database*

The CASIA Face Database V 5.0 includes 2500 color facial images from 500 subjects. The facial images of CASIA-FaceV5 were captured using the Logitech USB (Universal Serial Bus) camera in one session. The image resolution for the images was 640×480. The images were saved in a BMP (Bitmap) format and were in 16-bit color. The images were captured in different variations such as illumination, pose, expression, etc. Fig. 3 is a sample face image from the CASIA database.

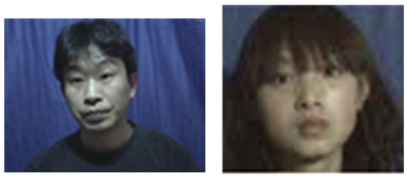


Fig. 3. CASIA face samples.

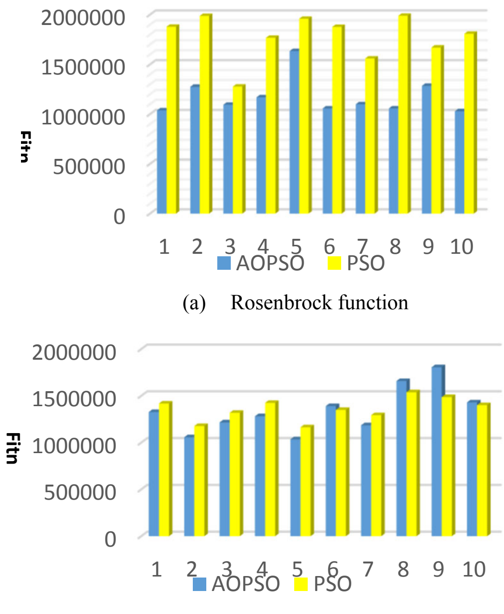
#### *2) FEI database*

The FEI face database is a Brazilian face database containing a set of face images pictured between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. There are 14 images each for 200 individuals, i.e., 2800 images, as shown in the following figure (Fig. 4).

Fig. 4. FEI face samples.

## IV. Results and Discussions

The performance of the suggested approaches in this study is assessed through three evaluation steps: (i) assessing the optimization process by two standard functions, (ii) evaluating them using accuracy performance, and (iii) evaluating them using computational time. These steps are illustrated in the following sections.




(a) Rosenbrock function

(b) Rastrigin

Fig. 5. Performance of the standard PSO and AOPSO methods based on the Rastrigin and Rosenbrock optimization functions.

### A. Evaluating the Optimization of the PSO and AOPSO Algorithms Using Two Standard Functions

The algorithmic performance of the suggested methods—PSO and AOPSO—is evaluated using the standard functions from Rosenbrock and Rastrigin. These standard functions are computed using the following Eqs. (5) and (6):

$$f_1(x) = \sum_{i=1}^{n}\left(100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right) \tag{5}$$

$$f_2(x) = \sum_{i=1}^{n}\left(x_i^2 - 10\cos(2\pi x_i) + 10\right) \tag{6}$$

Fig. 5 illustrates the performance of the AOPSO and the standard PSO methods on these functions in terms of their fitness values for different iterations.

### B. Evaluating the Classification Performance of the PSO-SVM and AOPSO-SVM Using Accuracy Performance

To analyze the classification performance of the standard PSO and AOPSO algorithms when combined with SVM as classification models, we conducted ten experiments on the CASIA and FEI face datasets. Table II illustrates the results of classification accuracy for PSO-SVM and AOPSO-SVM obtained from the two datasets. The "Experiments" column in Table II represents ten independent runs of 10-fold cross-validation conducted for both CASIA V5 and FEI datasets. Each experiment refers to one full round of training and testing the PSO-SVM and AOPSO-SVM models using a different fold partition. This repetition helps assess the consistency and stability of the models' performance across multiple runs.

The proposed AOPSO-SVM method attained higher accuracy in ten experiments, unlike the standard PSO-SVM.

TABLE II. THE ACCURACY VALUES OF THE PSO-SVM AND APSO-SVM FROM THE CASIAV5 AND FEI FACE DATASETS

| **Experiments** | **Accuracy (%) PSO-SVM** | **Accuracy (%) AOPSO-SVM** | **Accuracy (%) PSO-SVM** | **Accuracy (%) AOPSO-SVM** |
|---|---|---|---|---|
| | CASIA V5 dataset | FEI dataset | CASIA V5 dataset | FEI dataset |
| **1** | 87 | 91 | 72 | 79 |
| **2** | 83 | 89 | 76 | 80 |
| **3** | 90 | 90 | 70 | 76 |
| **4** | 82 | 92 | 72 | 75 |
| **5** | 92 | 90 | 66 | 70 |
| **6** | 83 | 92 | 74 | 78 |
| **7** | 80 | 87 | 75 | 75 |
| **8** | 85 | 92 | 73 | 75 |
| **9** | 88 | 91 | 71 | 77 |
| **10** | 84 | 90 | 69 | 70 |

### C. Evaluating the Standard PSO and AOPSO Based on the Computational Time

The third level of evaluation is based on the computational time for the PSO algorithm and AOPSO algorithm to determine the optimal parameters of SVM. Fig. 6 shows the computational time for the conventional PSO and AOPSO methods to determine the optimal parameters. AOPSO was shown to be faster than the conventional PSO in finding the optimal parameters for SVM. The figure shows that the AOPSO takes lesser computational time to perform the optimization process than the conventional PSO.

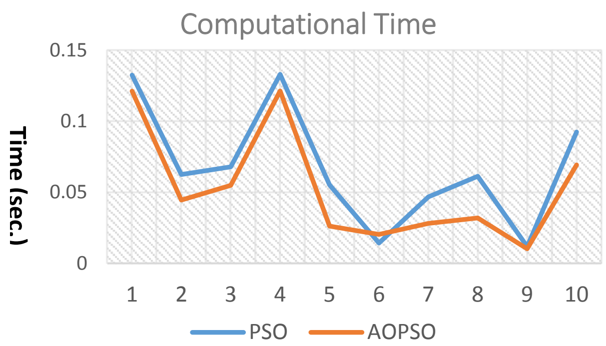



Fig. 6. The computational time of PSO and AOPSO methods.

## V. CONCLUSIONS

This paper presented a comparative evaluation of PSO-SVM and AOPSO-SVM approaches for face recognition, with feature extraction performed using Principal Component Analysis (PCA). The experiments were conducted on two benchmark face datasets: CASIA V5 and FEI. The performance of both models was assessed based on three criteria: classification accuracy, computational time, and optimization effectiveness. The experimental results demonstrate that the AOPSO-SVM model consistently outperforms the traditional PSO-SVM. Specifically, AOPSO-SVM achieved an average accuracy of 91.4% on the CASIA V5 dataset and 80.1% on the FEI dataset, compared to lower accuracy levels observed with PSO-SVM. In addition to higher accuracy, AOPSO-SVM also showed improved optimization performance based on fitness values and required less computational time to converge to optimal SVM parameters.

These findings confirm that integrating adaptive and opposition-based strategies into the optimization process significantly enhances the overall efficiency and robustness of SVM-based face recognition. Future work can extend this research by incorporating deep learning-based feature extraction, testing on larger and more diverse datasets, and optimizing the system for real-time applications. Future work may explore hybrid optimization strategies by combining AOPSO with other metaheuristics such as Genetic Algorithms or Cuckoo Search to boost convergence and accuracy. Additionally, replacing PCA with deep learning models like CNNs or autoencoders could enable more robust feature extraction. Evaluating the approach on larger, more diverse datasets such as LFW, CelebA, or MegaFace would better test its generalization capabilities. Lastly, adapting the model for real-time execution on embedded or mobile platforms would increase its practical applicability.

## APPENDIX

TABLE A1. NOMENCLATURES

| Classification | Parm Name | Description |
|---|---|---|
| parameters | O | Penalty parameter |
| | K | The size of the swarm |
| | $V_i^t$ | The velocity of the current particle |
| | E | Inertia weight |
| | $w_1$ and $w_2$ | Velocity coefficients |
| | $ra_1$ and $ra_2$ | Two random numbers with the range [0, 1] |
| | ${N_i}^{t+1}$ | Particle's location in the swarm |
| | $pee_{i\_best}$ | Best acquired solution of the certain particle |
| | $ge_{best}$ | Finest "particle's solution" in the whole swarm |
| Greek Symbols | $ke(x_i, x_j) = \phi x_i, \phi x_j$ | Kernel function |
| | $\sigma$ | Real number (positive). |
| Abbreviations | PSO | Particle Swarm Optimization |
| | AOPSO | Adaptive-Opposition Particle Swarm Optimization |
| | SVM | Support Vector Machine |
| | CASIA | Biometric data set (face, iris, etc.) |
| | ATM | Automated Teller Machine |
| | FERET | Face Recognition Technology (face data set) |
| | YALE | Face data set |
| | MATLAB | Matrix Laboratory |
| | RBF | Radial Basis Function |
| | PCA | Principal Component Analysis |

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Asaad Noori Hashim conceived the idea of this paper; Safaa Jasim Mosa conducted the research and wrote the paper; Ahmed J. Obaid developed the methodology; Abbas F. H. Alharan performed the formal analysis and examined the data; Asaad Noori Hashim, Ahmed J. Obaid developed the software; Safaa Jasim Mosa did the experimental studies; Ahmed J. Obaid Perform the statistical analysis and manuscript editing. All authors had approved the final version.

## REFERENCES


[1] A. K. Jain and A. Kumar, "Biometrics of next generation: An overview," *Second Generation Biometrics*, vol. 12, no. 1, pp. 2–3, 2010.

[2] B. Weyrauch, B. Heisele, J. Huang, and V. Blanz, "Component-based face recognition with 3D morphable models," in *Proc. 2004 Conference on Computer Vision and Pattern Recognition Workshop*, 2004, p. 85. https://ieeexplore.ieee.org/document/1384878

[3] W. Xia, S. Yin, and P. Ouyang, "A high precision feature based on LBP and gabor theory for face recognition," *Sensors*, vol. 13, no. 4, pp. 4499–4513, Apr. 2013.

[4] N. M. Khan, R. Ksantini, I. S. Ahmad, and B. Boufama, "A novel SVM+NDA model for classification with an application to face recognition," *Pattern Recognition*, vol. 45, no. 1, pp. 66–79, Jan. 2012.

[5] S. K. Kim, Y. J. Park, K. A. Toh, and S. Lee, "SVM-based feature extraction for face recognition," *Pattern Recognition*, vol. 43, no. 8, pp. 2871–2881, Aug. 2010.

[6] W. Li, L. Liu, and W. Gong, "Multi-objective uniform design as a SVM model selection tool for face recognition," *Expert Systems with Applications*, vol. 38, no. 6, pp. 6689–6695, Jun. 2011.

[7] Z. Li and X. Tang, "Using support vector machines to enhance the performance of bayesian face recognition," *IEEE Trans. Inform Forensic Secur.*, vol. 2, no. 2, pp. 174–180, Jun. 2007.

[8] T. S. Gunawan, M. H. H. Gani, F. D. A. Rahman, and M. Kartiwi, "Development of face recognition on raspberry Pi for security enhancement of smart home system," *IJEEI*, vol. 5, no. 4, pp. 317–325, Dec. 2017.

[9] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Proc. MHS'95 Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 1995, pp. 39–43. http://ieeexplore.ieee.org/document/494215/

[10] S. Verma, P. Rani, S. Gupta *et al.*, "An automated face mask detection system using transfer learning based neural network to preventing viral infection," *Expert Systems*, e13507, 2024.

[11] Z. M. Nabat, M. T. Mahdi, and S. A. H. Shnain, "Face recognition method based on support vector machine and Rain Optimization Algorithm (ROA)," *WEB*, vol. 19, no. 1, pp. 2170–2181, Jan. 2022.

[12] M. H. Abdulameer, D. Mohammed, S. A. Mohammed, M. Al-Azawi, Y. M. H. Al-Mayali, and I. A. Alameri, "Face recognition technique based on Adaptive-Opposition Particle Swarm Optimization (AOPSO) and Support Vector Machine (SVM)," *ARPN Journal of Engineering and Applied Sciences*, vol. 13, no. 6, pp. 2259–2266, 2018.

[13] M. H. Abdulameer, S. N. H. S. Abdullah, and Z. A. Othman, "Support vector machine based on adaptive acceleration particle

swarm optimization," *The Scientific World Journal*, vol. 2014, pp. 1–8, 2014.

[14] A. Rikhtegar, M. Pooyan, and M. T. Manzuri, "Comparing performance of metaheuristic algorithms for finding the optimum structure of CNN for face recognition," *IJNAA*, vol. 11, no. 1, Jan. 2020. https://doi.org/10.22075/ijnaa.2020.4296

[15] N. E. Chalabi, A. Attia, A. Bouziane, M. Hassaballah, and Z. Akhtar, "Recent trends in face recognition using metaheuristic optimization," in *Handbook of Nature-Inspired Optimization Algorithms: The State of the Art*, A. W. Mohamed, D. Oliva, and P. N. Suganthan, Eds. Cham, Switzerland: Springer International Publishing, 2022, pp. 85–112. https://link.springer.com/10.1007/978-3-031-07516-2_5

[16] P. Rani, S. Verma, S. P. Yadav, B. K. Rai, M. S. Naruka, and D. Kumar, "Simulation of the lightweight blockchain technique based on privacy and security for healthcare data for the cloud system," *International Journal of E-Health and Medical Communications (IJEHMC)*, vol. 13, no. 4, pp. 1–15, 2022.

[17] G. Meena, K. K. Mohbey, and K. Lokesh, "FSTL-SA: Few-shot transfer learning for sentiment analysis from facial expressions," *Multimed. Tools Appl.,* 2024. https://link.springer.com/10.1007/s11042-024-20518-y

[18] Y. Lijuan and Z. Yanhu, "A face recognition algorithm based on the combine of image feature compensation and improved PSO," *Sci. Rep.*, vol. 13, no. 1, 12372, Jul. 2023.

[19] H. Zhang, Z. Cai, L. Xiao *et al.*, "Face image segmentation using boosted grey wolf optimizer," *Biomimetics*, vol. 8, no. 6, p. 484, Oct. 2023.

[20] S. Kumar and S. K. Singh, "Feature selection and recognition of face by using hybrid chaotic PSO-BFO and appearance-based recognition algorithms," *International Journal of Natural Computing Research*, vol. 5, no. 3, pp. 26–53, Jul. 2015.

[21] A. Shelar and R. Kulkarni, "Analysis and design of optimal deep neural network model for image recognition using hybrid cuckoo search with self-adaptive particle swarm intelligence," *SIViP*, vol. 18, no. 10, pp. 6987–6995, Sep. 2024.

[22] R. Khalid, A. Ur Rahman, S. Ali, and B. Saqia, "Fine-tuned CNNs with self-attention mechanism for enhanced facial expression recognition," *International Journal of Data Informatics and Intelligent Computing*, vol. 4, no. 2, pp. 1–15, Apr. 2025.

[23] E. Madhan, A. Kaushik, and R. Raju, "An intelligent dog breed recognition system using deep learning," *International Journal of Data Informatics and Intelligent Computing*, vol. 1, no. 1, pp. 39–52, Sep. 2022.

[24] P. Rani, P. N. Singh, S. Verma, N. Ali, P. K. Shukla, and M. Alhassan, "An implementation of modified blowfish technique with honey bee behavior optimization for load balancing in cloud system environment," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–14, 2022.

[25] A. Shensa, J. E. Sidani, C. G. Escobar-Viera, G. E. Switzer, B. A. Primack, and S. Choukas-Bradley, "Emotional support from social media and face-to-face relationships: Associations with depression risk among young adults," *Journal of Affective Disorders*, vol. 260, pp. 38–44, 2020.

[26] CASIA face database. [Online]. Available: http://biometrics.idealtest.org/#/

[27] A. Georghiades, P. Belhumeur, and D. Kriegman, "Yale face database," *Center for Computational Vision and Control at Yale University*, vol. 2, no. 6, p. 33, 1997.