LAUTECH Journal of Engineering and Technology 19 (2) 2025: 30-40
10.36108/laujet/5202.91.0240

Development of an Enhanced Support Vector Machine Face Recognition System

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Article Info

Article history:

Received: Feb 16, 2025
Revised: April 07, 2025
Accepted: April 09, 2025

Keywords:

Face Recognition,
Support Vector Machine,
Principal Component Analysis,
Particle Swarm Optimization,
Biometric Authentication

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ABSTRACT

Face recognition biometric authentication focuses on uniquely recognizing human facial appearance based on inherent physical traits of the face for application in access control. The use of face for recognition has been proven to be highly reliable and effective. This research carried out a performance evaluation of SVM-based variants in the recognition of facial images. Six facial expression images, each from sixty individuals, were locally acquired using Canon EOS 2000D digital camera at 200×200-pixel resolution, 240 images were used for training while 120 images were used for testing. The acquired images were converted into grayscale and normalized using the histogram equalization method. Features classification was carried out using a Support Vector Machine for PCA-PSO and PCA respectively. The performance of the two techniques was evaluated and compared at a 0.42 threshold using Recognition Accuracy (RA), Precision (P), Sensitivity (S), and Recognition Time (RT). The validation of the techniques was done using t - a t-test at a significant 5% level. The RA, P, S, and RT were 97.50%, 97.80%, 98.89%, 1487.16 s, and 3.80s for PCA-PSO-SVM while the corresponding values for PCA-SVM were 95.83%, 96.70%, 97.78%, 1861.79 s and 22.96 s, respectively. The paired t-test was P = 0.001 with a mean difference of 2.5%. PCA-PSO-SVM technique performed better than PCA–SVM for all metrics. A face recognition system based on PCA-PSO-SVM is a more reliable security surveillance system than PCA-SVM.

INTRODUCTION

The unpredictable nature of crimes in Nigeria and across the world has called for the need for biometric security systems which have gained wide acceptance for providing safety and security against robbery, terrorist attacks, fraud, and kidnapping to mention a few (Chima and Joseph 2022, Toklo and Allor 2025). The demand for biometrics systems has risen due to their strength, efficiency, and availability. Facial feature recognition is one of the most efficient, highly authenticated, and effortlessly adaptable biometric technologies (Hernandez-Ortega *et al.,* 2020, Olayiwola *et al.,* 2024). In this highly digitally connected society, determining a person's identification is of utmost importance. Any identity management system's primary responsibility is to be able to confirm the identity of its users before allowing them access to its protected resources. The identification of a person wishing to access the services provided by an application like online banking or a facility like theme parks has traditionally been verified using passwords (knowledge-based schemes) and identity cards. These user authentication methods do have certain drawbacks; Passwords can be disclosed to unauthorized users resulting in a breach of security (Adedeji *et al.,* 2021; Okediran and Oguntoye, 2023). Moreover, simple passwords could be easily guessed by an intruder while complex passwords may be hard to recollect for a legitimate user. Identity cards, on the other hand, are susceptible to loss, forgery, and theft, which compromise the system's security. As a result, it is essential to use alternative authentication techniques that are based on a subject's identity rather than just what they know or possess (Ackerson *et al.,* 2021, Al Mahmud *et al*., 2025). However, an individual's biological traits cannot be misplaced, forgotten, copied, shared, stolen, or forged (Karampidis *et al*.,2022, Olaleye *et al*., 2025). Identification based on physiological attributes such as face is possible with the use of biometric-based technology (Hernandez-de-Menendez *et al.,* 2021; Abolade *et al.*, 2022).

Biometric authentication helps in enhancing the security infrastructure against threats (Kumar *et al*., 2024). After all, physical characteristics are not something that can be lost, forgotten, or passed from one person to another. Facial recognition examines the features of images of an individual's face that are captured by a digital video camera and measures the dimensions of the entire face structure, including those between the edges of the eyes, mouth, nose, and chin. These measurements are retained in a gallery and used as a comparison when a user stands before the camera. One of the few biometric techniques that has the benefits of high accuracy and little intrusion is face recognition (Adetunji *et al.,* 2015; Adetunji *et al.,* 2018). It has the truthfulness of a physiological approach without being intrusive (Teo *et al*., 2025). Face recognition can be used for verification (one-to-one matching) or Identification (one-to-many matching) (Papada and Vradis 2025). The performance of selected SVM-based variants (PCA-PSO-SVM and PCA-SVM) in the recognition of facial images was evaluated. Principal Component Analysis was used to perform dimensionality reduction by projecting into eigenfaces which served as input images for both PSO and SVM in each case. For PCA-PSO, the PSO which has obvious advantages of very high convergence speed was selected while the optimum facial feature and the similarity measurement of selected features were done using a Support Vector Machine. PCA-SVM in its case used Support Vector Machine (SVM) to perform the classification of the extracted features by the PCA.

METHODOLOGY

A performance evaluation of SVM-based variants in the recognition of facial images was carried out. The following stages were implemented image acquisition, image preprocessing, and image feature extraction using PCA. The classifier SVM was enhanced with PSO (an optimization algorithm for better performance) and then compared with PCA only without PSO (i.e. comparing PSO-SVM Face Recognition System and SVM Face Recognition System. Figure 1 shows the Scheme of methods under study.

Image Acquisition

Facial images were captured with the use of a Canon EOS 2000D digital camera with a default size of 1200 x 1200 in an uncontrolled environment. The acquired images were downsized into suitable pixels of 50 x 50, 100 x 100, 150 x 150, and 200 x 200. All face images were taken in a light color background. Two hundred and forty (240) facial expression images were trained, and one hundred and twenty (120) images were used to test the two techniques at different resolutions.

Image Pre-processing

The image pre-processing step comprised operations like image scaling, image brightness and contrast adjustment, filtering, cropping, and other image enhancement operations (Ogundepo *et al.*, 2022). In this phase, image pre-processing was performed by converting the colored images into grayscale and normalizing face vectors by calculating the average face vector and subtracting it from each face vector. This was performed to remove noise and other unwanted elements from the facial images. Each of the grayscale images was expressed and stored in the form of a matrix in MATLAB which was converted to vector images using Adobe Illustrator. The conversion to a face vector was made to aid the normalization process.

Feature Extraction

This requires extraction of features such as eyes, nose, and upper lip from the face image and converting the faces into a vector before Principal Component Analysis (PCA) was applied. The application of Principal Component Analysis produced a dimension reduction of all the trained images without a significant loss of information, which led to the development of eigenfaces.

The dimensionality of the original training set was reduced before eigenfaces were calculated. Eigenfaces were extracted from the image data using a mathematical tool called Principal Component Analysis (PCA).

The normalized training images were stored in a vector of size N. Then, the eigenspace was created using training images. Next, the training images were projected into the eigenspace. Images used for testing were recognized by projecting them into eigenspace and they were compared to the projected training images.

Facial Feature Selection and Classification

Effective feature selection aims to select a subset of the most discriminating features from the whole feature set for building robust learning models. In uncontrolled environments, the extracted features usually contain a large number of elements with noises caused by different facial variations and environmental conditions. Therefore, it is necessary to conduct feature selection to remove the redundant information and to improve the prediction performance, reduce the computational burden, and facilitate the analysis and understanding of the structure of the features. The classification was used to extract the models describing significant data.

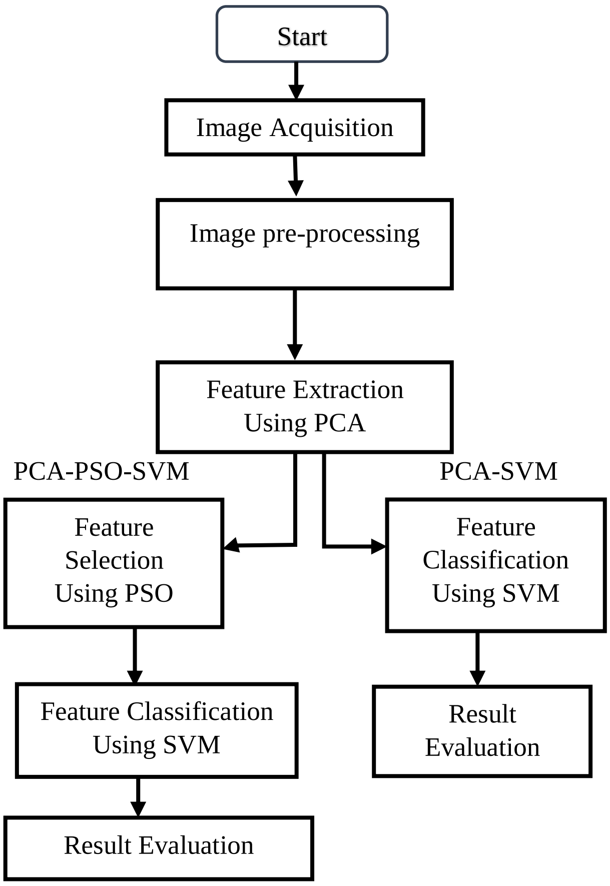

Figure 1. The Structure of the Methods

The PCA-PSO-SVM Technique

In the development of the PCA-PSO-SVM technique; PCA was used at first for feature extraction and dimension reduction of the face images while Particle Swarm Optimization (PSO) was used to further select the most useful features extracted by PCA (Ola *et al.*, 2019; Ola *et al.*, 2020). Support Vector Machine was used to perform the actual classification or feature matching which is the actual recognition process.

PSO for Feature Selection

During the training phase, the facial image features extracted by PCA were presented to the PSO model for training.

Support Vector Machine

Support Vector Machine was employed to classify the similarity between the test vector and the reference vectors in the gallery.

The PCA-SVM Technique

In the development of the PCA-SVM technique, PCA was used at first for feature extraction and dimension reduction of the face images while SVM was used to classify the facial features extracted by PCA.

Evaluation of Techniques

The performance evaluation of these techniques (i.e. PCA-PSO-SVM and PCA-SVM) on trained and recognized faces was evaluated based on recognition accuracy, specificity (i.e. True negative rate), false positive rate, sensitivity (i.e. True positive rate), and average recognition time. These were tested as follows TP, FP, FN, and TN.

RESULTS AND DISCUSSION

Table 1 shows the time spent increases as the dimension (size) of the images increases, which implies that the time used depends on the features in the training set for both the PCA-PSO-SVM technique and the PCA-SVM technique.

Table 1: The average training time at different resolutions for PCA-PSO-SVM and PCA–SVM techniques.

Dimension Size	Method	Time 1(s)	Time 2(s)	Average Time (s)
50 by 50	PCA-PSO-SVM	729.86	718.23	724.04
	PCA-SVM	753.00	750.04	751.52
100 by 100	PCA-PSO-SVM	884.39	885.45	884.92
	PCA-SVM	1035.72	1140.24	1087.98
150 by 150	PCA-PSO-SVM	1070.13	1040.24	1037.98
	PCA-SVM	1145.23	1151.28	1148.26
200 by 200	PCA-PSO-SVM	1484.27	1490.05	1487.16
	PCA-SVM	1860.71	1862.88	1861.79

The average training time generated by the application of the PCA-PSO-SVM technique for the subjects with 50 by 50-pixel resolution is 724.04s, 100 by 100-pixel resolution is 884.92s, 150 by 150-pixel resolution is 1037.84s, 200 by 200-pixel resolution is 1487.16s as presented in Table 1. Similarly, the average training time generated by the application of the PCA-SVM technique for the subjects with 50 by 50-pixel resolution is 751.52s, 100 by 100-pixel resolution is 1087.98s, 150 by 150-pixel resolution is 1148.26s, 200 by 200-pixel resolution is 1861.79s as also presented in Table 1. The result revealed that the PCA-PSO-SVM technique has a lower training time when compared with that of the PCA technique. The PCA-PSO-SVM technique and

PCA-SVM technique were experimented with by implementing the face recognition system using 50×50, 100 ×100, 150 × 150, and 200 ×200 pixel resolutions.

Table 2: Results for PCA-PSO-SVM

(a) 50×50 pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	87	3	3	27	96.67	96.67	95.00	3.34
0.62	85	5	4	26	94.44	95.51	92.50	2.80
0.82	85	5	4	26	94.44	95.51	92.50	3.27

(b) 100×100 pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	88	2	3	27	97.78	96.70	95.83	6.72
0.62	86	4	3	27	95.56	96.63	94.17	4.58
0.82	86	4	3	27	95.56	96.63	94.17	4.61

(c) 150 ×150 pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	88	2	2	28	97.78	97.78	96.67	3.02
0.62	88	2	2	28	97.78	97.78	96.67	2.57
0.82	88	2	2	28	97.78	97.78	96.67	2.49

(d) 200 × 200-pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	89	1	2	28	98.89	97.80	97.50	3.80
0.62	89	1	2	28	98.89	97.80	97.50	2.78
0.82	89	1	2	28	98.89	97.80	97.50	4.02

The techniques under consideration were tested and evaluated by using the following performance metrics: sensitivity, recognition accuracy, precision, and recognition time. Table 2 shows the experimental result for applying the PCA-PSO-SVM technique at different resolutions concerning different threshold values. It also presented performance evaluated based on sensitivity, precision, recognition accuracy, and average recognition time concerning PCA-PSO-SVM classification at different resolutions and threshold values. All performance metrics were analyzed using a square dimensional size of 50 x50, 100 x 100, 150 x 150, and 200 x 200 pixel resolution at different threshold values. Table 2 deduces that the percentage accuracy does not increase significantly with an increase in the threshold values. The results in Table 2 (a), Table 2 (b), Table 2 (c), and Table 2 (d) show that an increase in the dimensional size has a significant effect on the performance of the system. This implies that the increase in the features in the training set significantly increases the performance of the PCA-PSO-SVM technique. Similarly, considering all the dimensions as shown in Table 2 (a), Table 2 (b), Table 2 (c), and Table 2 (d); it was observed that the PCA-PSO-SVM technique performed best at a dimension size of 200 x 200 pixel resolution. Table 2 (d) for the dimension size 200 x 200 pixel resolution when compared to other dimensions performed best concerning all metrics at the threshold value of 0.42 and has a sensitivity of 98.89%, precision of 97.80%, and accuracy of 97.50% at 3.80 seconds.

Table 3. Experimental result for PCA-SVM

(a) 50 x 50-pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	85	5	5	25	94.44	94.44	91.67	21.46
0.62	84	6	6	26	93.33	93.33	90.00	14.00
0.82	84	6	6	26	93.33	93.33	90.00	14.37

(b) 100 x 100-pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	86	4	4	26	95.56	95.56	93.33	15.74
0.62	85	5	5	25	94.44	94.44	91.67	15.18
0.82	85	5	5	25	94.44	94.44	91.67	15.87

(c)150 x 150-pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	86	4	3	27	95.56	96.63	94.17	12.17
0.62	86	4	3	27	95.56	96.63	94.17	15.68
0.82	87	3	4	26	96.67	95.60	94.17	13.44

(d) 200 x 200-pixel resolution

Threshold	TP	FN	FP	TN	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
0.42	88	2	3	27	97.78	96.70	95.83	22.96
0.62	87	3	3	27	96.67	96.67	95.00	16.09

0.82	87	3	3	27	96.67	96.67	95.00	10.43

The table also shows that the computation time is within the range of 2.78 to 4.02 seconds with an increase in the threshold values. Table 3 presents the performance of PCA-SVM evaluated based on sensitivity, precision, recognition accuracy, and average recognition time at different resolutions and threshold values.

A similar analysis was carried out just as while using the PCA-PSO-SVM technique. Table 3 deduces that the percentage accuracy does not increase significantly with an increase in the threshold values like that of the PCA-PSO-SVM technique. The result shows that an increase in the dimensional size has a significant effect on the performance of the system based on the aforementioned performance metrics. This implies that an increase in the features in the training set significantly increases the performance of the PCA technique. From the results obtained from Table 3(a), Table 3(b), Table 3(c), and Table 3 (d) it was also discovered that the PCA-SVM technique also performed best at the threshold value of 0.42 across all dimension sizes. Table 3(d) for the dimension size 200 x 200-pixel resolution when compared to other resolutions has the best performance concerning all metrics at the threshold value of 0.42 having a sensitivity of 97.78%, precision of 96.70%, and accuracy of 95.83% at 22.96 seconds. The table also shows that the computation time ranges between 22.96 to 10.43 seconds with an increase in the threshold values.

Table 4. Table showing combined results with PCA-PSO-SVM and PCA-SVM at the threshold value of 0.42 for all metrics.

Pixel Resolutions	Algorithm	Sensitivity (%)	Precision (%)	Accuracy (%)	Recognition Time (sec)
50 X 50	PCA-PSO-SVM	96.67	96.67	95.00	3.34
	PCA-SVM	94.44	94.44	91.67	21.46
100 X 100	PCA-PSO-SVM	97.78	96.70	95.83	6.72
	PCA-SVM	95.56	95.56	93.33	15.74
150 X 150	PCA-PSO-SVM	97.78	97.78	96.67	3.02
	PCA-SVM	95.56	96.63	94.17	12.17
200 X 200	PCA-PSO-SVM	98.89	97.80	97.50	3.80
	PCA-SVM	97.78	96.70	95.83	22.96

$$T_R = 1E - 12dm^3 - 8E - 08dm^2 + 0.0013dm + 0.5497 \qquad R^2 = 0.9999 \qquad (1)$$

$$T_R = 2E - 13dm^3 + 2E - 08dm^2 + 0.001dm + 23.87 \qquad R^2 = 0.9999 \qquad (2)$$

To ascertain the technique with the best performance based on the performance metrics, the results obtained in Table 2 (a) - (d) were compared with those of Table 3(a) - (d). Table 4 shows the combined results of the PCA-PSO-SVM and PCA-SVM techniques at the threshold value of 0.42 for all metrics. Results obtained in Table 4 deduced that the PCA-PSO-SVM technique has a lower recognition time compared with the corresponding value with the PCA-SVM technique in each dimension size as well as in each threshold value concerning Table 2(a) - (d) and Table 3(a) - (d). The PCA-PSO-SVM technique has an average recognition time of 3.34s, 6.72s, 3.02s,, and 3.80s while the PCA-SVM technique has a corresponding average recognition time of 21.36s, 15.74s, 12.17s and 22.96s for the dimensional size of 50 by 50, 100 by 100, 150 by 150 and 200 by 200 at a threshold value of 0.42 respectively. Similarly, the Recognition accuracy, Precision, and Sensitivity of the PCA-PSO-SVM technique and the PCA-SVM technique are compared at 200 by 200-dimensional size; the study discovered that the PCA-PSO-SVM technique has better performance in Recognition accuracy, Precision, and Sensitivity than the PCA technique as enumerated in Table 4. The Recognition accuracy of 97.50% with the PCA-PSO-SVM technique and 95.83% with the PCA-SVM technique. The PCA-PSO-SVM technique has a Precision of 97.80% and Sensitivity of 98.89% while the PCA-SVM technique has a Recognition accuracy of 95.83% Precision of 96.70% and Sensitivity of 97.78% at 200 by 200-dimensional size.

Discussion of Results

The results shown in Table 1 show that the PCA-PSO-SVM technique trains the dataset much faster than the PCA-SVM technique. Therefore, the PCA-PSO-SVM technique is less computationally expensive compared to the PCA-SVM technique. The training time increases with an increase in the features of the training set.

The results obtained in Table 2 and Table 3, showed the performance of the techniques under consideration. The results showed that the performance of both techniques does not depend absolutely on threshold values. However, the optimum performance is obtained at a threshold value of 0.42. Moreover, the dimension of the images has a significant effect on the performance of both techniques. Generally, the percentage accuracy increases with the increase in dimension size and with optimum performance at 200 by 200-pixel resolution. Table 4 deduces that the PCA-PSO-SVM technique outperformed the PCA-SVM technique concerning all performance metrics though by a very small margin. The PCA-PSO-SVM technique achieved 97.50% while the PCA-SVM technique achieved 95.83% recognition accuracy. Similarly, the PCA-PSO-SVM model achieved a precision of 97.80% and sensitivity of 98.89% while the PCA-SVM model achieved a precision of 96.70%, the sensitivity of 97.78% at a threshold value of 0.42 and 200 by 200-pixel resolution. It can be inferred from the results based on the performance metrics that the PCA-PSO-SVM technique gave an increase of 1.67% recognition accuracy, 1.10% precision, and 1.11% sensitivity over the PCA-SVM technique. Therefore, the PCA-PSO-SVM technique outperformed the PCA-SVM technique concerning the performance metrics.

Statistical Analysis

Statistical analysis was carried out on the result obtained for the accuracy and computation time. A t-test value was measured between the recognition accuracy and recognition time of PCA-PSO-SVM and PCA-SVM. The paired t-test analysis conducted between recognition accuracies of PCA-PSO-SVM and PCA-SVM revealed that there is not much distinction in the test result; having a mean difference ($\mu = 2.50$). Nevertheless, the result confirmed that the PCA-PSO-SVM technique is statistically significant at $P < 0.01$; $P = 0.001$ with $\mu = 2.5,\ df = 11\ and\ t\ value = 24.47$. The t-test result further validates the fact that the PCA-PSO-SVM outperformed the PCA-SVM technique concerning recognition accuracy. Also, the paired t-test analysis conducted between the recognition time of PCA-PSO-SVM and PCA-SVM revealed that there was a difference in these test results; having a mean difference ($\mu = -11.95$). Nevertheless, the result confirmed that the PCA-PSO-SVM technique is statistically significant at $P < 0.01$; $P = 0.001$ with $\mu = -11.95,\ df = 11\ and\ t\ value = -11.403$. The statistical analysis revealed that PCA-PSO-SVM significantly outperformed PCA-SVM in both recognition accuracy and computation time, with t-test values confirming statistical significance at P<0.01, validating its effectiveness for facial recognition systems (Atanda *et al.*, 2023).

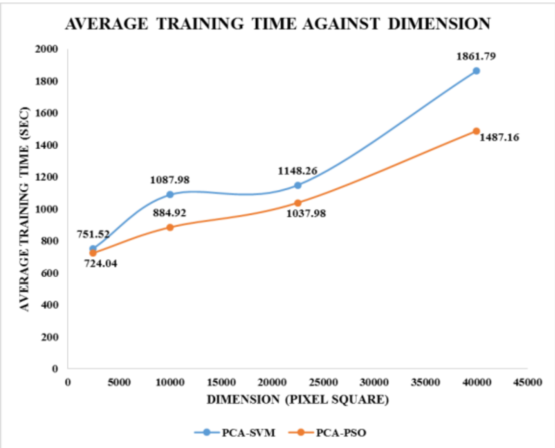

Figure 2. The Graph of Average Training Time against Dimension Size.

Figure 2 shows the graph of average training time against the dimension size. The relationship between the average training time (T_t) and the dimension size (dm) is found to be linear with a high correlation coefficient for both the PCA-PSO-SVM technique and PCA-SVM technique as shown in equations 3 and 4 respectively.

$$T_t = 0.0198dm + 661.76 \qquad R^2 = 0.98 \qquad (3)$$

$$T_t = 0.0275dm + 697.56 \qquad R^2 = 0.93 \qquad (4)$$

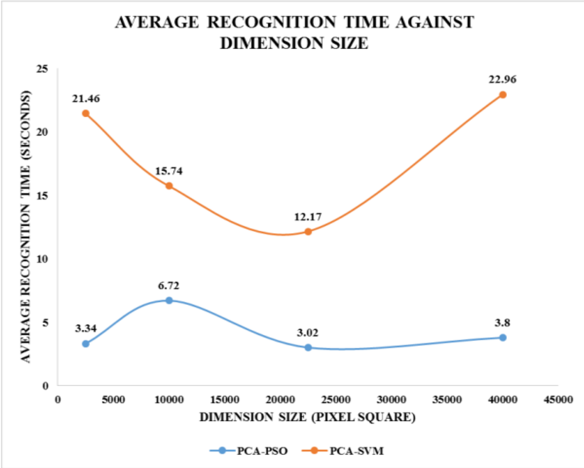

Figure 3. The Graph of Average Recognition Time against Dimension Size.

Also, Figure 3 shows the graph of average recognition time against the dimension size. The relationship between the average recognition time (T_R) and the dimension size (dm) is found to be polynomial of order 3 with a high correlation coefficient for both the PCA-PSO-SVM technique and PCA-SVM technique as shown in equations 1 and 2 respectively.

The t-test result further confirms the fact that PCA-PSO-SVM performs better than the PCA-SVM technique based on the recognition time. Hence, the PCA-PSO-SVM is less computationally expensive than the PCA-SVM technique. Given this, the PCA-PSO-SVM technique is more sensitive, precise, accurate, and less computationally expensive than the PCA-SVM technique. However, future works can be carried out by investigating the effect of the Support Vector Machine (SVM) involving feature extraction and optimization algorithms other than PCA and PSO respectively (Ola *et al.*, 2017; Oguntoye *et al.*, 2023). Also, modalities such as voice can be combined with face to perform speaker recognition.

Declaration of Competing Interest

No conflict of interest between the authors

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