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# A Hybrid System Using Vector Support Machine Techniques and Particle Swarm Optimization for Facial Expression Recognition

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## *Abstract*

Our main goal in this study was to create a support vector machine (SVM) model that used principal component analysis (PCA) to extract features and particle swarm optimization (PSO) to optimize them. We compared the average execution times of SVM with PSO and SVM across different resolutions to assess the performance of our suggested model. With error rates of 5.72 percent, 8.40 percent, 11.82 percent, and 14.62 percent for resolutions of 65 by 65, 110 by 110, 155 by 155, and 200 by 200, respectively, the results demonstrated that SVM with PSO consistently outperformed SVM. Additionally, we performed an analysis using pixel-level data and discovered that SVM with PSO outperformed SVM with a resolution of 200 by 200 at a threshold value of 0.85 in terms of performance. SVM alone only managed an accuracy of 89.23%, whereas the accuracy of SVM with PSO was measured at an impressive 92.31%. Based on our thorough research, we draw the conclusion that the SVM+PCA+PSO model produces incredibly promising outcomes. This study advances feature extraction and optimization machine learning techniques by demonstrating the potential of combining SVM, PCA, and PSO for enhanced performance across a range of applications.

**Keywords:** Support Vector Machine, Algorithm, PCA, Particle Swarm Optimization,MATLAB

## Introduction

People often use the facial expression system, a type of cognitive nonverbal behaviour, to communicate their inner feelings in a variety of situations (Hegde & Seetha, 2017). Thoughts and feelings are a potent and common form of multi-channel communication. People can express their emotions by changing their voice, facial expression, body language, and emotional and psychological state. For behavioural shifts and human gestures to be translated into useful commands for control functions, a reliable feeling or sensing approach is required. Due to the fact that not everyone expresses their emotions verbally or physically, emotional identification can be very difficult. The interdisciplinary approach to automatic human emotion recognition incorporates psychology, voice analysis, machine vision, and computer learning (Qayyum, Majid, Anwar, & Khan, 2017).

The analysis of facial expressions for emotion is a skill that allows one to communicate feelings clearly. It provides thorough information on a person's mental state by probing their inner feelings. Recent years have seen an increase in research on human facial expression recognition systems for autonomous and human-computer interaction, or HCI, with a variety of applications in automation (Refat, Sarker, Islam, Kaushal, Kaur, and Kaur, 2023). Facial expression, which is regarded as the second most effective form of communication between two people after speech signals, is heavily used in human-computer interaction, or HCI. External stimuli lead to changes in facial dimensions, and each of these changes reflects a different emotional state. It is still very difficult to create a facial recognition system that can identify emotions. Age, facial lighting, and various emotional expressions have an impact on facial images and recordings. Assembled by Qayyum *et al.* (2017)

There are many techniques for identifying facial expressions, and most of these systems have made significant advancements in the field. This study combined particle swarm optimization (PSO) with support vector machines (SVM) to enhance human face expression recognition. This study combined particle swarm optimization (PSO) with support vector machines (SVM) to enhance human face expression recognition. The natural phenomena of swarming birds, interpersonal interactions, and schools of fish served as inspiration for the particle swarm optimization (PSO) algorithm. PSO is a metaheuristic algorithm that was specifically used as an inspiration for the cooperative behaviour of biological groupings (Bouallegue, Haggege, & Tebbikh, 2011).

For addressing problems with optimization algorithms, particle swarm optimization is a crucial form of swarm intelligence (Fuzhang, 2016). This method's unfathomably high intelligence makes it ideal for use in engineering and scientific research. Because of this, the PSO algorithm has attracted much interest from academics researching evolutionary computation and has produced numerous scientific findings over time (Liu, 2016). Like PSO, which is easy to use and has demonstrated success in managing a variety of optimization issues due to its soundness, effectiveness, and dominance in the direction of sizable search areas for the best solutions. Using the particle swarm optimization algorithm, the study aims to determine the best parameter for support vector machine (SVM) classification to have a good sense of facial expressions.

In this study, the effectiveness of combining the support vector machine technique with particle swarm optimization is estimated. Rapid convergence is definitely a benefit of PSO. We used a face dataset with a wide range of facial expressions and gestures. The input image from the PSO model was projected into Eigenfaces using Principal Component Analysis (PCA) to reduce the dimensionality. The best face feature subset was chosen using the Support Vector Machine (SVM), which categorizes features. The goal of this study is to develop a method for identifying human facial emotions using support vector machines (SVM) and PSO.

## REVIEW OF RELATED WORKS

Poon, Ashraful, and Hong (2011) looked at PCA-based FER methods for distorted images. They use a variety of databases, including the CMU (Carnegie Mellon University) and ORL databases, both of which are in good lighting, to compute Eigenfaces. In this study, the results with the CMU database were 100% and the ORL database was 90% when comparing the recognition rates.

Samad and Hideyuki (2011) have demonstrated the use of Gabor features and edge-based feature extraction. Gabor was used to filter the image, and several edge detectors were combined. Because each edge detector had a problem with manual threshold value selection, they used a lot of edge detectors. After the features were dimension-reduced by PCA and classified by SVM, the Facial Expressions and Emotions Database from the Technical University of Munich, FEEDTUM, received the highest recognition based on a subject rate of 91.7%.

Rahulamathavan, Phan, Jonathan, and David (2013) created a FER with an encrypted domain using Local Fisher Discriminant Analysis, LFDA.

A novel face expression recognition method based on genetic algorithms and Gabor filters was presented by Boughida, Kouahla, and Lafifi in 2021. Gabor characteristics are drawn from the interesting regions of the human face, which can be distinguished by facial landmarks. Additionally, a genetic method was created to simultaneously select the best features and enhance SVM hyperparameters. The experimental results

showed that, with recognition rates of 96.30%, 94.20%, and 94.26%, respectively, the approach outperformed the datasets for the JAFFE, CK, and CK+ datasets.
A 16-layer efficient CNN method was presented for classifying human facial expressions with data augmentation, according to Refat *et al*.'s study from 2023. The FER2013 benchmark dataset, a well-known facial expression recognition test, was then used to test it. The suggested method also performs better than a number of earlier studies, with a testing accuracy of 89.89% as of right now.
The use of support vector machines (SVM) and particle swarm optimization (PSO) for face recognition tasks is not well covered in the literature, despite the extensive research on face recognition using machine learning models. The existing research primarily focuses on other machine learning algorithms, such as deep neural networks, without specifically examining the potential advantages and enhancements that can be realized by combining SVM and PSO. As a result, in order to fill this gap in the literature, research is required to examine the functionality and efficacy of SVM and PSO for face recognition, both separately and in combination.

## METHODOLOGY

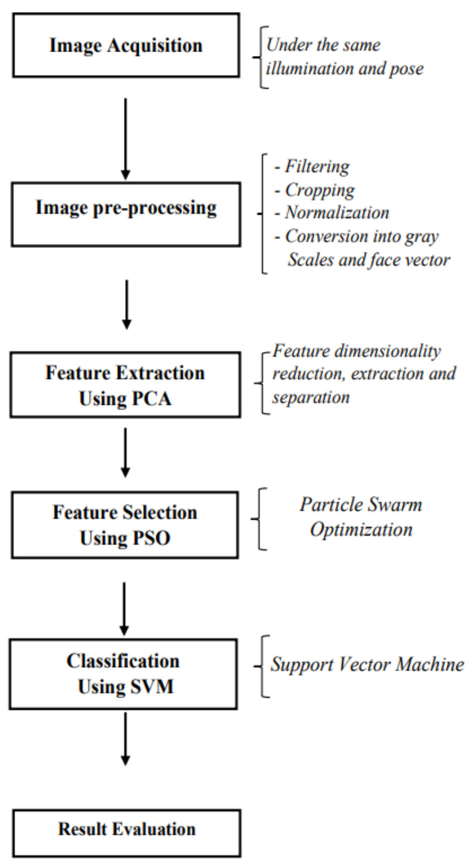



Figure 1: The Structure of the Facial Expression Recognition System

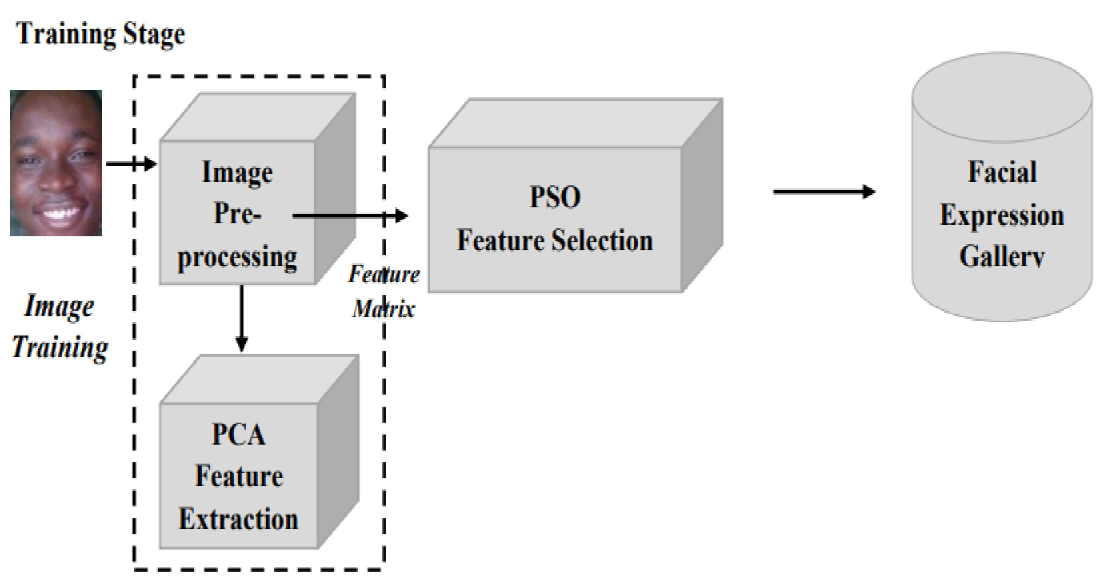
**Facial PSO Selection and Classification**

The face expression recognition system used in this study combined support vector machines and particle swarm optimization. In order to evaluate the intrinsic PSO property of quick convergence ability, SVM was used. The PSO algorithm was applied to the SVM parameter optimization to obtain a faster convergence time and higher precision, specificity, and accuracy. PSO chooses a parameter for SVM that minimizes the number of feature subsets in the total features that were extracted from the images, thereby reducing noise and redundant data. The block diagram illustrating the method's workflow is shown in Figure 2 below.

**Implementation for Training and Testing Facial Expression**

To evaluate how well the developed technique worked with the facial expression recognition system, this experiment was run twice. The training dataset underwent PSO-SVM preprocessing (grayscale conversion, face vector normalization) during the learning phase, and then PCA was used for dimension reduction and facial feature extraction. Out of the complete set of facial features generated by PCA, the best feature subset was chosen using PSO. The gallery then contained the trained dataset.

In the testing phase, pre-processing is performed on the input test images (test dataset), as shown in Figure 3, and then PCA is used to reduce dimension and extract facial features. The best feature was selected using PSO from the complete set of facial features extracted by PCA and sent to SVM for classification. The results of the classification were compared to training features that were stored in a library for recognition. Based on the recognition of the test images, the system's final output was displayed.



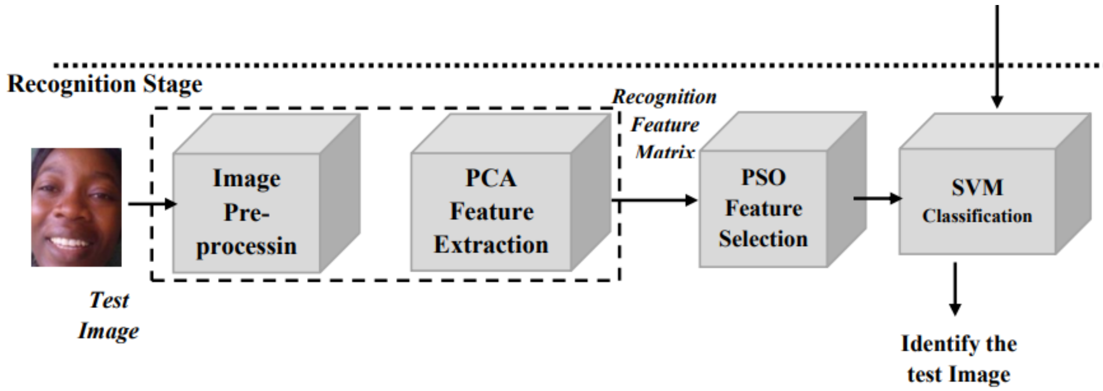



**Figure 2:** The block diagram illustrating the proposed methods' process flow

### Support Vector Machine (SVM)

Both classification and regression tasks can be accomplished using the support vector machine (SVM). In SVM, a hyperplane is used as a decision boundary to divide a collection of data points into various categories. These data points may or may not be linearly separable, but the SVM uses a mathematical operation known as a kernel to divide them into distinct classes. SVM's primary goal is to classify data points using examples from the training dataset (Iliyas *et al.*, 2021).

### Particle Swarm Optimization (PSO)

The nature-inspired algorithm and population-based optimization method known as particle swarm optimization (PSO) were inspired by the behaviour of schools of fish, animal populations, and flocks of birds (Eberhart and Kennedy, 1995). The population is known as a swarm in phenomena such as schools of fish, bird swarming, and interpersonal relationships, and hypothetical solutions that correspond to the individuals or swarm members are known as particles. Fish and birds usually travel in packs without bumping into each other. As a result, each particle modifies its associated position and velocity to reflect a potential fix while utilizing the collective knowledge to locate a place to live and eat. A particle's position is affected by both its nearest neighbours and its optimal solution (Ying-Yi, Angelo, & Arnold, 2016).

Particle swarm optimization has been used to solve a wide range of optimization problems, including issues with multiple objectives, many options, and dynamic context optimization (PSO). PSO has proven to be a computationally effective technique in terms of effective convergence, parameter selection, simplicity of implementation, adaptability, and robustness (Poli, Kennedy, & Blackwell, 2007). It also has the ability to combine various algorithms with many others (Ying-Yi *et al.*, 2016). Individuals are known as particles in PSO. A position-vector is used to express the position of each particle $\underline{x}_n$ and a velocity-vector, which represents a velocity $\underline{v}_n$. Each particle modifies its search path after each iteration depending on its previous velocity $\underline{v}_n(t)$ the top spot is typically referred to as *local or personal best ( $_b$)*. It has achieved the best location $G_b$ that the swarm of particles has yet to achieve (called *global best*). To put it another way, every particle adjusts its position and speed in accordance with equations (2.7) and (2.8), respectively (Attiya and Zhang, 2017):

$$\underline{v}_{mn}(t+1) = \omega \underline{v}_{mn}(t) + c_1 r_1 \left(P_b - \underline{x}_{mn}(t)\right) + c_2 r_2 \left(G_b - \underline{x}_{mn}(t)\right) \ldots\ldots\ldots(1)$$

$$\underline{x}_{mn}(t+1) = \underline{x}_{mn}(t) + \underline{v}_{mn}(t+1) \ldots\ldots\ldots(2)$$

Where $\underline{v}_{mn}(t+1)$, locations of the particle $m^{th}$ at iterations $n^{th}$ and n,$\underline{x}_{mn}(t+1)$, particle velocities at iterations n, are used, inertia weight should be used to reduce the influence of previous history of velocities. The iteration number is denoted by t, the cognition learning factor is $_1$ the social learning factor is $c_2$, and the random integers $r_1$ and $r_2$ are uniformly distributed between [0, 1]. Below is a presentation of the Particle Swarm Optimization algorithm's step-by-step process (Alam *et al.*, 2015):

1. Set parameter $\omega_{min}$, $\omega_{max}$, $c_1$ and $c_2$ of PSO
2. Initialize population of particles having positions $x_n$ and velocities $v_n$
3. Set iteration n = 1
4. Calculate fitness of particles $F_{mn}(t) = f(\underline{x}_{mn}(t))$ and find the index of the best particle $b$
5. Select $Pbest_{mn}(t) = \underline{x}_{mn}(t)$ and $Gbest_n(t) = x_{bn}(t)$
6. $\omega = \omega_{max} - n \times (\omega_{max} - \omega_{min})/Maxnum$
7. Update velocity and position of particles

$$\underline{v}_{mn}(t+1) = \omega \underline{v}_{mn}(t) + c_1 r_1 \left(P_b - \underline{x}_{mn}(t)\right) + c_2 r_2 \left(G_b - \underline{x}_{mn}(t)\right)$$

$\underline{x}_{mn}(t+1) = \underline{x}_{mn}(t) + \underline{v}_{mn}(t+1)$

8. Evaluate fitness $F_{mn}(t+1) = f(\underline{x}_{mn}(t+1))$ and find the index of the best particle $b_1$
9. Update $Pbest$ of population

If $F_m(t+1) < F_{mn}(t)$ then $Pbest_{mn}(t+1) = \underline{x}_{mn}(t+1)$ else $Pbest_m(t+1) = Pbest_{mn}(t)$

10. Update $Gbest$ of population

If $F_b(t+1) < F_{bn}(t)$ then $Gbest_n(t+1) = Pbest_{bn}(t+1)$ and set $b = b_1$ else $Gbest_b(t+1) = Gbest_n(t)$

11. If $n < Maxnum$ then $n = n + 1$ and goto step 6 else goto step 12
12. Output optimum solution as $Gbest(t)$.

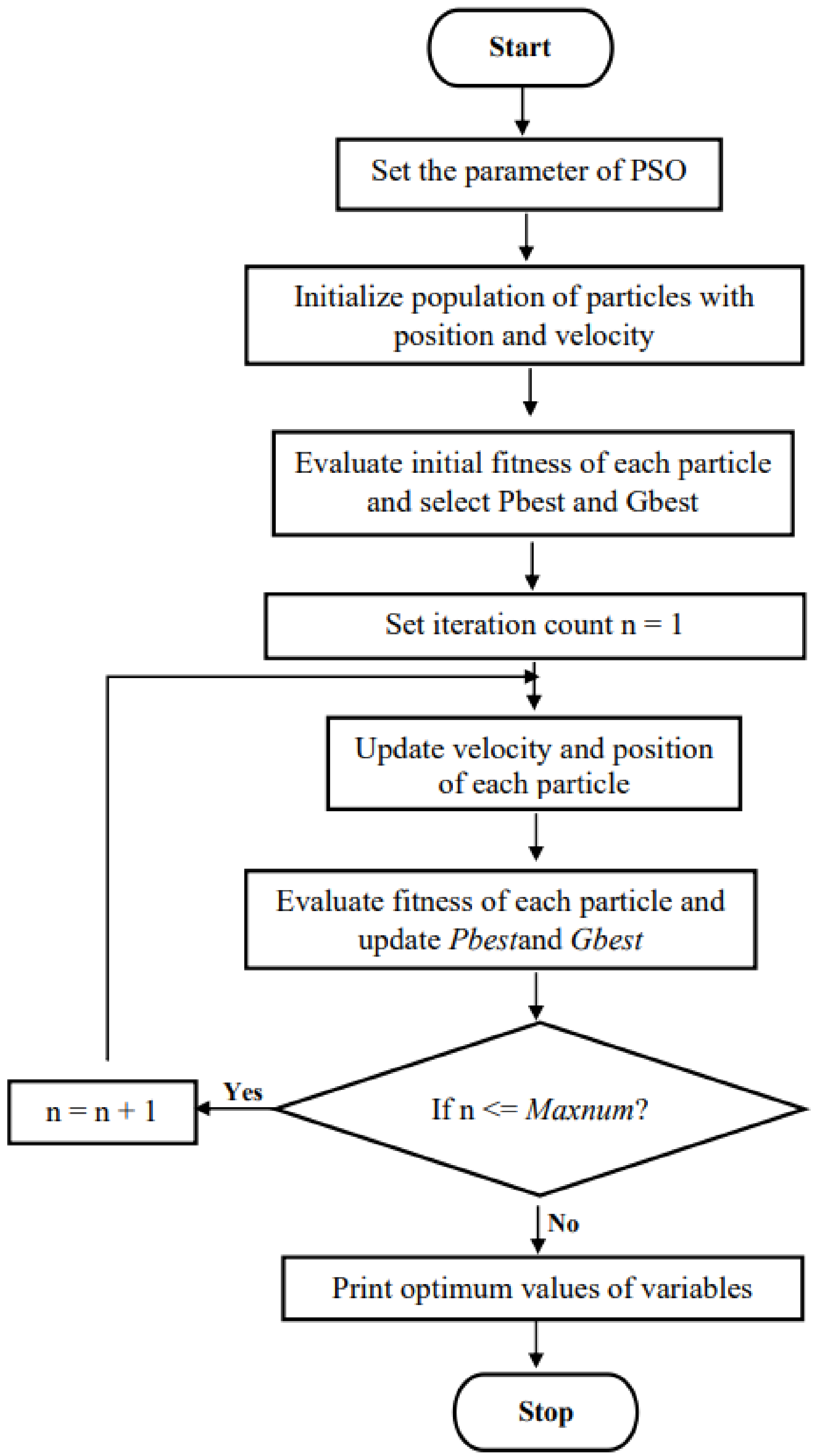



**Figure 3:** Particle Swarm Optimization Process *Source*: (Alam *et al.*, 2015)**.**

**The Particle Swarm Optimization for Feature Selection**

The PCA characteristics were supplied to the PSO model throughout the training and testing phases. Figure 3 depicts the procedure of the PSO model as described by Tang and Chen (2013) with little modifications. The following is a step-by-step explanation of the learning and testing procedure.

**Step 1:** Create initial swarms

Initialize parameters *c1, c2, rand1, rand2, max-iterations*, $_{max}$.

**Step 2: Generate *N* particles with random positions and velocities**

Before the PSO method application, every position $x_{p,i}(t)$ and velocity $v_{p,i}$ was created randomly in the range [0, 1], where $p = 1, 2, \ldots, P$ represents the $p$th swarm, $i = 1, 2, \ldots, I$ represents the $i$th particle, and $t$ denotes the $t$th generation.

**Step 3***:* Update every position

**Step 3.1***:* Evaluate the performance function of each *Particle*

To assess each particle's performance function, the fitness computation of each particle was performed. The definition of the fitness function is as follows:

$$F = \sqrt{\frac{1}{N}\sum_{d=1}^{N} \left(y_d - \underline{y}_d\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

Where $y_d$ represents the $d$th model output; $\underline{y}_d$ represents the $d$th desired output, and $N$ represents the number of input data.

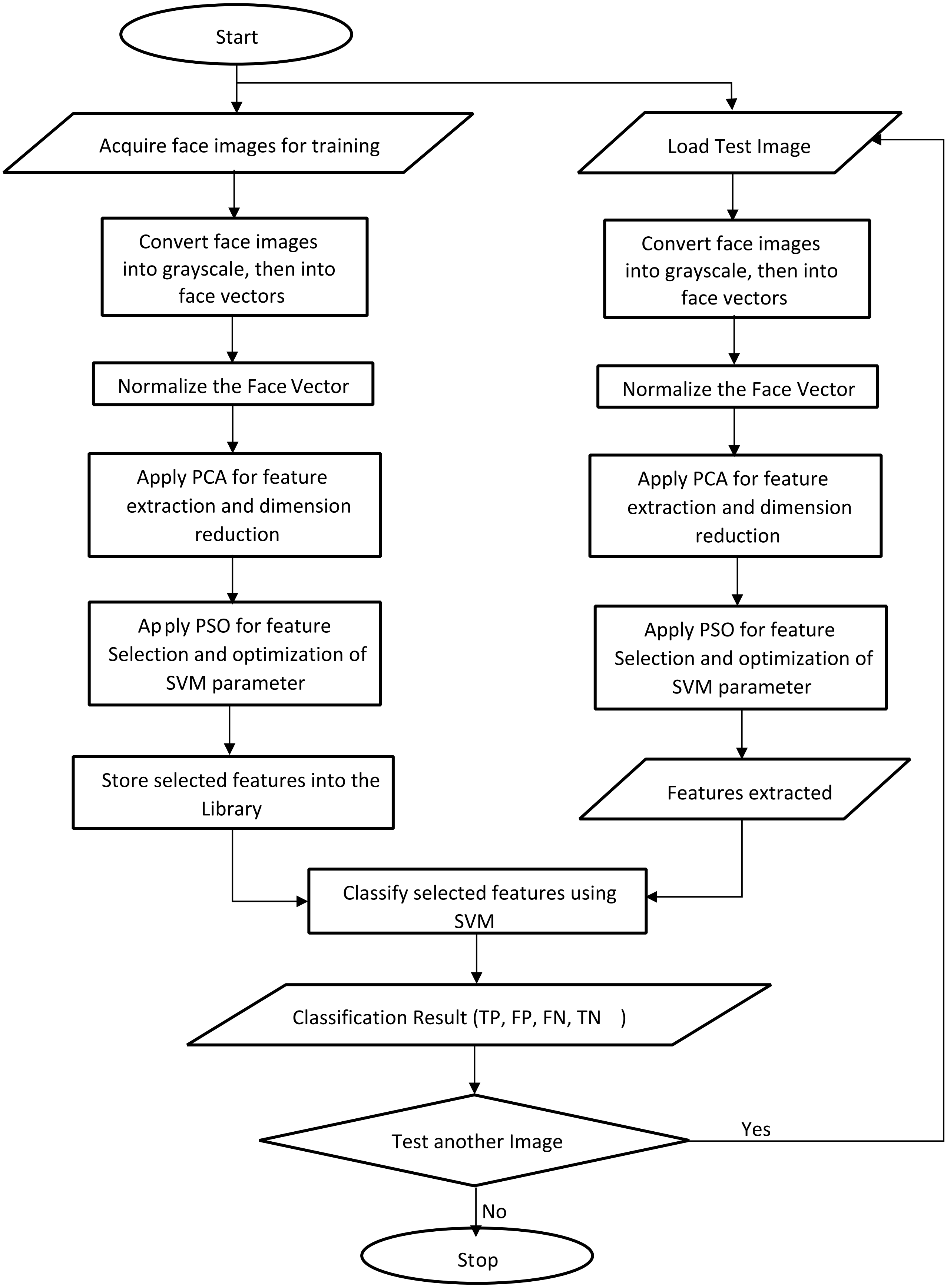



**Figure 4:** Flowchart showing trained and tested faces with CPSO-SVM.

**Evaluation Measures**

The performance of the support vector machine (SVM) systems on training and recognized faces was evaluated based on recognition accuracy, false positive rate, sensitivity, specificity, and average recognition time. Using a confusion matrix, the performance metrics' efficacy was assessed. It contains TP, FP, FN, and TN.

A specific number of entries make up the tuple's TP (true positive) column. This indicates that the tuple was correctly identified as positive. The FP (false positive) category contains the number of entries for predicted positive but actually negative tuples. The true number (TN) is the proportion of anticipated negative tuples that actually happen (true negative). FN represents the proportion of positive tuples that ought to be negative (false negative). Accuracy, precision, recall, and specificity calculations also used these terms as inputs.

$$Precision(Predicted\ Positive\ value) = \frac{TP}{TP+FP} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$Recall\ or\ Sensitivity(True\ Positive\ Rate) = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$Specificity(True\ Negative\ Rate) = \frac{TN}{TN+FP} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$$False\ Positive\ Rate = \frac{FP}{TN+FP} = 1 - Specificity \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$Overall\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$Average\ Recognition\ Time = \frac{Total\ recognition\ time}{Number\ of\ recognized} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

## RESULTS AND DISCUSSIONS

Table 1: Average training time at different resolutions for PSO-SVM and SVM

| Dimension | Techniques | 1st Trial | 2nd Trial | Average Time (s) |
|---|---|---|---|---|
| **65 by 65** | PSO-SVM | 5.71 9.47 | 5.73 | 5.72 |
| | SVM | | 9.72 | 9.59 |
| **110 by 110** | PSO-SVM | 8.42 | 8.37 | 8.40 |
| | SVM | 17.76 | 17.40 | 17.58 |
| **155 by 155** | PSO-SVM | 11.09 | 12.54 | 11.82 |
| | SVM | 22.75 | 21.66 | 22.20 |
| **200 by 200** | PSO-SVM | 14.88 | 14.36 | 14.62 |
| | SVM | 34.66 | 35.88 | 35.27 |

Table 4 shows that the threshold value of 0.85 produced the best performance across all dimension sizes. However, when compared to other dimensions, the model with a dimension size of 200 by 200 pixels outperformed them all at the threshold value of 0.85.

Table 2: PSO-SVM & SVM at 200 by 200-pixel resolution and 0.85 threshold value

| Algorithm | FPR (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Accuracy (%) | Recognition Time (sec) |
|---|---|---|---|---|---|---|
| **PSO-SVM** | 2.63 | 85.19 | 97.37 | 95.83 | 92.31 | 19.99 |
| **SVM** | 7.69 | 84.62 | 92.31 | 88.00 | 89.23 | 43.26 |

The PSO-SVM model have a precision of 95.83%, specificity of 97.37%, sensitivity of 85.19% and false positive rate of 2.63% while the SVM model have a precision of 88%, specificity of 92.31%, sensitivity of 84.62% and false positive rate of 7.69% at the threshold value of 0.85 for 200 by 200-dimensional size in binary classification scheme.

Table 3: Facial Expression Recognition Rate

| Expression | PSO + SVM (%) | SVM (%) |
|---|---|---|
| **Anger** | 90.77 | 89.23 |
| **Disgust** | 92.31 | 90.77 |
| **Fear** | 89.23 | 87.69 |
| **Happiness** | 92.31 | 89.23 |
| **Sadness** | 90.77 | 87.69 |
| **Surprise** | 92.31 | 89.23 |
| **Average** | 91.28 | 88.97 |

The outcome in Table 4.3 indicates that the PSO-SVM has a higher recognition rate than the equivalent SVM. A t-test value was calculated between the PSO-SVM and SVM recognition rates. With a mean difference of only $\mu = 2.31$, the PSO-SVM and SVM paired ttest analysis shows that there is little difference in the test results. However, the outcome demonstrated that the PSO-SVM method is statistically significant at $p < 0.01$; $p = 0.01$ with
$\mu = 2.31$, $df = 5$ $nd\ t\ value = 6.708$. The t-test result further validates the fact the PSOSVM outperformed the existing SVM model.

**CONCLUSION**

The goal of our study was to create an SVM model using PCA to extract features and PSO to optimize it. We calculated the SVM with PSO and the SVM average time based on various resolutions. SVM with PSO outperformed SVM with error rates of 5.72%, 8.40%, 11.82%, and 14.62%, respectively, for resolutions of 65 by 65, 110 by

110, 155 by 155, and 200 by 200. Additionally, SVM with PSO outperformed SVM with a resolution of 200 by 200 and a threshold value of 0.85 when comparing the results obtained from pixel analysis. When compared to SVM alone, it had an accuracy of 92.31% as opposed to 89.23%. We draw the conclusion that the SVM+PCA+PSO model produced a good result in this study based on our findings.

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