

## Emotional Facial Expressions using Cat Swarm Optimization

<sup>1</sup>Putta Sujitha, <sup>2</sup>P.Hima, <sup>3</sup>Dr.Jose Moses Gummadi

<sup>1,2</sup>Assistant professor, Department of CSE, VFSTR(Deemed to be university), Guntur, Andhra Pradesh.

<sup>3</sup>Professor, Department of CSE, Malla Reddy Engineering College(A), Hyderabad,Telangana.

### Abstract

Many research and professional applications rely on recognition of facial expression. Under this study, the group presented a novel technique for identifying emotional expressions. First, designers extracted transformation function from face expressions using the wavelet transforms. Second, to reduce the characteristics, feature extraction has been used. Third, the classifier was indeed a singular mathematical computation. Eventually, and perhaps most notably, designers used Cat Swarm Optimization (CSO) to practice the classifier's weight values. The cat swarm optimization technique obtained an average precision of 90%, 0.76 percent after ten-fold stratified classification technique. It outperformed the neural network, particle swarm, and genetic algorithms with moment acceleration coefficients. Furthermore, our facial expression processing device outperformed two state-of-the-art methods.

**Keywords:**Facial expression process; Wavelet transform; Analyze the principal components; Cat swarm optimization

### 1. Introduction

Facial emotion identification is the study of identifying person's face feelings [1], which academic achievement refers to the movements and gestures of facial expressions under the skins of the face. The expression on the subject's face communicates nonverbally. FER is actually being used in a wide range of applications, including Parkinson's and schizophrenia [2,3], among others.

For resolve FER, several specific methods have been suggested. For example, integrated highly correlated assessment and Support Vector Machine (SVM) [4]. Later used greater spectrum, radon transformation, and SVM using a triangle graph of directed gradients and a genetic

algorithm [5,6].

Eventually, a discriminate function approach was employed. Use of biorthogonal wavelet entropy [7]. Nonetheless, the above methods have the following flaws: (i) The code is incapable of detecting the feeling "disgust" efficiently. (ii) The computing time was excessively long. (iii) They have poor classification accuracy. This has been attributed to a inefficiency of an applications and classifier. Designers presented a novel framework wavelet - based, factor analysis, as well as a Singular Neural Network (SNN) in this study. In addition, designers trained the SNN using the CSO technique.

The dataset was obtained from comparison [7]. Designers have such a maximum of 700 objects here, with 100 images with each feeling.

- Class 1 is joyful; Class 2 is depressing; Class 3 is surprised; Class 4 is angry; Class 5 is disgusted; Class 6 is afraid; and Class 7 is neutral. Feelings of Men face and a women shown in Figures 1 and 2.



Figure1.7 Feelings of Men Face



Figure 2.7 Feelings of Women Face

## 2. Featureremovalanddecrease

Figure 3 depicts processing families: The first version is known as the Fourier Transform (FT), the second period was known as the Short-Time Fourier Transform (ST-FT), and the third method is known as the Wavelet Transform (WT). The differential type of WT is known as

Differential Wavelet Transform (DWT). In this case, A = Magnitude, F = Intensity, T = Period, and S = Level.

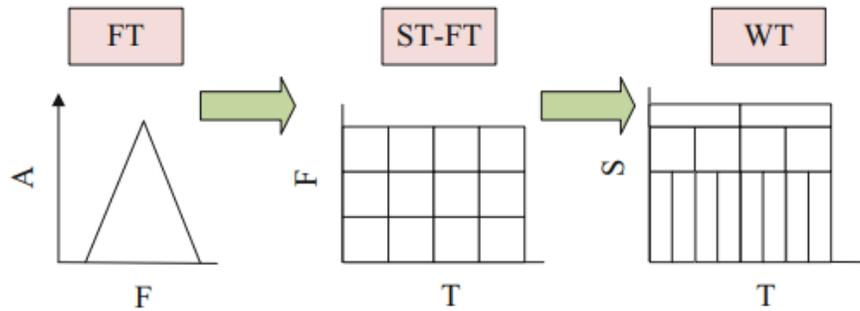


Figure3.The advancement in signal analysis

Assume  $x(n)$  is a period signal,  $g(n)$  and  $h(n)$  are indeed the impulse responses of a low and a high-pass filter, respectively, but an estimation coefficient  $a_1(n)$  and information coefficient  $d_1(n)$  of first stage as can be seen here.

$$X' = (a \times b) \downarrow 2 \dots\dots\dots 1$$

$$Y' = (a \times c) \downarrow 2 \dots\dots\dots 2$$

$$X'' = (a' \times b) \downarrow 2 \dots\dots\dots 3$$

$$Y'' = (a' \times c) \downarrow 2 \dots\dots\dots 4$$

Here 'X' represents the linear transformation and the descending trajectory represents under sampling The 2-level estimation coefficient  $a'$  nor information coefficient  $d'$  are therefore calculated.

This cascading procedure continues till the defined decomposed stage  $j$  was reached. Certain essential function methods usually include the shape allow transformation, the different levels, the combined filter, and so on. The standard factor analysis is used to the wavelets.

## 2.1 Classifier

Many classifiers have been suggested by researchers, including the decision tree, regression analysis, classification Algorithm, vector regression, and artificial neural network. They were all very successful in both research and industrial applications. Most famous seems to be the ANN, which can relate to every feature at a certain level thanks to the high predictive principle.

One form of ANN seems to be the Singular Neural Network (SNN). It converts an input feature function into levels of discrimination by constructing a completely linked feedback control computational model with only one hidden units. Figure 4 Illustrates the SNN structure and the arrangements. Assume  $c$  is the set of training and  $E$  is indeed the element of the input data, and we now have:

$$E(N) = [ E1(N), E2(N).....Ep(E)]^T \dots\dots\dots 5$$

$$Z(L) \xi [1,2,3.....p] \dots\dots\dots 6$$

Here,  $E(N$  and  $Z(L)$  ,  $n=1,2,3,.....p$  shoes upto  $P^{th}$  training dataset.

SNN training dataset will be arrived from hidden neuron i.e  $Y_i(L)$ ;

$$Y_i(L) = Q_1(E(N) * w1+b1), R = 1.2.3....Z \dots\dots\dots 7$$

Here,  $w1$  and  $w2$  and  $b1$  and  $b2$  are weight and bias factor. Whereas  $Q1$  is the functional factor and  $M$  is the variable.

$$Z_k(N) = F_2[Z(N) * w2+b2) \dots\dots\dots 8$$

Final equation arrived was;

$$E(N) = \operatorname{argmax}([Y1(N), Y2(N).....Yp(N)]^T) \dots\dots\dots 9$$

Finally mean square value was obtained from the formula 10;

$$\min \sum_{n=1}^N [Y(N) - Y(N) \dots\dots\dots (10)$$

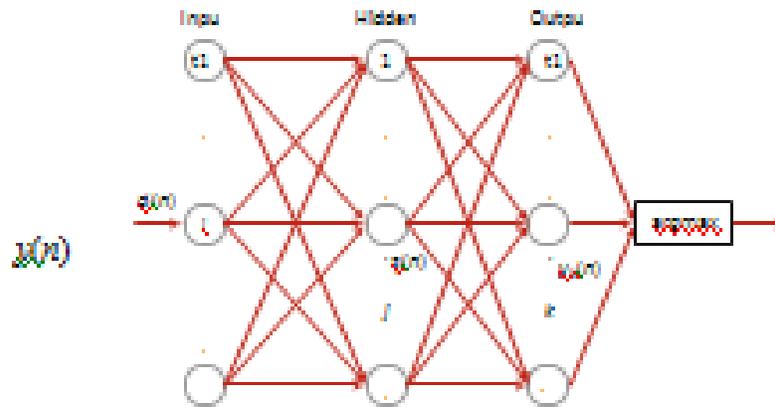


Figure 4 illustrates the SNN structure

## 2.2 CatSwarmOptimization

Conventional ways utilized feature extraction as well as its derivatives to practice the set of weights of SNN. Orthodox strategies, but at the other hand, could be trapped in a regional optimum value. As a result, bio-inspired approaches have been proposed. Particle Swarm Optimization (PSO) [8], for instance, is commonly then used practice SNN. Furthermore, Jotheeswaran and Koteeswaran[9] trained SNN using a Genetic Algorithm (GA). Showed that time-varying displacement coefficient PSO (TPSO) outperforms PSO [10].

Throughout this analysis, we used the CSO approach to increase efficiency even more. Chu et al. [11] suggested the CSO by imitating cat behaviors. Cats, according to them, have 2 types: searching phase and tracking phase, as illustrated in Figure 5. The two phases are discussed herein:

Seeking Phase: While cats remain active, they sleep the majority of the day. The movements were sluggish.

Tracing Phase: The cats chase the goals. In conclusion, Table 1 depicts the PSO procedural code.

## 3. ModelValidation

For evaluate the approach with others, we use ten-fold stratified classification technique. The

TFSCV configuration, which includes 8 flips for instruction, 1 bend for testing, and 1 fold for testing shown in Figure 6. The stratification ensures that every fold will have the same range.

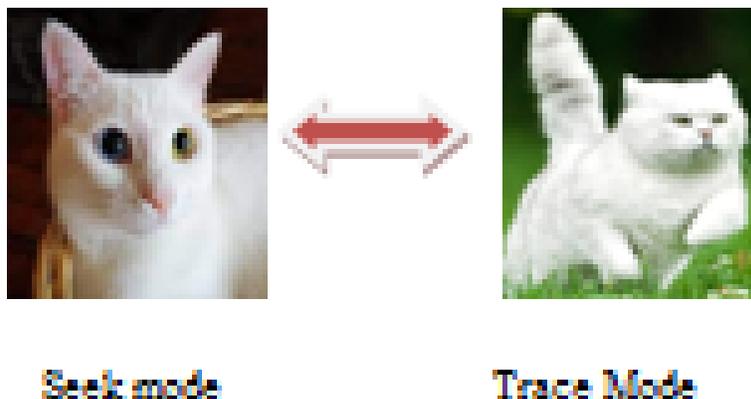


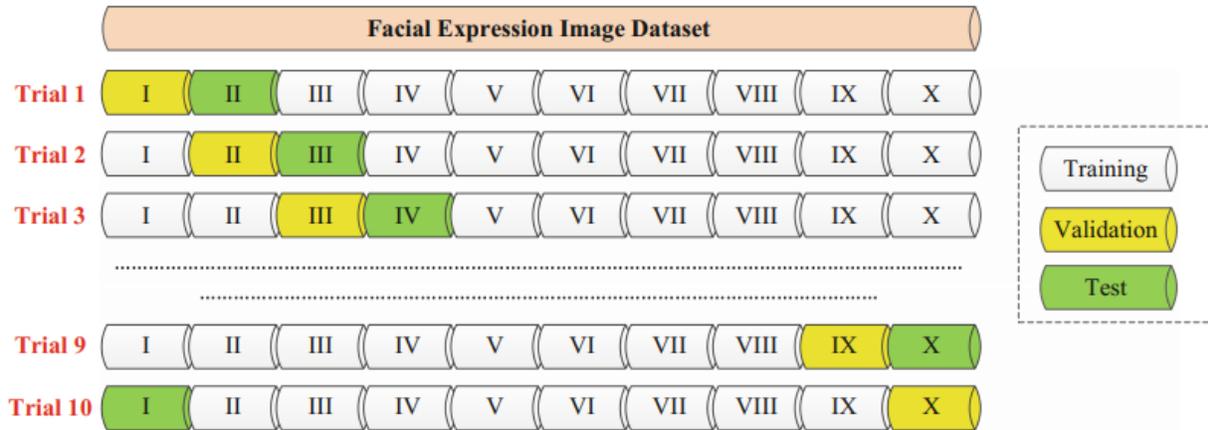
Figure5.Modes ofCSOalgorithm

The confusion matrices of ten trials are added together. TFSCV's output can thus be calculated in this manner. That a no expense function F seems to be as follows:

Table1.CSO Feature vectors

Step	Execution
1	Start the cat swarm.
2	Spray the cats into optimal solution at once and give the numerical number.
3	The tracking function cats were chosen at random, while another was switched to pursuing setting. This is known as the combination ratio
4	Measure each cat's fitness worth and remember best cat.
5	The cats should be moved in accordance with their signs. When a cat has been in searching phase, use the search system; else, use the tracking system. The two methods are described in detail with in references.

6	Split the swarm through searching and tracking modes once more.
7	Examine the closure state. If satisfied, exit the programme and output the better cat's status; else, repeat Steps 4–6.



**Fig. 6.** Setting of TFSCV

$$\mathcal{F} = \begin{bmatrix} 100 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 100 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 100 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 100 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 100 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 100 \end{bmatrix} \quad (11)$$

This indicates that all 7 groups have been properly identified. In practise, the classifier will still make errors; thus, assume that the TFSCV was operated for a total of ten times. The ten-fold classification is shaped carelessly for each path. As a result, we record Sk and O's mean and standard deviation.

#### 4. Observations and Discussions

Designers created the software entirely in-house. This software being operated on a Toshiba windows desktop with an i7-3461 3.50 GHz and 4 GB RAM. Our development programme was Matlab 2015a. Testing methods are used to determine the optimized values of the program.

Figure 6 displays the sensitivities from each group multiplied by ten times the TFSCV. The first group correlates to Rage, the second class to Anger, the third class to Anxiety, the fourth class to Happiness, the fifth class to Neutral, the sixth class to Disappointment, and the seventh class to Confusion. Figure 7 displays our classifier's overall accuracy.

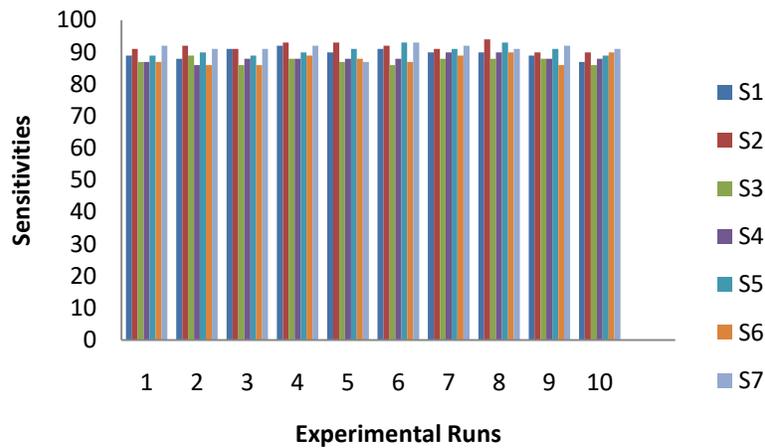


Figure 6. Sensitivities ( $S_k$ ) of each class by CSO (Unit: %)

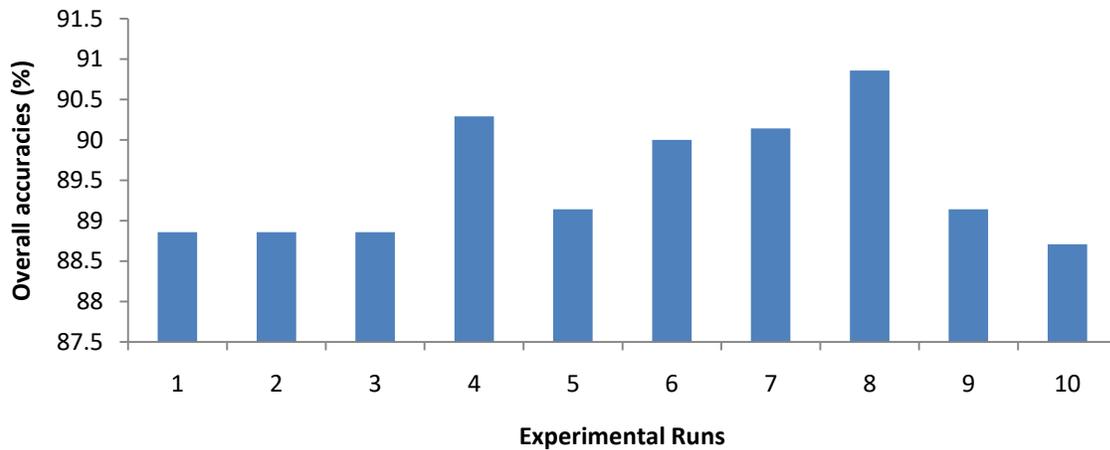


Figure 7. Overall accuracies ( $O$ ) by CSO (Unit: %)

### 4.1 Comparative study of Learning Algorithms

In the second study, designers contrasted CSO to a standard PSO, GA and a time-varying displacement coefficient TPSO. The input data are the report's decreased functionality. Most of the other options seem to be the same. Figure 8 displays the performance comparison.

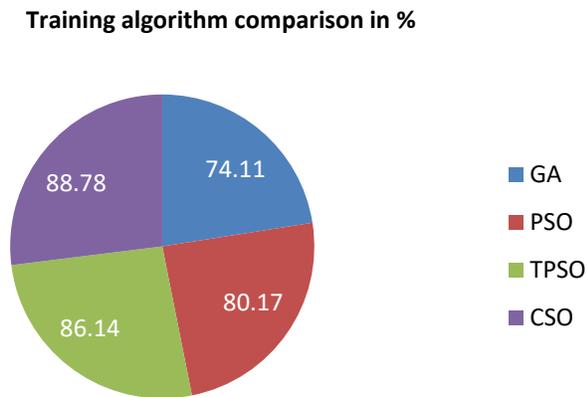


Figure 8 compares learning algorithms (Unit: percent )

Figure 9-11, demonstrate the sensitivities of GA, PSO, and TPSO, respectively. Figure 12 shows their average levels of accuracy.

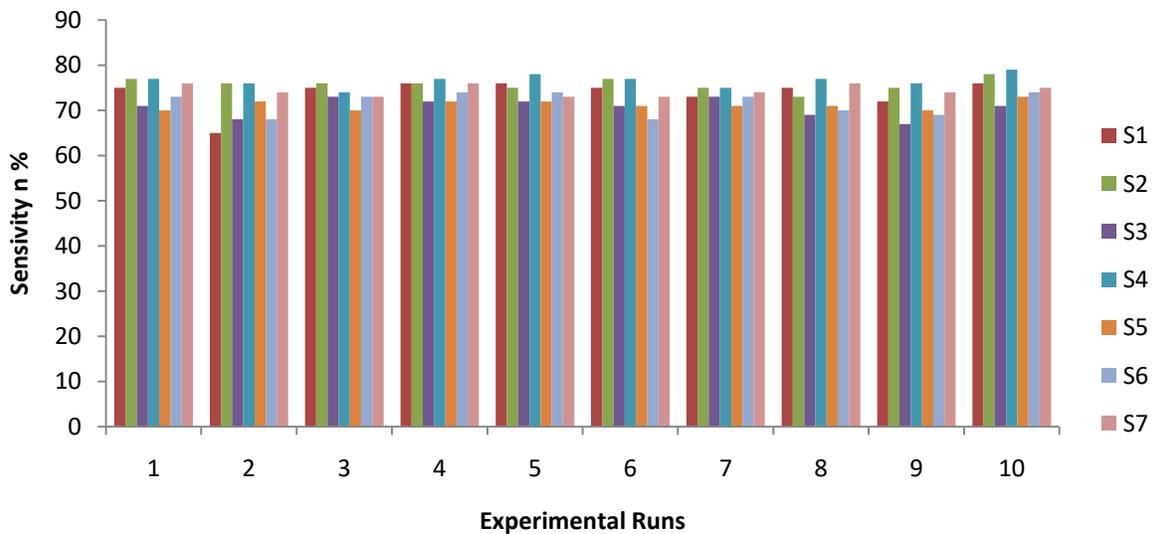


Figure 9.SensitivitiesofeachclassbyGA in%

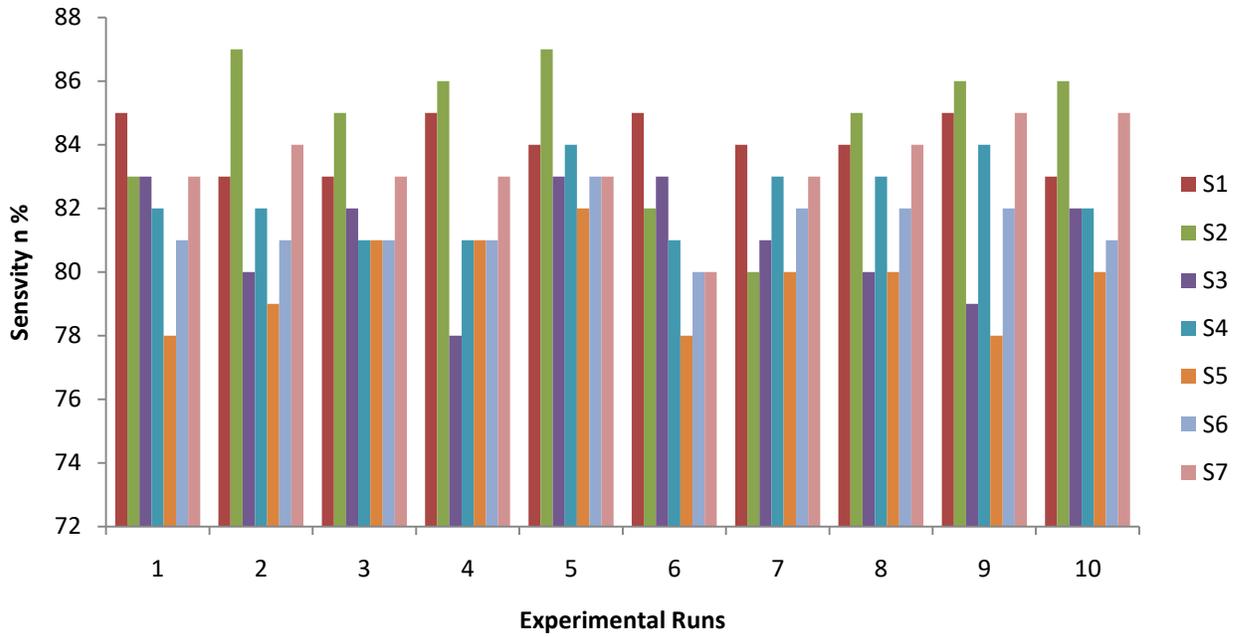


Figure 10 Sensitivities ( $S_k$ ) of each class by PSO[8] (Unit: %)

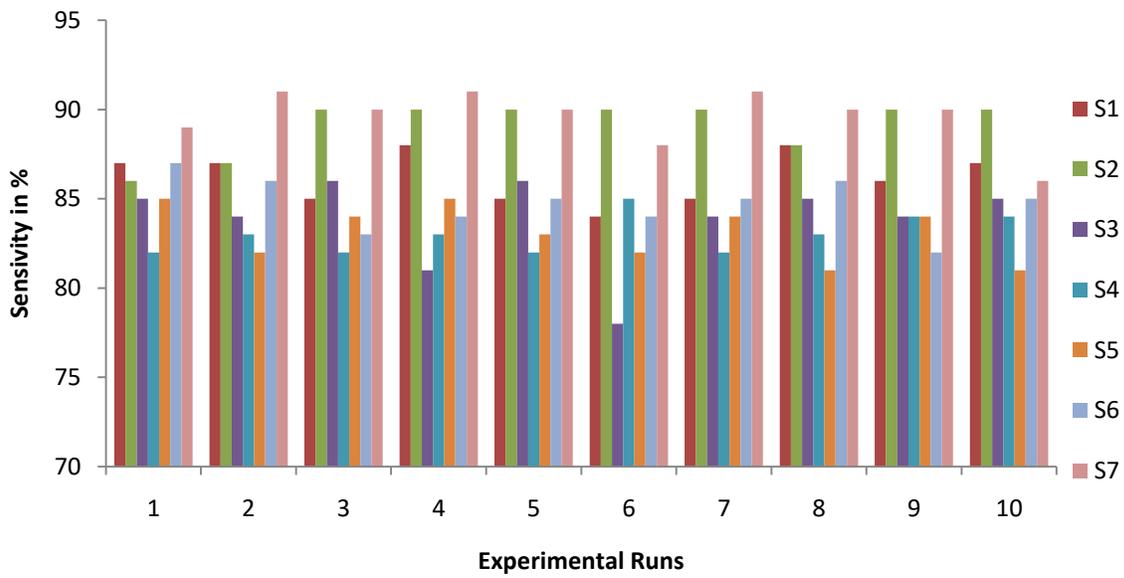


Figure 11. Sensitivities ( $S_k$ ) of each class by TPSO[11] (Unit: %)

## 4.2 Method of Comparison

Two methods were compared to our proposed “DWT + PCA + SNN + CSO” process. They are i) HOS-RT-SVM and (ii) PCA-SVM, respectively. Figure 12 shows the comparison results in terms of overall accuracy (O).

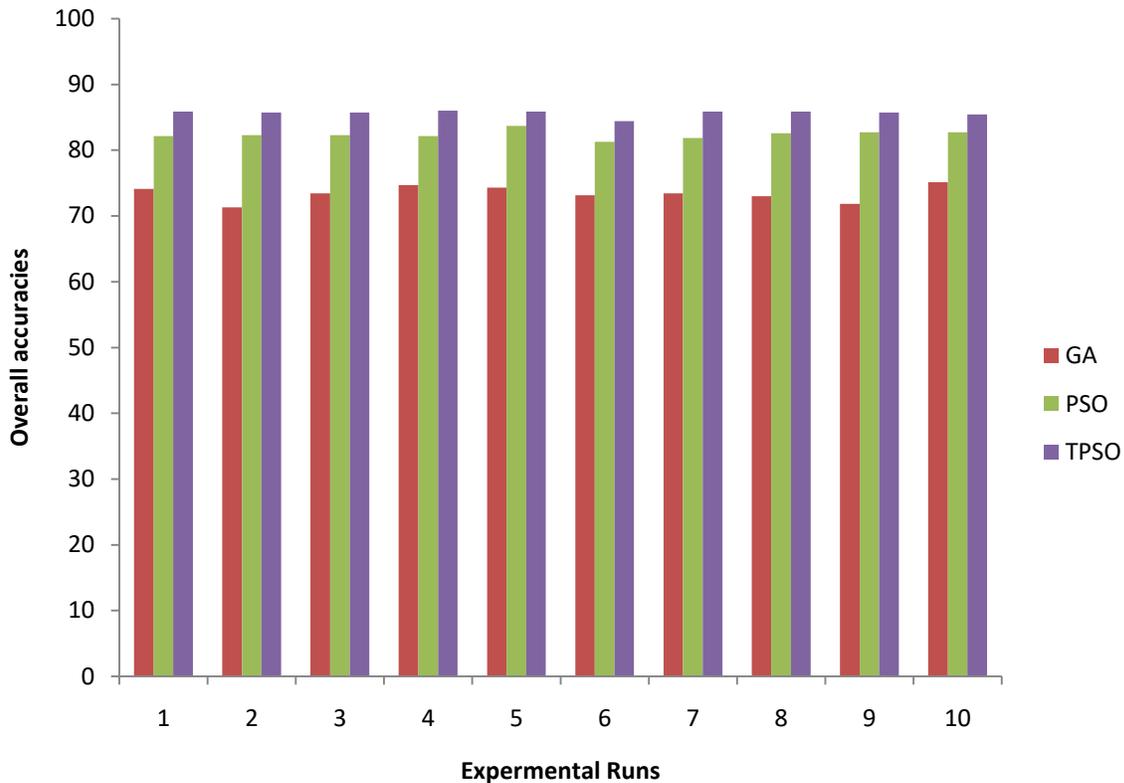


Figure 12 Overall accuracies (O) by GA, PSO, and TPSO in percentages

Figure 13 reveals that the HOS/RT/SVM method is worst. It has a total precision of 85.51 percent. PCA-SVM comes in a close second, with an accuracy rate of 88.22 percent. Nonetheless, the system outperforms other twice in terms of the overall precision, with a classification accuracies of 90.14 percent.

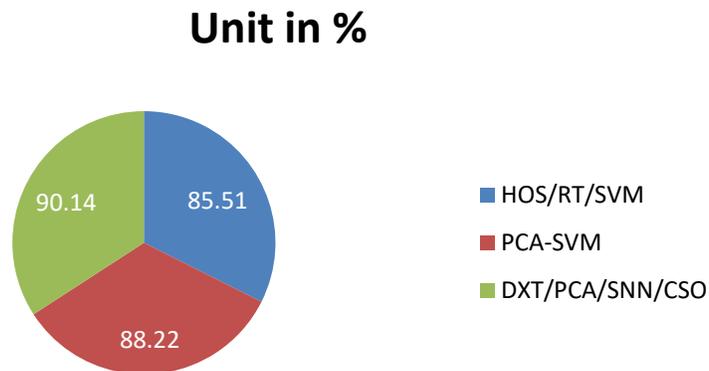


Figure 13. Methods of Comparison

Our system has a flaw from that designers did not anticipate that brightness transition. In the meantime, we will attempt to eliminate the impact of brightness variance. Many specialised classifiers, including the optimization algorithm, fuzzy SVM, and generalised eigenvalue proximal SVM, would be tested. Convolution neural networks and autoencoders are two machine learning methods.

## 5. Conclusions

WT, PCA, a single-hidden-layer genetic algorithm, and CSO are all used in our modern face recognition technology. CSO outperformed GA, PSO, and TPSO in a ten-fold stratified validation data study. In addition, our machine outperformed two recently developed methods: PCA/SVM and HOS/RT/SVM.

## References

1. Lee, S.H., Ro, Y.M.: Partial matching of facial expression sequence using over-complete transition dictionary for emotion recognition. *IEEE Trans. Affect. Comput.* 7, 389–408 (2016)
2. Argaud, S., et al.: Does facial amimia impact the recognition of facial emotions? An EMG study in Parkinson's disease. *PLoS One* 11, Article ID: e0160329 (2016)
3. Hargreaves, A., et al.: Detecting facial emotion recognition deficits in schizophrenia using dynamic stimuli of varying intensities. *Neurosci. Lett.* 633, 47–54 (2016)
4. Drume, D., Jalal, A.S.: A Multi-level classification approach for facial emotion recognition. In:

- International Conference on Computational Intelligence And Computing Research, pp. 288–292. IEEE (2012)
5. Ali, H., et al.: Facial emotion recognition based on higher-order spectra using support vectormachines. *J. Med. Imaging Health Inform.* 5, 1272–1277 (2015)
  6. Boubenna, H., Lee, D.: Feature selection for facial emotion recognition based on geneticalgorithm. In: 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), pp. 511–517. IEEE (2016)
  7. Lu, H.M.: Facial emotion recognition based on biorthogonal wavelet entropy, fuzzy support vector machine, and stratified cross validation. *IEEE Access* 4, 8375–8385 (2016)
  8. Ji, G.: A comprehensive survey on particle swarm optimization algorithm and its applications. *Math. Probl. Eng.* 2015, Article ID: 931256 (2015)
  9. Jotheeswaran, J., Koteeswaran, S.: Mining medical opinions using hybrid genetic algorithm-neural network. *J. Med. Imaging Health Inform.* 6, 1925–1928 (2016)
  10. Yang, J.F., Sun, P.: Magnetic resonance brain classification by a novel binary particle swarm optimization with mutation and time-varying acceleration coefficients. *Biomed. Eng.- Biomed. Tech.* 61, 431–441 (2016)
  11. Chu, S.-C., Tsai, P.-W., Pan, J.-S.: Cat swarm optimization. In: Yang, Q., Webb, G. (eds.) *PRICAI 2006*. LNCS, vol. 4099, pp. 854–858. Springer, Heidelberg (2006). doi:10.1007/978-3-540-36668-3\_94
  12. Yang, J.: Preclinical diagnosis of magnetic resonance (MR) brain images via discrete wavelet packet transform with Tsallis entropy and generalized eigenvalue proximal support vector machine (GEPSVM). *Entropy* 17, 1795–1813 (2015)
  13. Ghamisi, P., et al.: A self-improving convolution neural network for the classification of hyperspectral data. *IEEE Geosci. Remote Sens. Lett.* 13, 1537–1541 (2016)