

# Intelligent Facial Emotion Recognition using modified-PSO

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## Abstract:

In this paper, a facial emotion recognition technique is proposed. The proposed technique employs modified-LBP, which conduct horizontal and vertical neighbourhood pixel comparison, to generate a discriminative initial facial representation. Then, a modified-PSO, is proposed to perform feature optimization.[2]

The Facial emotion recognition system consists of three steps: 1) Feature Extraction; 2) Feature Optimization; 3) Emotion Recognition. Firstly, we use modified local binary patterns (LBPs), i.e., horizontal and vertical neighbourhood comparison LBP, to extract the initial facial representation. Then, the proposed PSO algorithm is used to identify the most discriminative and significant features for differentiating distinct facial expressions. SVM(Support Vector Machine) and Multiple-SVM classifiers are used for recognizing six facial expressions.: 1) Happiness; 2) Sadness; 3) Anger; 4) Fear; 5) Surprise; 6) Disgust.

**Keywords** — *Image pre-processing, Linear Binary Pattern (LBP), hvn-LBP, Feature Extraction, Feature Optimization, Emotion Recognition, PSO, SVM*

## I. INTRODUCTION

Facial emotion recognition has made human-computer interaction easy and has provided benefits in computer vision applications, such as surveillance, healthcare, event detection robotics, etc. [1-5]. Emotion classification depends on effective facial representation. However, it is still a challenging task for identifying significant discriminative facial features that could represent the characteristics of each emotion because of the subtlety and variability of facial expressions [7].

The goal of this work is to propose a modified-PSO algorithm. The proposed algorithm incorporates a non-replaceable memory, a small-population secondary swarm, a new velocity updating strategy, a sub-dimension-based regional facial feature search strategy to overcome both premature convergence and local optimum problems encountered by conventional PSO.[2]

### A. Main Objectives

- 1).To improve LBP for feature extraction.
- 2). To modify PSO for expression recognition.

- 3). To analyze and compare the performance of PSO and modified-PSO in terms of success ratio

## II. PROPOSED SYSTEM

Figure below shows the block diagram for Facial Emotion Recognition system:

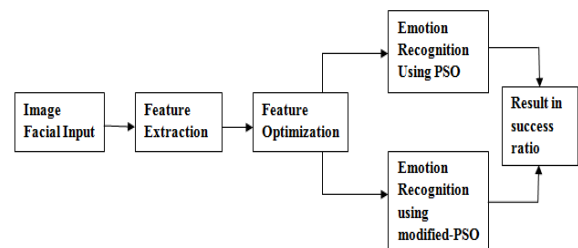


Figure1: Block diagram for proposed work

The facial emotion recognition system architecture is shown below. It consists of three steps or three main blocks:

- Feature Extraction
- Feature Optimization
- Emotion Recognition

### B. Feature Extraction

To improve the discriminative abilities of LBP, we propose horizontal and vertical neighbourhood pixel comparison LBP (hvnLBP). It is integrated with the Gabor filter for producing the discriminative facial representation.

There are four steps in the feature extraction process: 1) preprocessing for illumination changes and noise invariance; 2) face detection; 3) Gabor magnitude image generation; and 4) the proposed hvnLBP-based textural description. First of all, we apply histogram equalization and bilateral filter to compensate illumination variations and reduce noise in the input image, respectively. We then use a Haar-cascade face detector to detect faces. A 2-D Gabor filter is also applied to produce magnitude pictures. Finally, the proposed hvnLBP operator is used to generate the textural description of facial images.[2]

The mathematical representation of this proposed hvnLBP<sub>p,r</sub> operator is illustrated as follows:

$$hvnLBP_{p,r} = \{S(\max(l_0, l_1, l_2)), S(\max(l_7, l_3)), S(\max(l_6, l_5, l_4)), S(\max(l_0, l_7, l_6)), S(\max(l_1, l_5)), S(\max(l_2, l_3, l_4))\}$$

where p is the number of neighbourhood pixels, and r is the radius. L<sub>i</sub> represents the i<sup>th</sup> neighbor of pixel l while S denotes the comparison operation, as follows;

$$S(\max(l_j, l_k, l_m)) = \begin{cases} 1 & \text{if maximum} \\ 0 & \text{if non\_maximum} \end{cases}$$

where l<sub>j</sub>, l<sub>k</sub>, and l<sub>m</sub> represent the neighbourhood pixels in a row or column.[2]

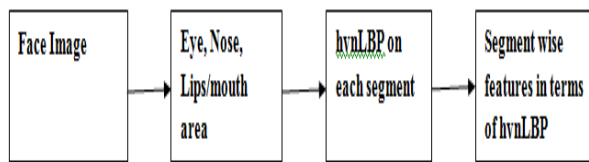
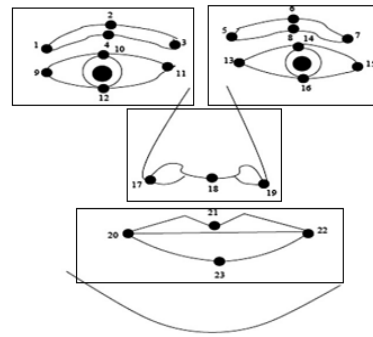


Figure 2: Feature Extraction Process



Geometric Features	Number of Features	Description
Eyes	4x2	Two extreme corners, upper and lower midpoints
Nose	3	Two nostrils and nose tip
Lip/mouth	4	Two extreme corners, upper and lower midpoints

Figure 3: Facial Points of frontal image [25]

Haar-cascade based extracted face is further again fragmented in different parts using same haar-cascade containing, 1) Eyes 2) Nose 3) Lips/mouth.

By considering these regions, we can observe normally that depending on emotion, these areas of face are changing their appearances. By extracting features, in these areas we classify features using m-GA in following classes;

- 1) Happiness;
- 2) Sadness;
- 3) Anger;
- 4) Fear;
- 5) Surprise;
- 6) Disgust.

### C. Feature Optimization

#### 1. Modified-PSO:

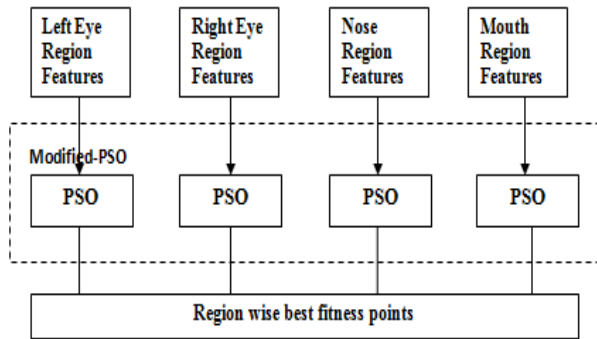


Figure 4: Modified-PSO

As PSO works on entire image, we apply PSO on each segment of image features. Each PSO obtains their respective fitness values and then we combine these points as single feature of respective face on the basis of region.

#### 2. PSO working:

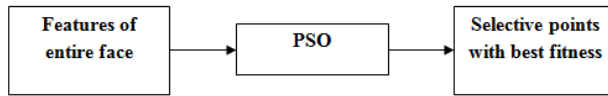


Figure 5: Working of PSO

PSO applied on features of entire face will optimize and find best fitness points irrespective of regions of face. This leads to less efficiency in recognition process. To improve this we use, the m-GA as modified PSO i.e. applying region wise PSO and obtaining region best fitness points.

### D. Emotion Recognition

Here, we conduct a study of six-class facial emotion recognition using the features automatically generated by the mGA-embedded PSO. For classification SVM classifier is used.

#### 1) SVM:

SVM (**support vector machines**) analyze data used for classification and regression analysis.

Consider a set of training examples, each marked with different categories. Then the SVM training algorithm assigns new examples to each one of the category and makes it a non-probabilistic binary linear classifier.

An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

SVMs can perform both linear and non-linear classification. To do so it uses kernel trick.

Images can also be classified using SVM. Accuracy of SVM is greater than traditional query refinement.

In many situations, multiclass classification is the problem of classifying instances into one of the two classes is called binary classification.

While some classification algorithms naturally permit the use of more than two classes, others are by nature binary algorithms; these can, however, be turned into multiclass classifiers by a variety of strategies. Multiclass classification should not be confused with multi-label classification, where multiple labels are to be predicted for each instance.

#### 2) Difference between One-vs-all and One-vs-one SVM classifier:

The difference is the number of classifiers, which strongly correlates with the decision boundary they create. Assume we have 'N' different classes. One-vs-all will train one classifier per class in total 'N' classifiers. For class 'i' it will assume 'i-labels' as positive and the rest as negative.

In one-vs-one you have to train a separate classifier for each different pair of labels. This leads to more numbers of classifiers than 'N'. This is much less sensitive to the problems of imbalanced datasets but is much more computationally expensive.

**III. RESULT & DISCUSSION**

1) Here the original image is taken as input to the system, as shown in figure:



Figure 6: Input Images

2) Here the face from original image is detected and extracted;

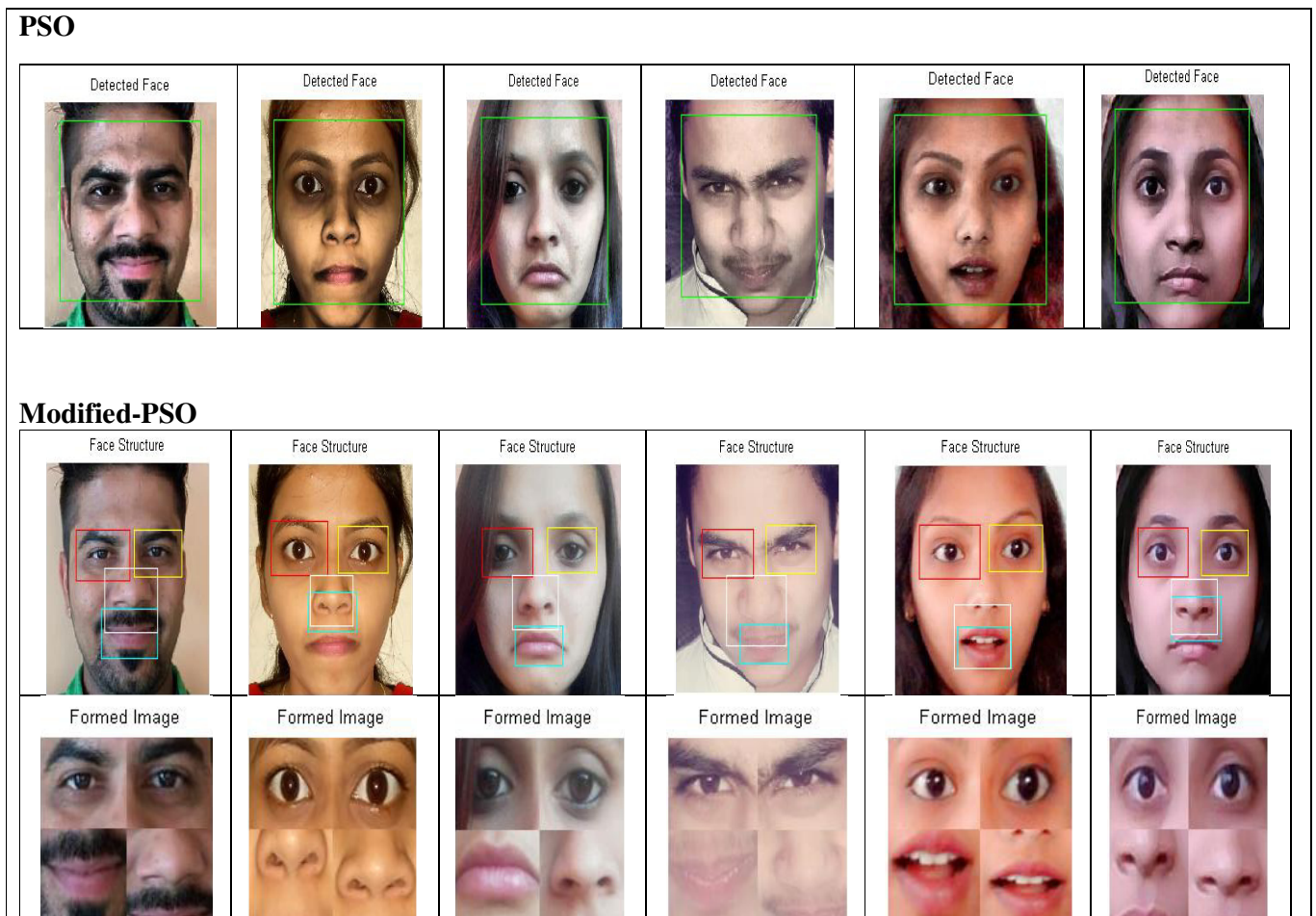


Figure 7:Face detection & extraction



3) Here we generate gabor magnitude image using gabor filter;

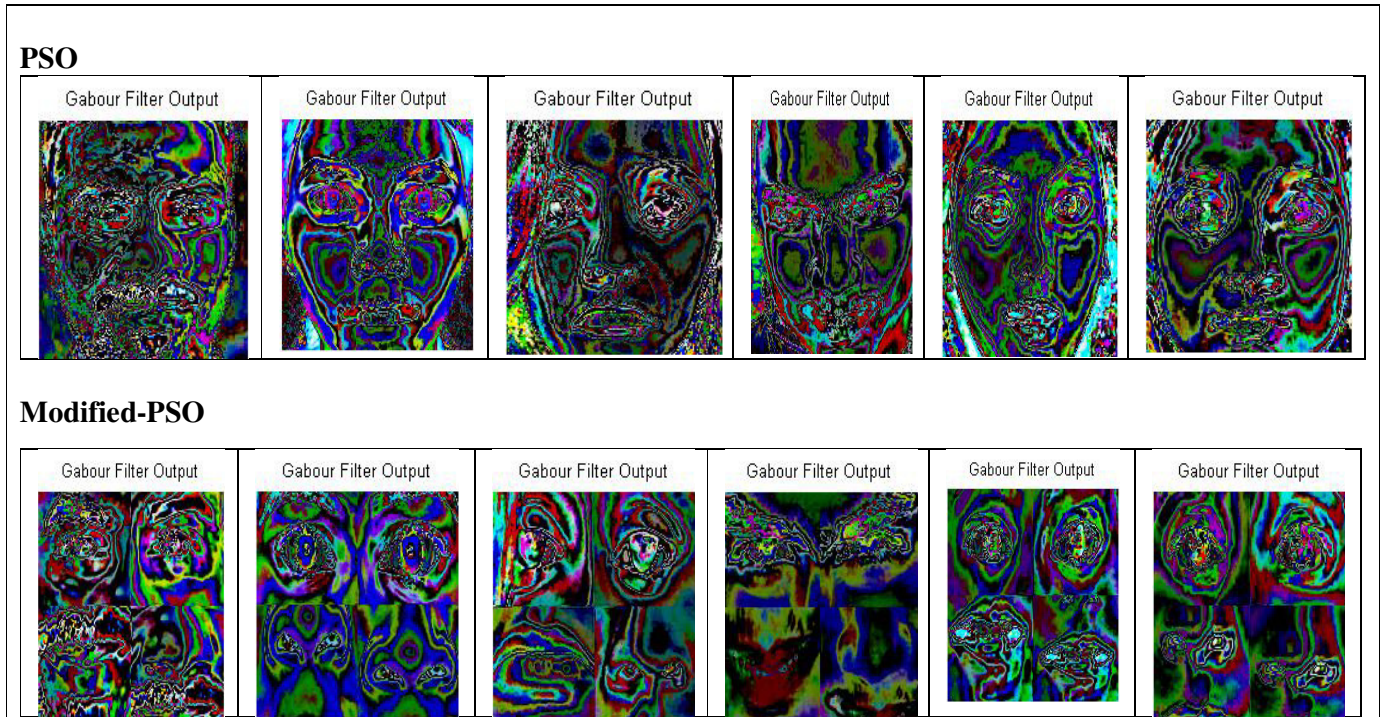


Figure 8: Gabor Magnitude Image Generation

4) Here we perform feature extraction, as shown in figure below;

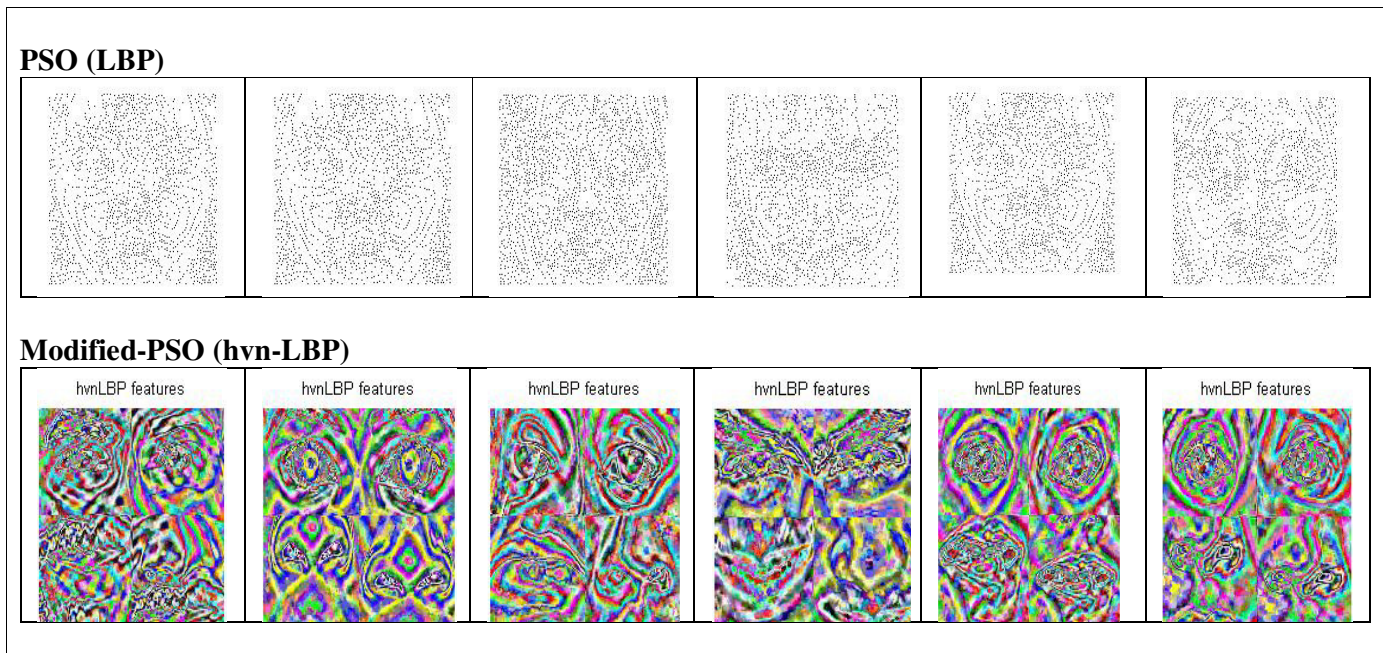


Figure 9: Feature extraction

5) Table below shows the GUI result of both the PSO & modified-PSO system;

PSO					
Result Happy	Result Angry	Result Angry	Result Happy	Result Fear	Result Happy
Status PSO Complete.	Status PSO Complete.	Status PSO Complete.	Status PSO Complete.	Status PSO Complete.	Status PSO Complete.
Modified-PSO					
Result Happy	Result Angry	Result Sad	Result Disgust	Result Surprise	Result Fear
Status mGA Complete!!	Status mGA Complete!!	Status mGA Complete!!	Status mGA Complete!!	Status mGA Complete!!	Status mGA Complete!!

Figure 10: Emotion Recognition

6) Simillary, 36 images of different expression of 6 classes were tested and success ratio is obtained as below;

• **SR (Success Ratio) = No. of accurately recognized emotions / Total no. of tests performed**

$$\begin{aligned}
 1. \text{ PSO (SR)} &= (15/36) * 100 \\
 &= 0.41666 * 100 \\
 &= 41.66 \%
 \end{aligned}$$

$$\begin{aligned}
 2. \text{ Modified-PSO} &= (35/36) * 100 \\
 &= 0.97222 * 100 \\
 &= 97.22 \%
 \end{aligned}$$

Success Ratio

Image Number	Original Class	Detected Emotion using PSO (Method-1)	Detected Emotion using m-GA (Method-2)
1	Angry	Angry	Angry
2	Angry	Angry	Angry
3	Angry	Angry	Angry
4	Angry	Fear	Angry
5	Angry	Disgust	Angry
6	Angry	Angry	Angry
7	Surprise	Surprise	Surprise
8	Surprise	Angry	Surprise
9	Surprise	Surprise	Surprise
10	Surprise	Angry	Surprise
11	Surprise	Surprise	Surprise
12	Surprise	Surprise	Surprise
13	Happy	Happy	Happy
14	Happy	Surprise	Happy
15	Happy	Surprise	Happy
16	Happy	Happy	Happy
17	Happy	Disgust	Happy
18	Happy	Angry	Happy
19	Sad	Angry	Sad
20	Sad	Angry	Sad
21	Sad	Surprise	Sad
22	Sad	Surprise	Sad
23	Sad	Surprise	Sad
24	Sad	Angry	Surprise
25	Disgust	Disgust	Disgust
26	Disgust	Surprise	Disgust
27	Disgust	Angry	Disgust
28	Disgust	Disgust	Disgust
29	Disgust	Happy	Disgust
30	Disgust	Angry	Disgust
31	Fear	Fear	Fear
32	Fear	Fear	Fear
33	Fear	Fear	Fear
34	Fear	Happy	Fear
35	Fear	Angry	Fear
36	Fear	Sad	Fear
		<b>Emotions Detected Correctly=15/36</b>	<b>Emotions Detected Correctly=35/36</b>

Figure 11: Success Ratio

#### IV. CONCLUSIONS

Using this system we can identify the most discriminative and significant features for differentiating distinct facial expressions.

Diverse classifiers are applied to recognize six emotions: 1) Happiness; 2) Sadness; 3) Anger; 4) Fear; 5) Surprise; 6) Disgust.

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