

## Facial Emotion Recognition Using Principal Component Analysis and Support Vector Machine

Akinrotimi, Akinyemi Omololu & Aremu, Dayo Reuben

<sup>1,2</sup>University of Ilorin, Ilorin Nigeria

Department of Computer Science

Faculty of Communication and Information Sciences

PMB 1515, Ilorin, Kwara State, Nigeria.

**E-mail:** [timiakin2011@yahoo.com](mailto:timiakin2011@yahoo.com)<sup>1</sup>, [draremu2006@gmail.com](mailto:draremu2006@gmail.com)<sup>2</sup>

### ABSTRACT

This paper presents an approach to recognize facial expressions on human faces. For this research work, facial features, such as the lips, the chin region and especially the eyes, were extracted for dimensionality reduction and a unique face representation using the Principal Component Analysis (PCA). However prior to doing this, the frontal faces were normalized using adaptive histogram equalization for removal of noise and illumination invariance. Experimental results demonstrate that this technique can efficiently classify expressions from the face, with 92% accuracy, using the Support Vector Machine (SVM). The system was implemented using the MATLAB programming language.

**Key words:** Facial Emotion Recognition, Principal Component Analysis and Support Vector Machine

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### 1. INTRODUCTION

Facial expression analysis has been attracting considerable attention in the advancement of human machine interface since it provides a natural and efficient way to communicate between humans. Some application areas related to face and its expressions include personal identification and access control, video phone and teleconferencing, forensic applications, human-computer interaction, automated surveillance, cosmetology, and so on. But the performance of the face detection certainly affects the performance of all the applications. Many methods have been proposed to detect human faces in images. They can be classified into four categories: knowledge-based methods, feature-based methods, template based methods and appearance-based methods. When used separately, these methods cannot solve all the problems of face detection like pose, expression, orientation, and occlusion. Hence it is better to operate with several successive or parallel methods.

Most of the facial expression recognition methods reported to date are focused on recognition of six primary expression categories such as: happiness, sadness, fear, anger, disgust and grief. For a description of detailed facial expressions, the Facial Action Coding System (FACS) was designed by Ekman and Friesen in the mid-70s. In FACS, motions of the muscles of the face are divided into 44 action units and any facial expressions are described by their combinations [2]. Developing such Facial Expression Recognition system (also referred to as a FER system) is not trivial task, due to the high variability of data. Images are represented under various conditions such as resolution, quality, illumination or size. All these constraints have to be taken into consideration for selecting appropriate methods, in order to deliver a system that is robust, person independent and works ideally in real time scenarios. This paper presents an Eigen face approach for the facial expression recognition with support vector machine.

## 2. RELATED WORKS

The table below highlights the related works as relating existing work on face and face emotion recognition.

**Table 1: Related Works As Relating Existing Work On Face And Face Emotion Recognition**

Reference	Method	Performance
[5]	PCA	This method provides better face recognition with reasonably low error rates
[4]	LBP (Local Binary Pattern)	Higher recognition accuracy, Low computational complexity
[1]	Active Appearance Model	The computational time and complexity was also very low
[4]	Haar Classifier	High detection accuracy
[3]	Fisher's Linear Discriminant	Recognition rate is low
[3]	Multilinear Image Analysis	Recognition rate higher, but only in grayscale images

## 3. PROPOSED SYSTEM

The proposed system has the basic stages that would be involved in the development of the system:

### A. Image Data Gathering

The system classifies images of people expressing one of the basic six emotions: disgust, anger, fear, happiness, sadness or surprise. The dataset used for training and testing the system was chosen out of the free and publicly available datasets on the web, namely Cohn-Kanade AU-Coded Facial Expression Database (more accurately, Version 2, also known as CK+).

### B. Image Preprocessing

In this module the images are normalized to improve the recognition of the system. The pre-processing steps implemented are as follows:

1. Image size normalization
2. Translation and rotational normalizations
3. Illumination normalization

### C. Feature Extraction

Principal component analysis (PCA) is a statistical dimensionality reduction method, which produces the optimal linear least-square decomposition of a training set. Kirby and Sirovich applied PCA for representing faces while Turk and Pentland extended PCA for identifying faces. In applications such as image compression and face recognition, a helpful statistical technique called PCA is often utilized. PCA is a widespread technique for determining patterns in data of large dimensions and it is commonly referred to as the use of Eigen faces [3].

The PCA approach is then applied to reduce the dimension of the data by means of data compression, and reveals the most effective low dimensional structure of facial patterns. The advantage of this reduction in dimensions is that it removes information that is not useful and specifically decomposes the structure of a face into components which are uncorrelated and are known as Eigen faces (M. A. Turk, et al, 1991). Each image of face may be stored in a 1D array which is the representation of the weighted sum (feature vector) of the Eigen faces. In case of this approach a complete front view of face is needed; or else the output of recognition will not be accurate. The major benefit of this method is that it can trim down the data required to recognize the entity to 1/1000th of the data existing [4].

The following steps summarize the process PCA. Let a face image  $X(x, y)$  be a two dimensional  $m \times n$  array of intensity values. An image may also be considering the vector of dimension  $mn$ , so that a typical image of size  $112 \times 92$  becomes a vector of dimension 10304. For, a training set of images  $\{X_1, X_2, X_3, \dots, X_N\}$ .

The average face of the set is defined by:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i \quad (1)$$

Calculate the estimate covariance matrix to represent the scatter degree of all feature vectors related to the average vector. The covariance matrix  $C$  is defined by:

$$C = \frac{1}{N} \sum_{i=1}^N (\bar{X} - X_i) (\bar{X} - X_i)^T \quad (2)$$

The Eigenvectors and corresponding Eigen-values are computed by using

$$CV = \lambda V \quad (V \in \mathbb{R}^n, \neq 0) \quad (3)$$

Where  $V$  is the set of eigenvectors matrix  $C$  associated with its eigenvalue  $\lambda$ . Project all the training images of  $i^{\text{th}}$  person to corresponding eigen-subspace:

$$y_k^i = w^T(x_i) \quad (i = 1, 2, 3, \dots, N) \quad (4)$$

Where the  $y_k$  are the projections of  $x$  and called the principal components also known as eigenfaces. The dimensionality can be reduced by selecting the first  $N$  eigenvectors that have large variances and discarding the remaining ones that have small variance.

#### D. Training Model.

The obtained feature from the PCA will be used to train the system and create a pattern extraction for each of the supplied face emotion via the support vector machine.

#### E. Emotion Classification or Recognition.

The concept of Support Vector Machines was firstly introduced by (Vapnik et al, 2008) and presently, they are one of the most widely used methods for pattern classification. An SVM is a supervised learning model, because it uses labeled examples in its training process, examples which correspond to only two categories [7,8]. This property makes the algorithm able to only tackle binary classification tasks. The model analyses the training examples and tries to derive a boundary that will linearly separate the data points into their corresponding classes. One of the most important features of this method, is that it does not only look for a separation boundary, but for the 'best boundary' [5].

This is done by maximizing the margin, which is the width by which the separation boundary can be increased until it hits a data point. There is a notable, difference between separating data with any border and separating it with SVM's optimal boundary. Support Vector Machines are not only one of the most popular choices in facial emotion classification, but it is also a complex robust model with great generalization properties, less prone to over-fitting [6]. Based on such characteristics, the SVM algorithm is chosen to support the prediction module of the FER system. The feature extraction stage, described earlier, produces a set of feature vectors for a subset of images, that are used as training examples. These are then fed into linear SVM model.

### 3.1 System Flow Chart

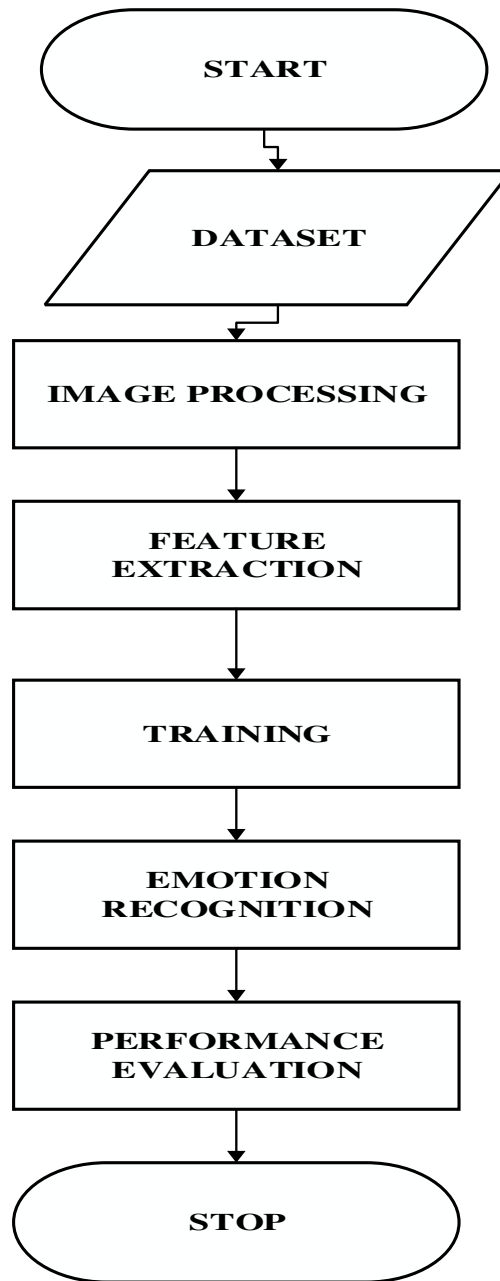


Figure 3.1: System Flowchart.

#### 4. IMPLEMENTATION AND RESULTS

##### A. Database

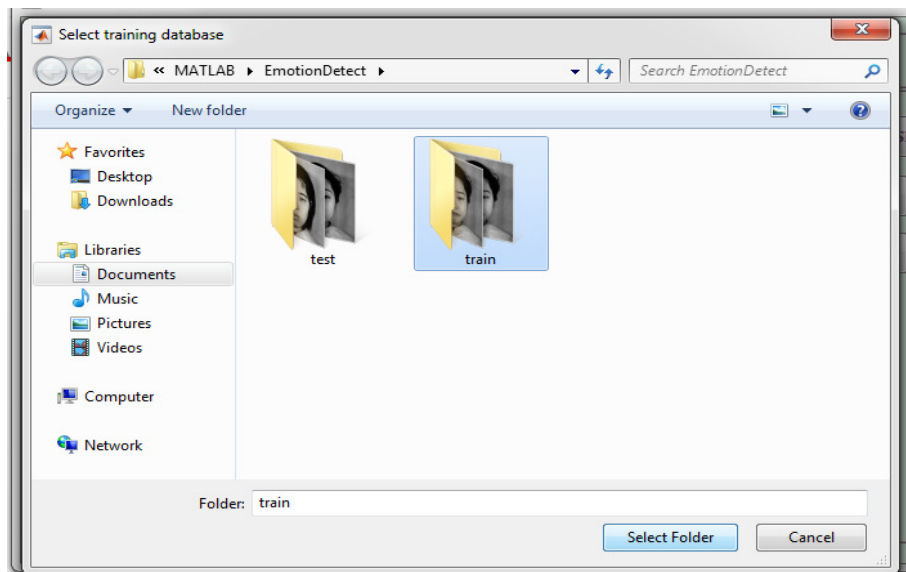
The sample of the database used to train and evaluate the system is shown below:



**Figure 4.1: Sample JAFFE database**  
*(Data Source: the Japanese Female Facial Expression (JAFFE) Database)*

##### B. Training Database

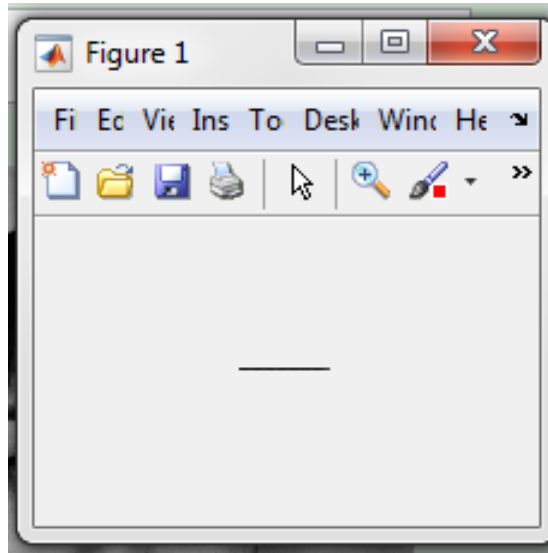
The system is trained so to adapt to experimental knowledge discovery. This is done by clicking on the training database image and selecting the train folder. At this point the principal component extraction was extracted from the face database so and stored as a feature vector.



**Figure 4.2: Training Selection**

**B. Feature Extraction**

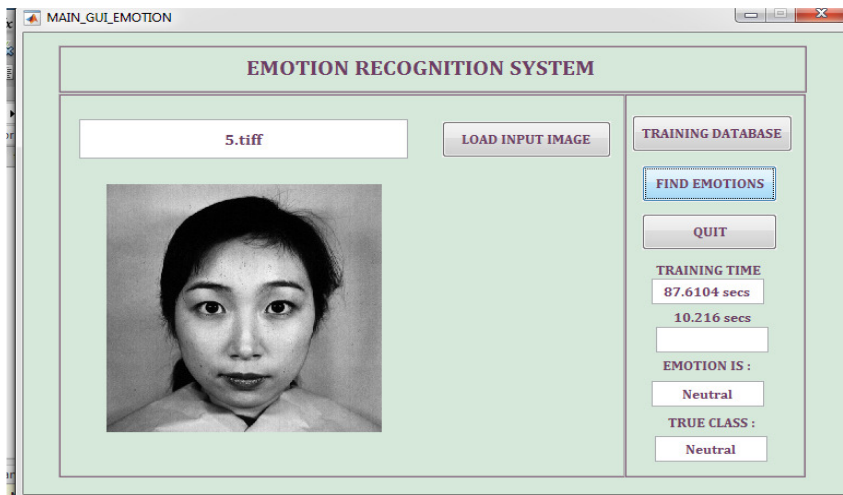
The feature extraction is the generation of matrix that represents each face emotion image. This stage obtained the following image processing result.



**Figure 4.3: Extracted feature**

**C. SAMPLE TESTING**

The figure below shows: when a test image is loaded into the system to recognize the state of expression of the image. This is achieved with help of the support vector for multi-class objective. The support vector helps to train the extracted template from the face emotion and store it in a database file. Also, the radial bias function was used as the kernel of the support vector machine. After successful training by the support vector machine, it then classifies new set of probe image to identify the emotion of the loaded face.



**Figure 4.4: Sample testing**

### A. Confusion Matrix

The confusion matrix is an indication of the correctly and incorrectly classified class. The table 4.1 gives the confusion matrix illustration with their various representations while table 4.2 shows the number of classes that were actually classified into their groups correctly, the misclassification and the group the misclassified instances fell into.

**Table 4.1: Class groups**

Class 1: Anxiety
Class 2: Disgust
Class 3: Fear
Class 4: Happiness
Class 5: Fear

The table 4.2 shows that only the class 2 has a misclassification of two instances, under class one, while other classes are classified as correct instances. The table also shows the correctly classified and incorrectly classified classes. The class1 was able to classify all as correct, class 2 classify 3 as correct and 2 as incorrect, class 3 classify 5 as correct while class 4 and class 5 also classified all the test image as correct.

**Table 4.2: Confusion matrix**

Class	1	2	3	4	5
1	5	0	0	0	0
2	2	3	0	0	0
3	0	0	5	0	0
4	0	0	0	5	0
5	0	0	0	0	5

### B. Total Training Time

Table 4.3: Total Training Time

TRAINING	TOTAL TRAINING TIME
TOTAL	19.1327 sec

### C. Average Testing Time

Table 4.4: Average Testing Time

TESTING	AVERAGE TESTING TIME
AVERAGE	5.817746 sec

The tables above, indicate that the system operated at a very good training speed with a high level of conditional testing, signifying high optimization.

#### D. Statistical metric evaluation

##### Confusion matrix values

TP = 5	FP = 2
TN = 18	FN = 0

**PRECISION = Positive Predictive Value (PPV) =  $TP / (TP+FP) = 5 / (5+2) = 0.7143$**

**SENSITIVITY = True positive rate =  $TP / (TP + FN) = 5 / (5+0) = 1 = \text{RECALL}$**

**SPECIFICITY = True negative rate =  $TN / (TN + FP) = 18 / (18+2) = 0.90$**

**ACCURACY =  $TP + TN / (FP + FN + TP +TN) = 5+18 / (2+0+5+18) = 0.92$**

**ERROR =  $FP + FN / (FP + FN + TP +TN) = 2+0 / (2+0+5+18) = 0.008$**

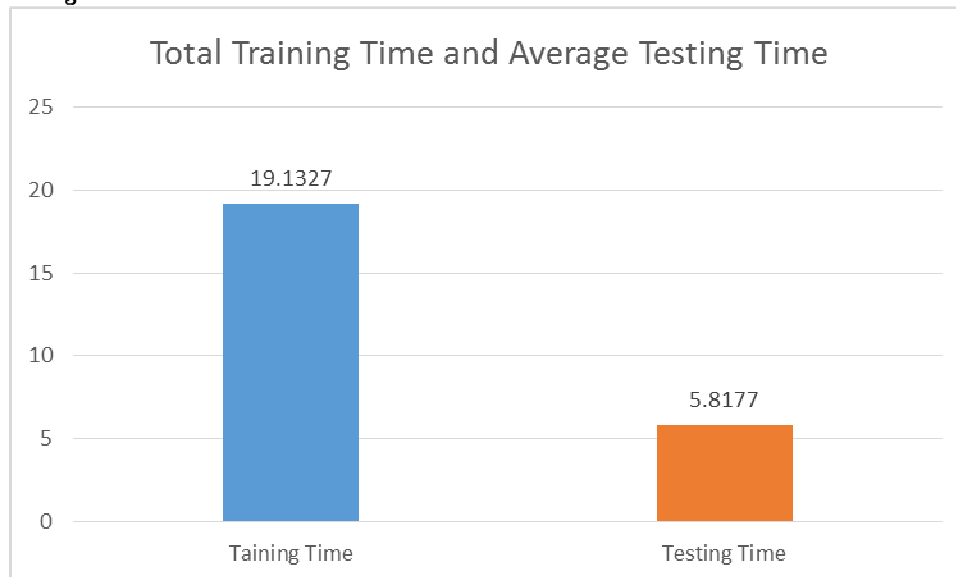
**Table 4.5: Table showing results for precision sensitivity specificity, accuracy and error**

PRECISION	0.7143	71.43%
SENSITIVITY	1	100%
SPECIFICITY	0.90	90%
ACCURACY	0.92	92%
ERROR	0.008	-

The obtained results gives a very good classification accuracy of 92% which defines the system accuracy and efficiency with high positive discovery rate, low negative discovery rate and very low error rate, which are identifiers of a good system performance.

#### 4.5.1 Graphical Presentation

##### A. Training Time



**Figure 4.4: Training and testing Time.**



## B. Performance Evaluation

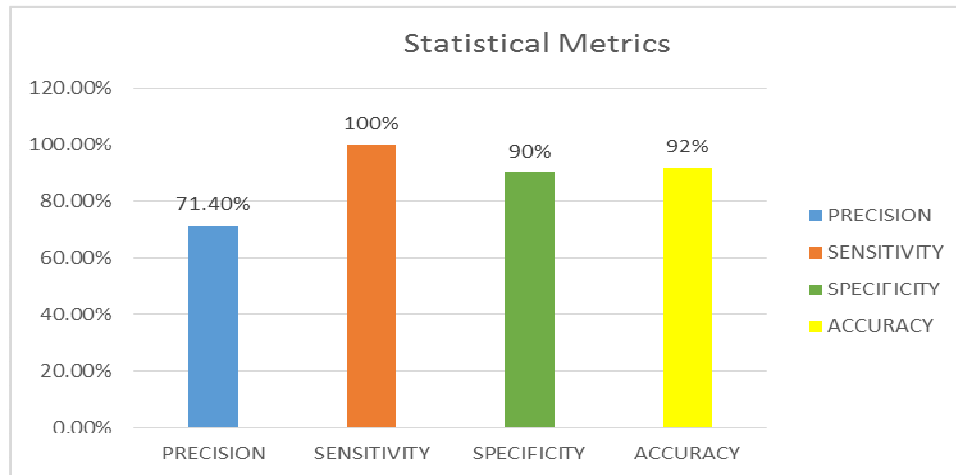


Figure 4.5: Performance Evaluation.

## 5. CONCLUSION

The proposed solution provides a system for recognizing facial expressions. The most important achievement consists of the integrated functionalities and the obtained results. The system includes an automatic face extraction mechanism and machine learning techniques tailored for the current problem. This research work achieved a high rate of system performance during its evaluation, using: principal component analysis for feature extraction and support vector machine for pattern classification. The developed system used the Japanese Female Facial Expression (JAFPE) Database for testing evaluation with 75% to 25% ratio for training and testing respectively. The system obtained a high classification accuracy of 92% with a very low error rate 0.008.

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