# DEAP BASE EMOTION DETECTION THROUGH COMPUTED EEG AND FACE EXPRESSION ANALYSIS

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## ABSTRACT

*The study of changes in physiological signals for emotion recognition in human subjects has generated immense interest in medical instrumentation. One of the effective ways of classifying emotions is by the use of the event-related potential (ERPs) of electroencephalogram (EEG) signals. This requires projection of an image on one computer system while simultaneously putting a marker on another computer system acquiring the EEG. Emotion plays an important role in our daily life. Real-time assessment and regulation of emotions will improve people's life and make it better. For example, in the communication of human –machine interaction, emotion recognition will make the process more easy. Another example, in the treatment of patients, especially those have expression problems, the real emotion state of patients will help doctors to provide them more appropriate medical care. Here we proposed a reliable method which efficient in detection of individual's health like whether they are normal or abnormal by using two factors mainly. (1) Face Expression (2) EEG info. This design can detect the condition of the individual person using image classifier and EEG analyzer using adaptive threshold detection method.*

**Keyword** *Emotion Recognition, Electroencephalogram, adaptive threshold, Event related potential.*

## 1. INTRODUCTION

Brain-computer interface (BCI) has been one of the most interesting biomedical engineering research fields for decades. It provides a technology that allowing humans to control external devices by modulating their brain waves. Real word scenarios was implemented by BCI applications have been developed for non-invasive brain signals processing which is practical. There are plenty of successful EEG-based BCI applications such as word speller programs[1] and wheelchair controllers [2]. Not only BCI be employed to mentally control devices, but also it can be implemented for understanding our mental state. Emotion recognition is one of such applications that Automatic emotion recognition algorithms potentially bridge the gap between human and machine interactions. A model of emotion can be characterized by two main dimensions called valence and arousal. The valence is the degree of attraction or aversion that an individual feels towards a specific objects. It ranges from negative to positive. The arousal is a psychological state of being awake or reactive to stimuli ranging from passive to active. The valence-arousal dimensional model of emotion is widely used in many research studies.

Communication between two or more individuals can take place in the form of a verbal language. Nonverbal communication involves many different aspects as well as proxemics, kinesics, appearance physical attractiveness, haptics, paralanguage, and facial expression. Emotion itself is derived from the physiological process stimulated by conscious and or unconscious awareness to any event or object related with the mental state, nature of a person. Emotion has a significant part in the communication between individuals. The emotion of an individual will influence the relationship with other people such as family, relatives and friends at home, workplaces or other environments that create connection with other people.

Based on those three components, it is obvious that emotions are not just about what appears, but they are more related to the responses of the brain manifested through the physiological signals. Understanding the emotions has become the nature of humans to be successful in communicating with other people.
The emotion recognition has become very popular in recent years a significant contributions in many applications. The most favored application of emotion recognition system is the facial expression recognition system. The Facial Action Coding System (FACS) to code the facial expression extracted from thousands of photographs and tens of thousands of filmed and videotaped facial expressions. The FACS can be extracted from the face and used as the features for facial expression classification.
The implementation of a facial expression recognition system can be realized in a similar way by using the biometric design. The facial expression recognition system applies more specific steps as follows:
A. Detection of the face.
B. Feature extraction (part of facial landmark such as eyes, mouth or the whole face).
C. Expressions classification.
The first step utilizes the sensor to collect physiological signal of facial expression from a person. For that purpose, a camera can be used to produce a still image of the face.
Alternatively, for continuous monitoring of facial expression, a video camera will be more suitable to be used for various conditions and environments.
In the facial expression recognition system, the most important part is feature extraction process. A proper feature extraction process will produce a better recognition system with a more accurate results. The algorithms used for facial features extraction can be classified into two main groups, namely: geometric based methods which collect feature points or motion of points by tracing them from the face images and classifying the expressions from the tracked features and appearance based methods which collect the whole or part of the face landmarks and arrange them as one long array feature vector and apply them in the classification process.
In existing system, less channels frontal EEG signal is used for emotion recognition as specified in Fig 1. By employing the asymmetry theory of frontal brain, a new method fusing spatial and frequency features was presented which adopted two channel of frontal EEG signals at two points. In order to estimate the efficiency of the method, a GBDT classifier was evaluated and the method was implemented on DEAP database. This method is extremely suitable for wearable EEG monitoring application in human daily life.

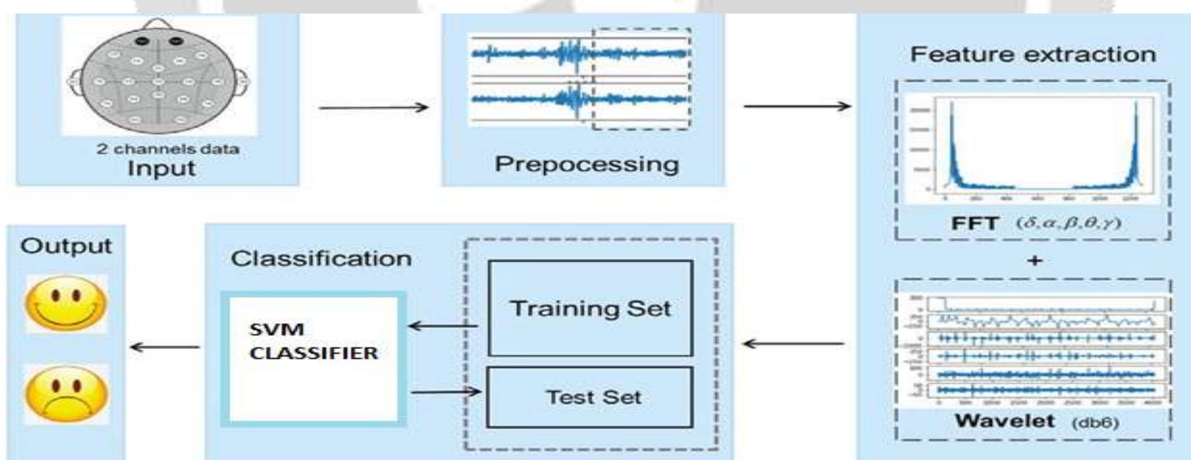


**Figure 1:**Block Diagram of Existing system.

## 2. PROPOSED SYSTEM

The block diagram consist of EEG signal as input in term as DEAP(Database for Emotional Analysis using Physiological signals).Different features are extracted from raw EEG signal.The EEG signal is selected from the database in terms of voltage and frequency.From Voltage and frequency values EEG signal is generated .The generated EEG can be alpha,beta,delta or theta wave. The type of the wave is detected and thepossibility of emotions is detected This is now given to the feature extraction.On the other side face expression is given as input.

The input face is preprocessed and RGB model is converted into gray scale image and noise are removed the face is separated as right eye, left eye, nose and mouth.This is done by feature extraction. The SVM classifier correlates the image and EEG signal, if both matches then result is produced. If not again the EEG signal and face expression is selected.

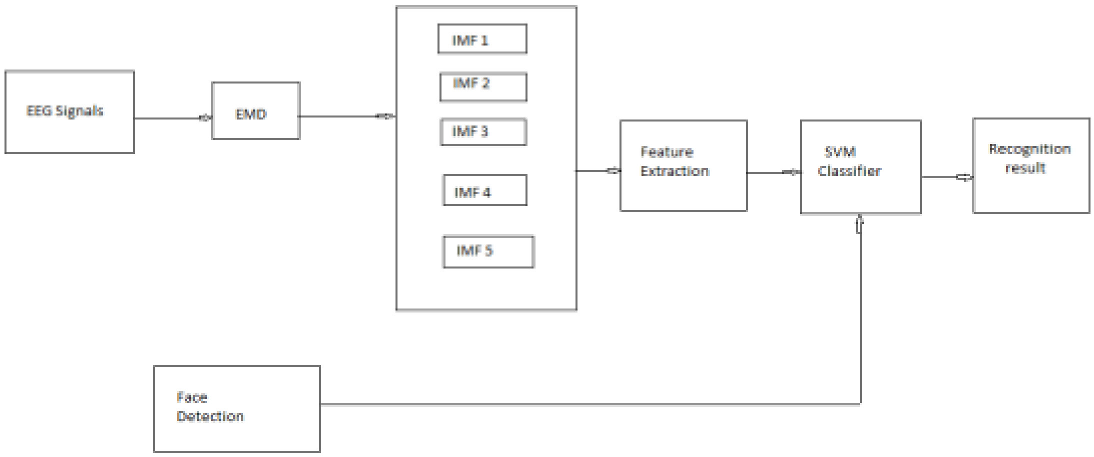


**Figure 2** Block Diagram

This method uses SVM algorithm to recognize emotions and the predefined threshold values are taken from the DEAP dataset. By implementing it the results are compared with previous experiments.

Step 1: Face Expression images Preprocessing:

The input RGB image is resized to a height of 320 pixels. The resized image undergoes two separate processing pipeline: a saturation-based one, and a color texture one. In the first one, the image is firstly gamma corrected and then the RGB values are converted to HSV to extract the saturation channel. These values are automatically thresholded and morphological operations are applied to clean up the obtained binary imageStep 2: EEG dataset Creation & Group Segmentation

This module consists of methods involved in getting the EEG data sets which matches the individual age group and emotions related with the age and mood swings. The EEG data set is processed in the MATLAB environment to segment it better by their alpha, beta, Gama, theta ranges.

Step 3: Classification

This module is used to classify the EEG info with respect to the face expression images and age group info to provide the individual's emotional status like normal or abnormal, happy or Sad etc. These features are further used for analysis purpose of the individual's emotional conditions and mood swings for psychological analysis.

## 3. SUPPORT VECTOR MACHINES (SVM)

Although the SVM can be applied to various optimization problems such as regression, the classic problem is that of data classification. The basic idea is shown in figure 1. The data points are identified as being positive or negative, and the problem is to find a hyper-plane that separates the data points by a maximal margin. The Fig. 3 only shows the 2-dimensional case where the data points are linearly separable. The mathematics of the problem to be solved is the following:

$$\min_{\mathbf{w},\mathbf{b}} \frac{1}{2}\, ||w||,$$

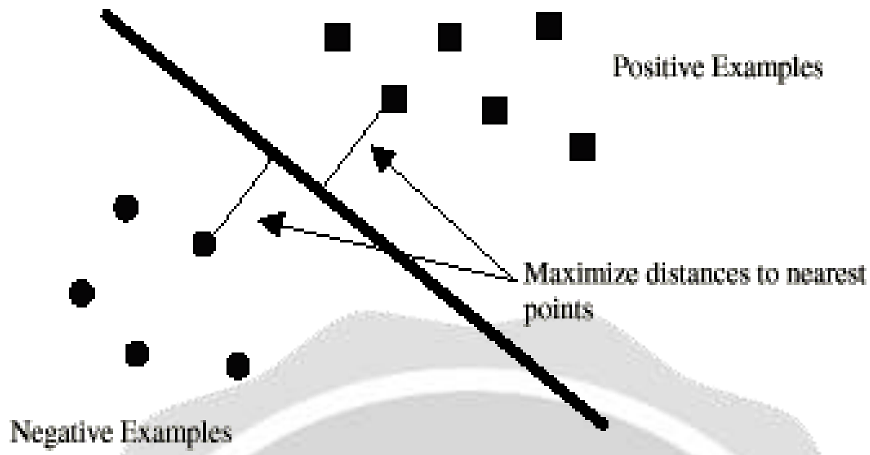


**Figure 3:** Data Classification

The identification of the each data point $x_i$ is $y_i$, which can take a value of +1 or -1 (representing positive or negative respectively). The solution hyper-plane is the following:

$$st\ \ y_i = +1 => w.x_i + b \geq +1$$

$$y_i = -1 => w.x_i - b \leq -1$$

$$u = w.x + b$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \qquad\qquad \alpha_i \geq 0, \quad \forall i$$

The scalar b is also termed the bias.A standard method to solve this problem is to apply the theory of Lagrange to convert it to a dual Lagrangian problem. The dual problem is the following.The variables $\alpha_i$ are the Lagrangian multipliers for corresponding data point $x_i$.

$$\min_{\alpha} \Psi\,(\vec{\alpha}) = \min_{\alpha} \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_i \left(\vec{x}_i . \overrightarrow{x_j}\right) \alpha_i \alpha_j - \sum_{i=1}^{N} \alpha_i$$

**3.1 Channel Selection**

To explore the minimum numbers of channels without influencing the performance for long term dynamic wearable EEG monitoring system. Firstly, we found that using no matter 2 channels (Fp1,Fp2), 4 channels (Fp1,Fp2,F7,F8)or 6 channels (Fp1,Fp2,F7,F8,F3,F4), they have almost the similar performance using SASI or EVI feature. We found that Fp1 and Fp2 channels have the same performance compared with those of 4 or 6 frontal EEG channels. The mean accuracy of 2 channels, 4channels and 6 channels of frontal EEG as shown in fig4.

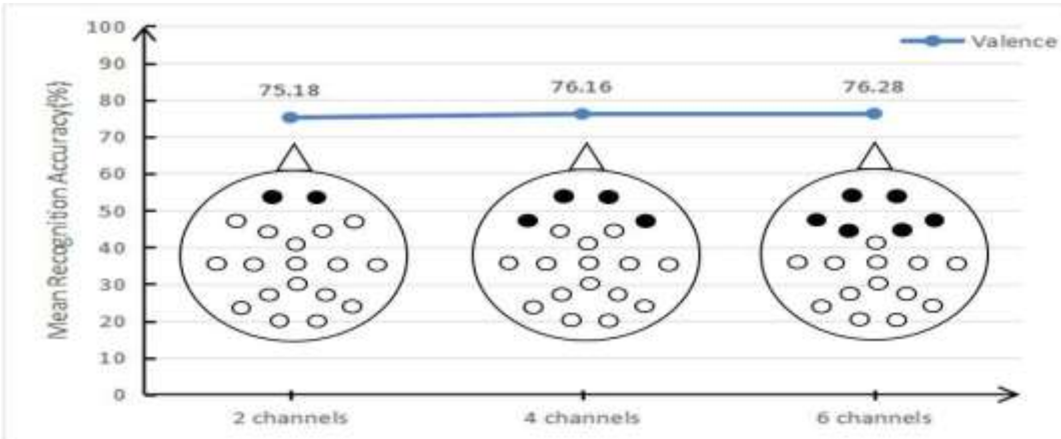


**Figure 4.** Mean accuracy of different channels

## 4. EXPERIMENTAL SETTINGS AND RESULTS

Input is given in terms of voltage and frequency. The input values are converted into EEG wave form as shown in Fig 5. The noise present in the input wave is removed and the wave is separated as gamma, beta, alpha, delta, theta is shown Fig 6.The face expression is also given as input. The input face expression should be related to the input EEG wave which is given already. The face features are separated as eyes, nose, mouth separately and obtained as in the Fig 7. The corresponding EEG which has alpha, beta, gamma, delta, theta have the emotion parameter possibilities for each. Based on the possibilities the features are extracted.

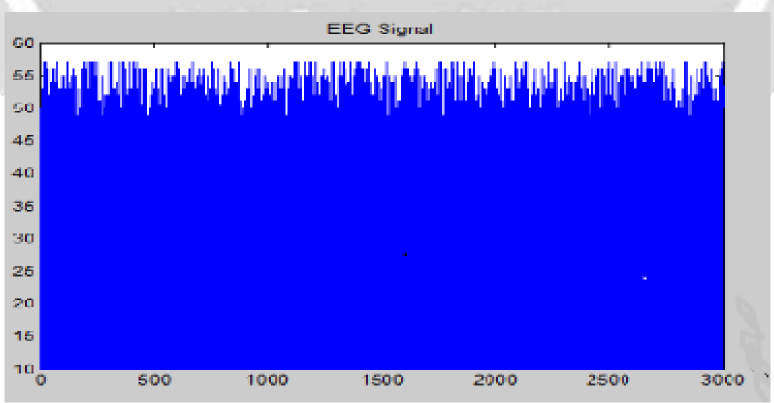


Figure 5 Input EEG signal

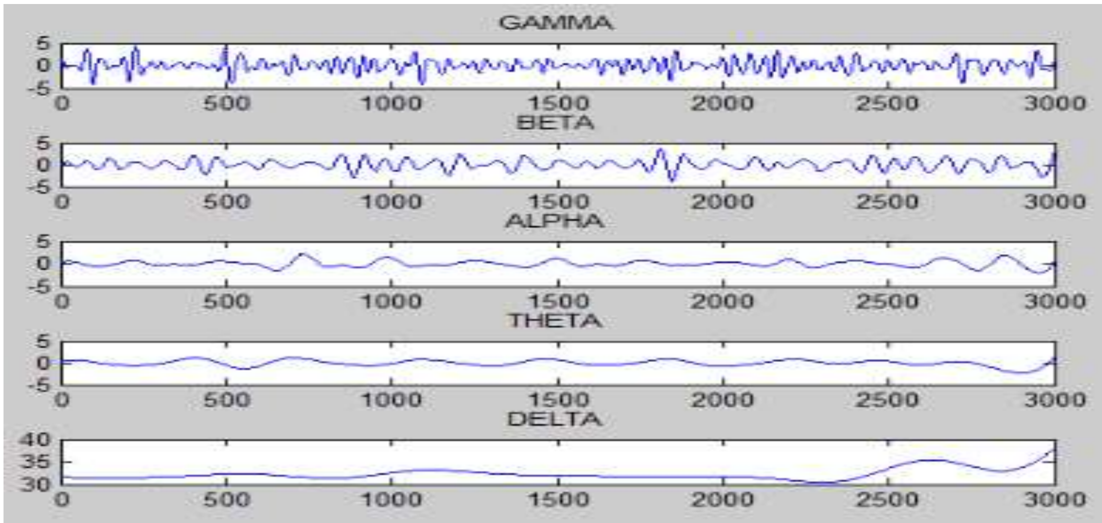


**Figure 6** Preprocessed EEG signal

The face expression segregation will have some emotion parameters, this too obtained by feature extraction. Using SVM classifier those parameter are correlated and give result whether the inputs matches or not. If both face expression and EEG signal parameter matches, then report is generated.

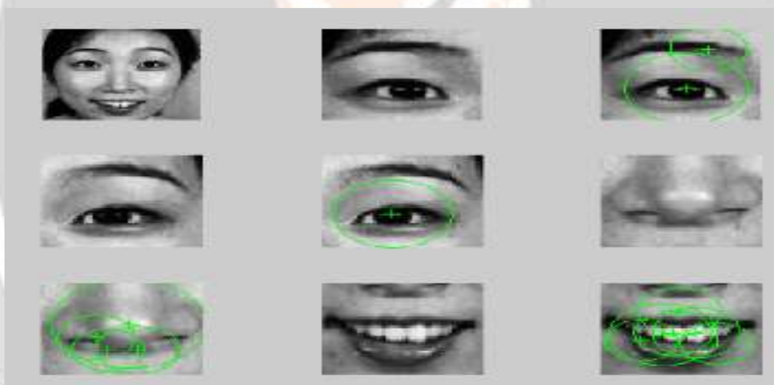

**Figure 7** Face expression segregration

The preprocessed the data of DEAP and divided them for each trial of each subject.Then, features were extracted and SVM classifier was used through adjusting parameters. In order to compare the performance of SVM classifier, a multiclassifier system was built. It verified that SVM hadthe best results among other methods. The numbers of mean accuracy of different methods are shown In Figure 6.There are totally 3462 samples in this experiment. The data were randomly divided into training dataset and test dataset at a ratio of 8:2. The classification accuracy was calculated by the following formula, where Acc represents the recognition accuracy, Ntestrepresents the number of the testing samples, Ncorrec*t*is the number of samples that have been classified correctly.The average accuracy was obtained by repeated experiments 5 times, which reached 75.18% for average and 1130 achieved the maximum accuracy of 76.34%.

Acc=Ncorrect/Ntest

Thus the results of SVM classifier obtained an accuracy to about 76% and it provided the efficient results compared to other classifiers.

## 5. CONCLUTIONS

As this method is implemented using matlab 2013, it asks for the input samples to test. The EEG samples are given as the input, then the facial expression is also given as input. The EEG signal is preprocessed and face expression features are extracted. This is now given to SVM classifier which is used to correlate the EEG signal parameter and face expression parameter and produce the result as normal or abnormal with the report based on the input given. The matching of EEG signals are given for testing and the results are obtained as perfectly matched if EEG signals and the facial expressions of the person. This method is efficient because without the direct contact of the person, by using the stored information the emotion of a person can be detected.

### 5.1 Future Enhancements

This is the one step improvement in the recognition of emotions. In future using the signals of the brain one can also control the thoughts and actions of a person by undergoing research in this field. This can be further improved by adding other types of waves and output can be detected and more face expressions can also be added. Some other algorithm can also be used for future enhancement. As this topic is under research any type of new technique which are efficient to separate EEG signal and face expression can be used. SVM classifier can give accurate output but not more than one sample can be detected at the same time. To overcome this drawback efficient algorithm can be used.

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