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# A Comprehensive Study on Emotional State Analysis of Humans from EEG Signals

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***Abstract*- Emotion plays an important role in the daily life of man and is an important feature of human interaction. Because of its role of adaptation, it motivates people to respond quickly to stimuli in their environment to improve communication, learning and decision making. With the increasing role of the brain-computer interface (BCI) in user-computer interaction, automatic recognition of emotions has become an area of interest in the last decade. The recognition of emotions could be facial expression, gesture, speech and text and could be recorded in different ways, such as electroencephalogram (EEG), positron emission tomography (PET), magnetic resonance imaging (MRI), etc. In this research work, feature extraction feature reduction and classification of emotions have been evaluated on different methods to recognize and classify different emotional states such as fear, sad, frustrated, happy, pleasant and satisfied from inner emotion EEG signals.**

**Keywords:** EEG Signal, Emotion Recognition, EEG, BCI, Feature Extraction, Feature Reduction, Classification, Accuracy**.**

## I. INTRODUCTION

Human emotion includes not only the psychological reaction of a human being to the external world or self-stimulation but also the physiological reaction to these psychological reactions. Human emotion is a combination of human thinking, feeling and behavior.

The role of emotion is ubiquitous in people's daily lives and work. Analyzing and estimating emotions has become an important interdisciplinary research topic in the fields of psychology, neuroscience, computer science, cognitive science and artificial intelligence.

In recent decades, researchers in multiple fields have proposed various methods for emotion recognition. They can be divided into three main methods. One is based on the study of non-physiological signals such as facial expressions [1] and speech [2]. The advantage of emotion recognition using non-physiological signals is that it is easy to perform and does not require special equipment.

The disadvantage is that people can disguise their true emotional states by disguising their facial expressions and phonetic intonations. Thus, the reliability of emotion recognition is not ensured. Moreover, the non-physiological signal recognition method cannot be used for people with disabilities or special diseases. The second approach is the study of physiological signals such as electroencephalogram (EEG) [3], electromyography (EMG) [4], electrocardiogram (ECG) [5], skin resistance (SR) [6], heart rate, pulse rate [6] and so on. These physiological indicators are intrinsic manifestations that are independent of the individuals' control. Therefore, they are more appropriate and effective for emotion recognition. Unlike other physiological signals, EEG is a noninvasive technique with good temporal resolution and acceptable spatial resolution. Therefore, EEG may play a major role in detecting emotions directly in the brain at higher spatial and temporal resolutions [7]. The third method is emotion recognition based on multimodal fusion.

## II. CLASSES OF EMOTIONS

Emotion is a mental or physiological state that is subjective and private, which involves many feelings, thoughts, behaviors and actions. Emotions play a very important role in our daily lives. Emotion helps to make interaction with people fluid. A person's mood influences not only the way they interact with people, but also their actions.

Therefore, it is important to study and recognize emotions. Emotions are easily captured by language, behavior and facial expressions [2]. But these can be falsely expressed by people. These pathways cannot be used effectively by patients with paralysis, strokes, ALS [3] or brain disorders. Therefore, the recognition of emotions is essential for people with conditions included. Therefore, it is important to study the physiological variables that vary with emotions.

Emotions represented along Valence Axis and Arousal axis results into four quadrants. Valence along X-axis has been divided into two main classes called Positive Valence which means high and Negative Valence which means low and keeping the arousal state as constant. Likewise, arousal along Y- axis has been divided into two major classes namely Positive Arousal meaning high and Negative Arousal meaning low keeping the valence state as constant. It results into four major classes of emotions such as High Valence High Arousal (HVHA), Low Valence High Arousal (LVHA), High Valence Low Arousal (HVLA) and Low Valence Low Arousal (LVLA). Figure 1.3 shows the four classes of emotions.

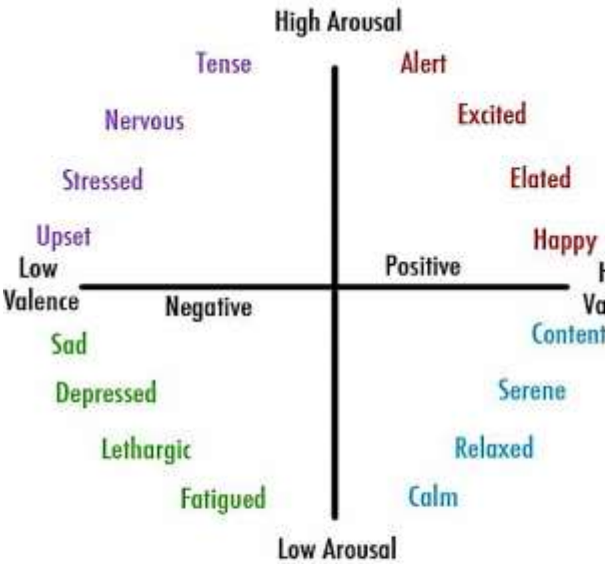


**Figure 1: Dimension of Emotions**

An emotional state of user has garnered increasing attention over the last few years in the research areas of Human Computer Interaction (HCI) and Brain Computer Interface (BCI). Emotions include cognitive as well as perspective process. Basic and dimensional model represents and classify the emotions. Basic model composed of eight basic emotions such as anger, fear, happiness, surprise, disgust, curiosity and acceptance [1].

Dimensional model uses emotion scale with respect to arousal and valence as shown in Fig.1. Arousal is more general property of stimulus which refers to level of activation indicating the degree of excitement i.e. calm to excite whereas valence indicates positive and negative emotions [3].

To standardize the experimental framework for research in human emotions against the two dimension scale, the International Affective Picture System (IAPS) database and International Affective Digitized Sound databases (IADS) are used which include pictures and sounds labeled with valence and arousal values [4][5].

In order to recognize the human emotion by computer or machine various approaches exist such as facial expressions, speech and gestures. The signals captured from Autonomous Nervous System (ANS) are also contribute to human emotion recognition approaches [6]. Moreover, it is accepted that Central Nervous System (CNS) usage is beneficial for emotion recognition over above mentioned emotions recognition approaches. In CNS, signals are captured from origin of the emotion genesis i.e. from brain signals which are captured with the help of Electroencephalogram (EEG), Positron Emission Tomography (PET), Magnetoencephalogram (MEG) and functional Magnetic Resonance Imaging (fMRI). EEG appears to be less intrusive and one of the best time suiting than other three aforementioned [7][8].

## III. RELATED WORK

Nicolaou et al. [30] used the audiovisual methods to detect the valence and excitement in the database of the week. They used the Support Vector Regression (SVR) and long-term bi-directional long-term recovery networks (BLSTM-RNN) to continuously capture emotions over time and in size. Nicolaou et al. It has also been proposed to use anrelevant vector machine (RVM) that attenuates the RVM output for continuous detection of emotions. Although they showed how they improved RVM performance for continuous emotion recognition, they did not directly compare their performance with the recurrent BLSTM neural network.

Baltrusaitis et al. [31] used continuous conditional random fields (CCRF) to collectively determine the emotional dimensions of the continuing ONGO sub-challenge of 2012. They performed better than the SVR.

Bao et al. [32] used facial interaction, acoustics, movement and user functions recorded on cell phones and tablets to estimate film ratings. They found that individual responses are too different and unreliable to be taken into consideration and focus on the treatment of public responses.

McDuff et al. [33] measured the level of public smiles of video advertising in order to evaluate their preference for content. They collected a large number of samples from the crowdsourced users' webcam. In the end, they could see the desire to watch the video again and if the viewers liked the videos.

Chenes et al. [34] used a physiological connection between the different viewers to detect the highlights of the video. Skin temperature and skin galvanic response (GSR) detected the salient points of the video through a physiological link. The precision obtained of 78.2% in detection is underlined by the proposed method.

In a more recent study, Fleureau et al. [35] used simultaneously the GSR responses of a group of listeners to create an emotional trace of the film. It has been shown that the traces produced by physiological resting positions correspond to the highlighting specified by the user.

Kierkels et al. [36] extended these results and analyzed the efficacy of markers detected by the physiological signals for the personalized emotional mark of the video. The quantized excitation and valence values for a clip were then mapped to the emotions tags. This association allowed you to retrieve video clips based on keyword queries. A similar approach was adopted with a linear peak regression for the emotional characterization of music videos. Excitement, valence, domination and equivalence / antipathy were determined by physiological signals and video content.

Koelstra et al. [37] used EEG and peripheral physiological signals to emotionally mark music videos. In a similar study [38], multimodal emotional staining was performed with EEG and a pupillary reflex.

Khomami Abadi et al. [39] recorded and analyzed Magnetoencephalogram (MEG) signals as an alternative to EEG signals with the ability to monitor brain activity.

Ralph Adolph et al. [40] discussed the recognition of emotions that characterize a number of structures. The techniques of recognition of emotions discussed in this article are facial expressions and prosodic detection.

R.J. Ramteke and Khachane Monali [41] discussed the method that explained the method for k-NN as a classifier. Furthermore, the multivariate approach is estimated on the basis of mutual information from the nearest neighbor.

Changmok Oh et al. [42] discussed the classification of EEG patterns that will be useful in Brain Computer Interface. They used PCA and neural networks to classify EEG models.

Vaishnavi et al. [43] proposed method consists of four phases: data collection, pre-processing, extraction of characteristics and classification. Themes are stimulated for sad and happy emotions. The statistical characteristics are then assigned to a k-NN classifier. The nearest adjacent classifier offers different classification accuracy for different combinations of training and test records. The system has been tested on a number of topics to observe the performance of the k-NN classifier.

In this paper a comparative study of EEG based emotion recognition techniques is discussed on the basis of some parameters.

Table 1 depicts the comparison based on above mentioned parameters. Feature extraction method indicates method used to extract the appropriate features from recorded EEG data related to emotions. Classification method indicates classifier used for discriminating different emotions, number of channels or electrodes of EEG recording device, frequency bands used for analyzing particular emotion, location of electrodes on brain. Time constraint specifies whether it is real time emotion recognition or not. All whole emotion recognition process is classified as good or better based on its percentage accuracy.

**Table 1: Comparison of Existing EEG based Emotion Recognition**

| Ref. | Dataset and Features | Technique | Accuracy |
|---|---|---|---|
| [15] | Discrete Wavelet Transform (DWT) | ANN | 55.58% |
| [16] | Raw data band power feature of 4 frequency bands | SVM | 65% |

| | | | |
|---|---|---|---|
| [17] | Raw data and individual normalization Entropy and Energy of gamma frequency band | KNN | 86.75% Valence 84.05% Arousal |
| [18] | Preprocessed data statistical features, band power, Hjorth parameters and fractal dimension | SVM | 73.14% Valence 73.06% Arousal |
| [19] | Preprocessed data power ratio, power spectral density, entropy, Hjorth parameters and correlation | ANN | 72.87% Valence 75.00% Arousal |
| [20] | Preprocessed data PSD and DE | SVM | 85.20% Valence 80.50% Arousal |
| [21] | Preprocessed data and channel normalization Entropy and Energy of gamma frequency band | KNN (10-fold cross-validation all samples) | 90% |

## IV. PROPOSED METHODOLOGY

The aim of this research is to classify different emotions as illustrated in figure 2. The system's methodology consists of four main steps. The first step was Signal acquisition. The second step was signal preprocessing, to remove the noises and unwanted data. The third step was features extraction from the EEG signals. The fourth step was classification of the signals to the corresponding emotions.

The proposed model categorizes human emotions into six classes based on valence and arousal as described below:

Class 1, High Arousal

Class 2, Low Arousal

Class 3, Normal Arousal

Class 4, High Valence

Class 5, Low Valence

Class 6, Normal Valence

Further for deciding the emotion following rules are followed as:

Rule 1: High Arousal Low Valence (HALV) representing anger, upset, stress, and frustrated.

Rule 2: High Arousal High Valence (HAHV) representing happy, excited, and interested.

Rule 3: Low Arousal High Valence (LAHV) representing relief, relaxed, and comfortable.

Rule 4: Low Arousal Low Valence (LALV) representing tired, bored, and sad.

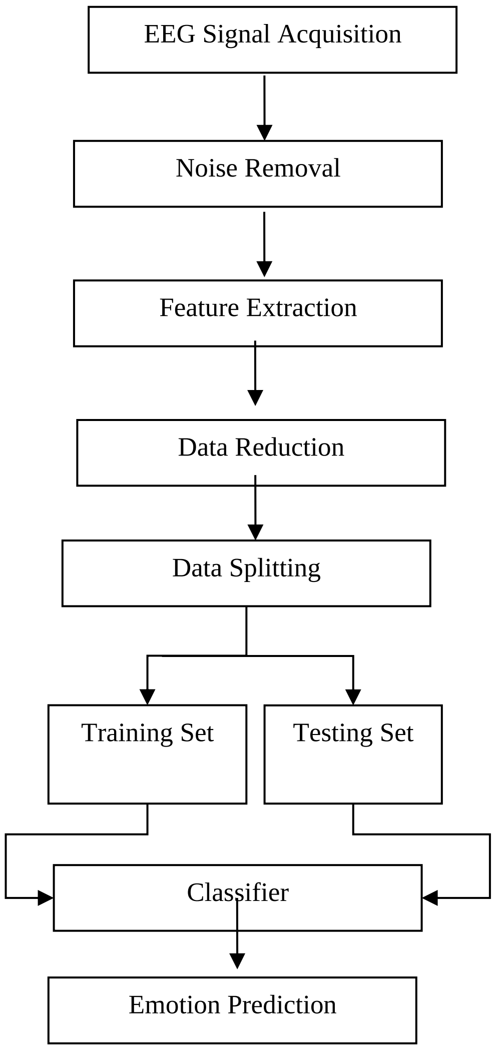


**Figure 2: Flow Chart of Proposed Methodology**

## V. CONCLUSION

The recognition of emotions is very important, especially in terms of application, for example patient monitoring and the treatment management system of this patient. In this work, an EEG-based emotion recognition system is developed, consisting of a feature extraction subsystem and a classification subsystem. Measuring emotions in BCI could improve the quality and efficiency of human-computer interaction and could also be a new way for computers to understand human emotions and behaviors. This research presents the development of an emotion recognition system based on the processing of the EEG signal.

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