EEG-based emotion recognition approach for e-healthcare applications

Conference Paper · July 2016

DOI: 10.1109/ICUFN.2016.7536936

4 authors:

Mouhannad Ali
Alpen-Adria-Universität Klagenfurt

Ahmad Haj Mosa
PwC Vienna

Fadi Al Machot
Norwegian University of Life Sciences

Kyandoghere Kyamakya
Alpen-Adria-Universität Klagenfurt

EEG-Based Emotion Recognition Approach for E-Healthcare Applications

Mouhannad Ali, Ahmad Haj Mosa, Fadi Al Machot and Kyandoghere Kyamakya
Institute of Smart System Technologies
Alpen-Adria University
Klagenfurt, Austria
Email: forename.surname@aau.at

***Abstract*—Emotions play an extremely important role in how we make a decision, planning, reasoning and other human mental states. The recognition of these emotions is becoming a vital task for e-healthcare systems. Using bio-sensors such as Electroencephalogram (EEG) to recognise the mental state of patients that could need a special care offers an important feedback for Ambient Assisted Living (AAL). This paper presents an EEG-based emotion recognition approach to detect the emotional state of patients. The proposed approach combines wavelet energy, modified energy, wavelet entropy and statistical features to classify four emotion states. Three different classifiers are used (quadratic discriminant analysis , k-nearest neighbor, and support vector machines) to recognise the emotion of patients robustly. The new approach is tested based on the EEG database "DEAP" using four electrodes. It shows high performance compared to existing algorithms. An overall classification accuracy of 83.87% is obtained.**

I. Introduction

The mental status of patient's is widely used to understand the behavioral and cognitive functioning, e.g., people with depression often have worse physical health, as well as worse self-perceived health, than these without depression. Additionally, patients with both depression and physical health problems are at particular risk because the related physical problem can complicate depression assessment and treatment by masking or mimicking its symptoms [1]. Therefore, e-healthcare systems are highly required to improve the overall quality of patients' life. Currently, there are several works to detect emotions using different types of sensors, e.g., microphones to analyse the audio signals [2], thermal cameras [3] or wearable sensors and smart phones [4].

However, visual and audio sensors were widely used for emotion recognition during several decades ago. This tend to be less effective due to the fact that, facial expressions can be faked and the voice data are not always available because of the noise of the environment. Nowadays, e-healthcare systems based on biological signals started to get the attention from the research community.

This paper focuses on a specific type of biological signals called Electroencephalogram (EEG). The EEG is a measure of electrical activity of the brain along the scalp. These activities are acquired by attaching a number of electrodes over the scalp [5]. Consequently, the placement of the electrodes on the scalp is based on the International 10-20 System [6] which ensures standardized reading (reproducibility) in order to compare subjects to each other and compare subject's studies over time. Human's brain waves compose from five different frequency bands called delta (0.1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-64 Hz) [7].

Our target is to improve the recognition rate of patient's emotion using the combination of wavelet energy [8], modified energy [9], wavelet entropy and statistical moments for feature extraction.

This paper is organized as follows: section 2 presents an overview of existing methods. Section 3 provides the research methodology by describing data acquirement, preprocessing, feature extraction and classification process. Section 4 provides the performance of the proposed approach. Finally, the concluding remarks are given in section 5.

II. Related Works

In the research field of EEG based emotion recognition, different approaches are proposed in the literature. The most well-known methods in the state-of-the-art use wavelet analysis [10], statistical measures [11] and Fourier analysis [12] to extract features from EEG signals. The resulting features are classified using different classifiers such as support vector machine (SVM) [13], fuzzy k-means [14], KNN [15]. These classifiers categorise the emotion states into two states of emotions [16], three states [10], four states [17], five states [11] and six states [18], where increasing the number of emotional states to be classified, it decreases the overall performance of the proposed classification approaches.

Additionally, Jirayucharoensak et al. proposed an algorithm based on power spectrum density and deep learning network in order to classify 9 distinct emotions from EEG signals [19]. The approach does not show high recognition rates. Furthermore, Jie et al. developed a methods based on sample entropy which gives a well accepted detection rate under real-time constraints but just for two different emotions [20].

Moreover, Liu et al. combined fractal dimension and higher order crossing analysis with statistical measures for classifying EEG signals from 4 electrodes [18]. The obtained results are promising for classifying two emotions in real-time but still need to be improved for 4 or more distinct emotions. However, further research is needed to improve the recognition rate and decrease the number of electrodes on scalp.

III. Research Methodology

This section provides a comprehensive presentation of EEG data selection and preparation. Then, the feature extraction step is explained using Discrete Wavelet Transform and Wavelet Energy. At the end of this section, the classification step is illustrated using different classifiers, e.g., quadratic discriminant analysis (QDA), k-nearest neighbor and support vector machines.

A. EEG Data Input

In this paper, a public available benchmark dataset for emotion analysis using physiological signals is used to test our new approach. The dataset is called (DEAP) which is collected by Koelstra et al. and includes the EEG and peripheral signals from 32 subjects. The number of test persons is 16 women and 16 men between 19 and 32 years old. The EEG signals were recorded over the scalp according to $10-20$ International System [21]. The positions of the 32 electrodes are: Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4 and O2, see Figure. 1.

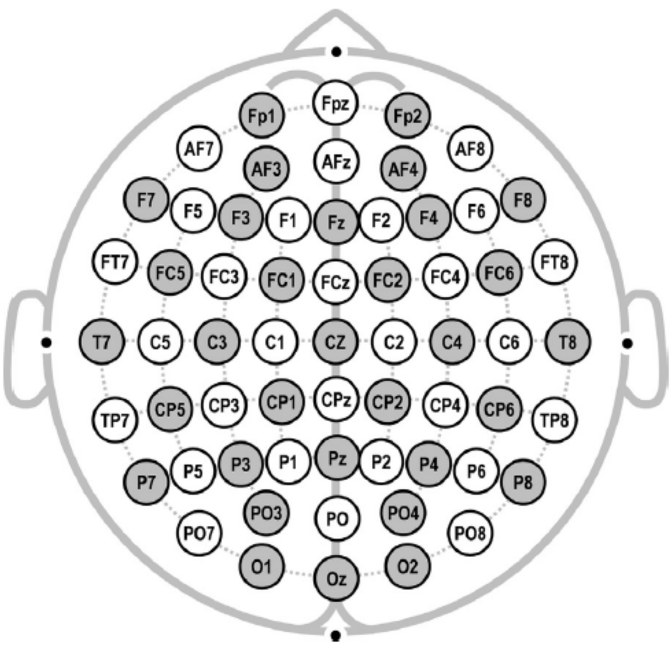

Fig. 1. International 10-20 system for 32 electrodes(Gray circles) [22].

In DEAP dataset, all the EEG data was downsampled to $128Hz$. Eye artifacts were eliminated by blind source separation technique and a bandpass frequency filter from $4.0 - 45.0Hz$ was applied.

In the experiments, each subject watched a 41 minutes music video and performed a self-assessment of their degree of valence and arousal using Self-Assessment Manikins (SAM) questionnaire [23]. SAM is a distinguished questionnaire that visualizes the degree of valence and arousal dimensions by manikins. The subjects had to select one number from 1 to 9 written below the manikins, see Figure. 2.

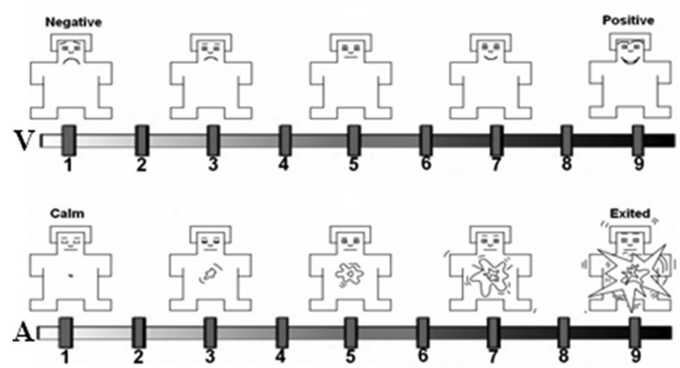

Fig. 2. Self-assessment manikins scales of valence (above) and arousal (below) [16].

In this study, we mapped the scales (1-9) into 2 levels of each valence and arousal states according to SAM ratings. The valence scale of $1-5$ was mapped to negative, $6-9$ to positive, respectively .The arousal scale of $1-5$ was mapped to passive, and $6-9$ to active, respectively.

B. Feature Extraction

Several features are proposed throughout literature to deal with EEG-based emotion recognition problems. In this section, we explain the chosen features that have been extracted from the EEG signals to detect the patient's emotions.

1) Discrete Wavelet Transform: Discrete Wavelet Transform (DWT) analyzes the signal at different resolutions. DWT decomposes the signal into several successive frequency bands by using a scaling and a wavelet function. It is a powerful analytical tool for the non-stationary signals, in our case, they are the EEG signals [24]. It represents various aspects of EEG signals such as trends, discontinuities, and repeated patterns [25].

Basically, it uses time-scale signal analysis, signal decomposition and signal compression. DWT decomposes the EEG signal into a set of sub-bands through consecutive time domain high-pass and low-pass filtering. Figure. 3 shows the sub-band decomposition of a signal f using DWT. The high-pass filter g decomposes the input signal and the output represents the detail coefficients. The low-pass filter h is its mirror version which gives the approximation coefficients [26].

The figure shows $A1$ and $D1$ that are the first level approximation and detail coefficients respectively.

In this work, the selection of suitable wavelets is required to analyze the EEG signals. Daubechies wavelets are appropriate to detect changes of EEG signals duo to its smoothing features [27]. The number of the wavelet's decomposition levels are determined depending on the dominant frequency components of the signals [26]. In our case, we use EEG signals at $128Hz$ sampling rate, therefore, five levels Daubechies wavelet of order 4 (db4) are used to extract the sub-bands of brain waves (Delta, Theta, Alpha, Beta, Gamma).

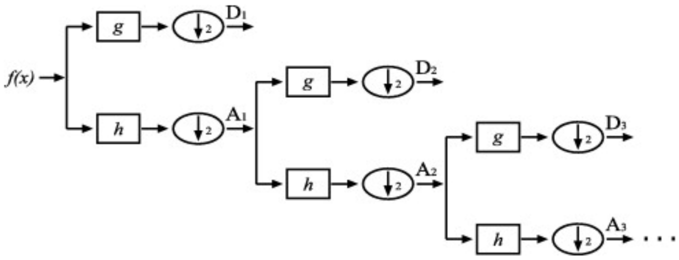

Fig. 3. Sub-band decomposition of DWT implementation

2) Wavelet Energy and wavelet entropy: After applying DWT on EEG signals, the wavelet coefficients at each sub-band (scale) l are used to estimate the wavelet energy and wavelet entropy as follows [28]:

$$E_l = \sum_{n=1}^{2^{S-1}-1} |C_X(l,n)|^2 \quad , \quad N = 2^S, 1 < l < S \tag{1}$$

$$E_l = \sum_{n=1}^{2^{S-1}-1} |C_X(l,n)|^2 \exp(|C_X(l,n)|^2) \qquad N = 2^S, 1 < l < S \tag{2}$$

where $C_X(l,n)$ is the discrete wavelet translation at the lth scale and S is the number of scales.

Moreover, an energy based feature Recursing Energy Efficiency (REE) [9] of each wavelet sub-band is used in order to analyze the characteristic natures of different EEG patterns. The calculation of REE of the Gamma band is given in Eq.(9) (the same for the rest). Additionally. the Logarithmic REE (LREE) and Absolute Logarithmic REE (ALREE) are considered as two more features, (see Eq. (10-12)).

$$REE_{gamma} = \frac{E_{gamma}}{E_{total}} \tag{3}$$

$$LREE_{gamma} = \log_{10}\left[\frac{E_{gamma}}{E_{total}}\right] \tag{4}$$

$$ALREE_{gamma} = \left|\log_{10}\left[\frac{E_{gamma}}{E_{total}}\right]\right| \tag{5}$$

$$E_{total} = E_{Delta} + E_{Theta} + E_{Alpha} + E_{Beta} + E_{gamma} \tag{6}$$

3) Statistical-Based Features: After the energy calculation of the signal, the following statistical moments proposed by [29] and [11] have been calculated to increase the overall performance of the classification technique. Given an EEG signal $X(n)$ where $n = 1, ..N$ and N is the total number of samples, the proposed statistical features can be defined as follows:

1) The mean of the raw signal

$$\mu x = \frac{1}{N}\sum_{n=1}^{N} X(n) \tag{7}$$

2) The standard deviation of the raw signal

$$\sigma x = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(X(n) - \mu x)^2} \tag{8}$$

3) The mean of the absolute values of the first differences of the raw signal

$$\delta x = \frac{1}{N-1}\sum_{n=1}^{N-1} \mid X(n+1) - X(n) \mid \tag{9}$$

4) The mean of the absolute values of the first differences of the standardized signal

$$\overline{\delta} x = \frac{1}{N-1}\sum_{n=1}^{N-1} \mid \overline{X}(n+1) - \overline{X}(n) \mid = \frac{\delta x}{\sigma x} \tag{10}$$

5) The mean of the absolute values of the second differences of the raw signal

$$\gamma x = \frac{1}{N-2}\sum_{n=1}^{N-2} \mid X(n+2) - X(n) \mid \tag{11}$$

6) The mean of the absolute values of the second differences of the standardized signal

$$\overline{\gamma} x = \frac{1}{N-2}\sum_{n=1}^{N-2} \mid \overline{X}(n+2) - \overline{X}(n) \mid = \frac{\gamma x}{\sigma x} \tag{12}$$

where $\overline{X}(n) = (X(n) - \mu x)/\sigma x$ is the standardized signal.

C. Classification

For classification, three different classifiers have been used in order to complete an efficient emotion recognition model.

1) Quadratic Discriminant Analysis (QDA): Quadratic Discriminant Analysis (QDA) is the most commonly used method for training a classifier. It assumes that the likelihood of each class is normally distributed and uses the posterior distributions to estimate the class for a given test point [30], [31]. The normal (Gaussian) parameters of each class are usually estimated from training points with maximum likelihood (ML) estimation [32].

2) k-Nearest Neighbor (KNN): KNN is a simple and intuitive method to classify unlabeled samples (testing data) by its similarity with the training data. In general, giving an unlabeled sample X, the KNN classifier finds the K closest neighborhood samples in the training data and labels the sample X with the class label which appears most frequently in the neighborhood of k time [33].

3) Support Vector Machines (SVMs): The SVM is a classifier that separates a set of objects into classes so that the distance between the class borders is as large as possible. The idea of SVM is to separate both classes with a hyperplane so that the minimal distance between elements of both classes and the hyperplane is maximal [34]. In our approach, the training data are not linearly separable due to noise or the classes distribution of EEG data. Therefore, the training data points are projected into a higher-dimensional space where the data points effectively become linearly separable using kernel trick techniques, e.g., polynomial kernels, Multilayer perceptron kernels and Radial Basis Function (RBF). After testing these kernels for transforming the feature space, the RBF kernel was chosen empirically.

IV. Experimental Results

The 32 subjects of DEAP dataset have been considered in our experiments. The data of each subject were clipped into 2 second time window where each one should be classified into one labeled emotion. In this paper, we classify the data into 4 main classes, 2 classes of each valence and arousal states, see Figure. 4. The classes are:

- High Valence/High Arousal (HVHA). This class includes positive emotions such as happy and excited.
- High Valence/Low Arousal (HVLA). This class includes emotions such as relaxed, calm and pleased.
- Low Valence/High Arousal (LVHA). This class includes emotions such as angry, fear and distressed.
- Low Valence/Low Arousal (LVLA). This class includes negative emotions such as sad and depressed.

Regarding the number of EEG electrodes (channels), we considered only 4 channels from 32 that have been included in this study. The positions of these channels according to the $10-20$ System were $Fp1, Fp2, F3$, and $F4$. These channels were chosen based on the following research studies [35], [36], [28]. These studies prove the role of the prefrontal cortex in emotion regulation and conscious experience which justify our channel selection. To evaluate the system performance, EEG data is divided into 70% for training and 30% for testing. The training and test sets are spilt from different subjects to insure the independence between both sets. Table I shows the classification accuracy of each emotion state using 3 classification methods (quadratic discriminant analysis (QDA), k-nearest neighbor, and support vector machines (SVMs)). The best performance is given by SVMs classifier which exhibits an accuracy value of 83.87%. In order to illustrate more information about the performance of SVMs classifier, Table II lists different performance measures (Specificity, Precision and Recall) of each emotion state using SVMs classifier. We can see the recall and precision performances are changing from class to another. These changes occur due to several reasons, i.e., the emotion-relevant signal patterns may widely differ from person to person or from a specific situation to another. Moreover, it is hard to find the exact correlation between the classes (patterns) due to the problem of the precise definition of emotions and their meanings [37]. In general, comparing with other approaches, our approach can recognize four emotions and achieves better accuracy with fewer electrodes.

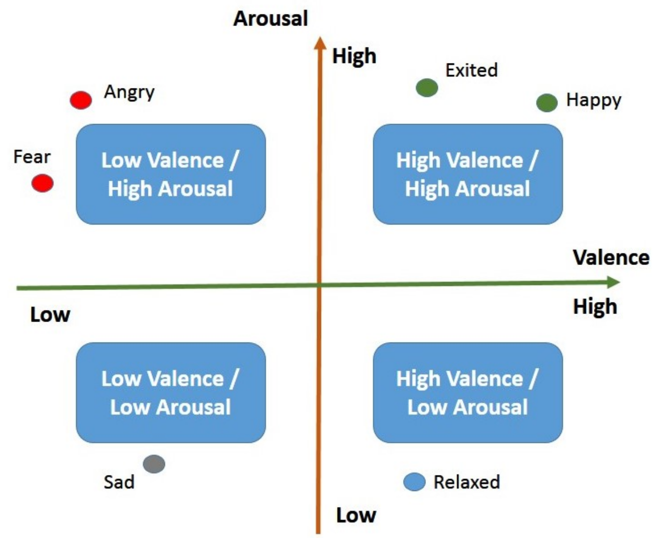

Fig. 4. Arousal-valence based emotion states.

TABLE I
Classification accuracy of different classifiers.

Method	HVHA	HVLA	LVHA	LVLA	Overall
QDA	55.33%	67.15%	60.03%	60.59%	60.78%
KNN	76.75%	72.90%	76.90%	75.54%	75.53%
SVMs	84.95%	84.14%	83.12%	83.25%	83.87%

TABLE II
Performance measures of SVMs classifier.

Measure	HVHA	HVLA	LVHA	LVLA	Overall
Specificity	83.06%	89.15%	91.86%	90.95%	88.76%
Precision	77.02%	56.28%	63.95%	52.86%	62.53%
Recall	85.06%	61.14%	54.64%	46.98%	61.96%

V. Conclusion

E-healtcare systems based on EEG signals can be deployed and applied in different smart environments, e.g., smart cars, smart homes and Ambient Assisted Living systems. Furthermore, they can help disabled subjects to move or control several machines, computers and artificial limbs.

This work, we have presented an approach to detect the mental state of patients using Electroencephalogram (EEG) signals. For this, we propose to use wavelet energy, modified energy, wavelet entropy and statistical moments from brain electrical activity. In contrast to other approaches, the proposed approach did consider the requirements of such systems; (a) high detection rate and (b) minimal number of electrodes to detect the humans emotions robustly.

As a part of the future work, it is intended to fuse the EEG signals with several other sensors (wearable sensors) in order to obtain better classification which in turn provides better results and comfort to the patients.

References

[1] D. Goldberg, "The detection and treatment of depression in the physically ill," *World Psychiatry*, vol. 9, no. 1, pp. 16–20, 2010.

[2] F. Al Machot, A. H. Mosa, K. Dabbour, A. Fasih, C. Schwarzlmuller, M. Ali, and K. Kyamakya, "A novel real-time emotion detection system from audio streams based on bayesian quadratic discriminate classifier for adas," in *Nonlinear Dynamics and Synchronization (INDS) & 16th Int'l Symposium on Theoretical Electrical Engineering (ISTET), 2011 Joint 3rd Int'l Workshop on*. IEEE, 2011, pp. 1–5.

[3] A. Kolli, A. Fasih, F. Al Machot, and K. Kyamakya, "Non-intrusive car driver's emotion recognition using thermal camera," in *Nonlinear Dynamics and Synchronization (INDS) & 16th Int'l Symposium on Theoretical Electrical Engineering (ISTET), 2011 Joint 3rd Int'l Workshop on*. IEEE, 2011, pp. 1–5.

[4] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*. IEEE, 2013, pp. 671–676.

[5] E. Niedermeyer and F. L. da Silva, *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins, 2005.

[6] R. W. Homan, J. Herman, and P. Purdy, "Cerebral location of international 10–20 system electrode placement," *Electroencephalography and clinical neurophysiology*, vol. 66, no. 4, pp. 376–382, 1987.

[7] A. Konar and A. Chakraborty, *Emotion Recognition: A Pattern Analysis Approach*. John Wiley & Sons, 2014.

[8] L. Guo, D. Rivero, J. A. Seoane, and A. Pazos, "Classification of eeg signals using relative wavelet energy and artificial neural networks," in *Proceedings of the first ACM/SIGEVO Summit on Genetic and Evolutionary Computation*. ACM, 2009, pp. 177–184.

[9] M. Murugappan, N. Ramachandran, Y. Sazali *et al.*, "Classification of human emotion from eeg using discrete wavelet transform," *Journal of Biomedical Science and Engineering*, vol. 3, no. 04, p. 390, 2010.

[10] M. Murugappan, M. Rizon, R. Nagarajan, S. Yaacob, I. Zunaidi, and D. Hazry, "Eeg feature extraction for classifying emotions using fcm and fkm," *International journal of Computers and Communications*, vol. 1, no. 2, pp. 21–25, 2007.

[11] K. Takahashi, "Remarks on svm-based emotion recognition from multi-modal bio-potential signals," in *Robot and Human Interactive Communication, 2004. ROMAN 2004. 13th IEEE International Workshop on*. IEEE, 2004, pp. 95–100.

[12] M. Akin, "Comparison of wavelet transform and fft methods in the analysis of eeg signals," *Journal of medical systems*, vol. 26, no. 3, pp. 241–247, 2002.

[13] N. Cristianini and J. Shawe-Taylor, *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press, 2000.

[14] J. De Gruijter and A. McBratney, "A modified fuzzy k-means method for predictive classification," *Classification and related methods of data analysis*, pp. 97–104, 1988.

[15] P. Cunningham and S. J. Delany, "k-nearest neighbour classifiers," *Mult Classif Syst*, pp. 1–17, 2007.

[16] S. Hatamikia, K. Maghooli, and A. M. Nasrabadi, "The emotion recognition system based on autoregressive model and sequential forward feature selection of electroencephalogram signals," *Journal of medical signals and sensors*, vol. 4, no. 3, p. 194, 2014.

[17] S. N. Daimi and G. Saha, "Classification of emotions induced by music videos and correlation with participants rating," *Expert Systems with Applications*, vol. 41, no. 13, pp. 6057–6065, 2014.

[18] Y. Liu and O. Sourina, "Real-time subject-dependent eeg-based emotion recognition algorithm," in *Transactions on Computational Science XXIII*. Springer, 2014, pp. 199–223.

[19] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "Eeg-based emotion recognition using deep learning network with principal component based covariate shift adaptation," *The Scientific World Journal*, vol. 2014, 2014.

[20] X. Jie, R. Cao, and L. Li, "Emotion recognition based on the sample entropy of eeg," *Bio-medical materials and engineering*, vol. 24, no. 1, pp. 1185–1192, 2014.

[21] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *Affective Computing, IEEE Transactions on*, vol. 3, no. 1, pp. 18–31, 2012.

[22] H. J. Yoon and S. Y. Chung, "Eeg-based emotion estimation using bayesian weighted-log-posterior function and perceptron convergence algorithm," *Computers in biology and medicine*, vol. 43, no. 12, pp. 2230–2237, 2013.

[23] M. M. Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.

[24] R. Panda, P. Khobragade, P. Jambhule, S. Jengthe, P. Pal, and T. Gandhi, "Classification of eeg signal using wavelet transform and support vector machine for epileptic seizure diction," in *Systems in Medicine and Biology (ICSMB), 2010 International Conference on*. IEEE, 2010, pp. 405–408.

[25] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of eeg records in an epileptic patient using wavelet transform," *Journal of neuroscience methods*, vol. 123, no. 1, pp. 69–87, 2003.

[26] U. Orhan, M. Hekim, and M. Ozer, "Eeg signals classification using the k-means clustering and a multilayer perceptron neural network model," *Expert Systems with Applications*, vol. 38, no. 10, pp. 13 475–13 481, 2011.

[27] A. Subasi, "Eeg signal classification using wavelet feature extraction and a mixture of expert model," *Expert Systems with Applications*, vol. 32, no. 4, pp. 1084–1093, 2007.

[28] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from eeg using higher order crossings," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 14, no. 2, pp. 186–197, 2010.

[29] R. W. Picard, E. Vyzas, and J. Healey, "Toward machine emotional intelligence: Analysis of affective physiological state," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 23, no. 10, pp. 1175–1191, 2001.

[30] T. Hastie, R. Tibshirani, J. Friedman, T. Hastie, J. Friedman, and R. Tibshirani, *The elements of statistical learning*. Springer, 2009, vol. 2, no. 1.

[31] S. Srivastava, M. R. Gupta, and B. A. Frigyik, "Bayesian quadratic discriminant analysis." *Journal of Machine Learning Research*, vol. 8, no. 6, pp. 1277–1305, 2007.

[32] F. Scholz, "Maximum likelihood estimation," *Encyclopedia of Statistical Sciences*, 1985.

[33] L. E. Peterson, "K-nearest neighbor," *Scholarpedia*, vol. 4, no. 2, p. 1883, 2009.

[34] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.

[35] C. P. Niemic and K. Warren, "Studies of emotion," *A Theoretical and Empirical Review of Psychophysiological Studies of Emotion.(Department of Clinical and Social Psychology). JUR Rochester*, vol. 1, no. 1, pp. 15–19, 2002.

[36] R. Davinson, D. Jackson, and N. Kalin, "Emotion, plasticity, context and regulation," *Psychological Bolletin*, vol. 126, no. 2, pp. 890–909, 2000.

[37] J. Kim, *Bimodal emotion recognition using speech and physiological changes*.