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Wavelet based machine learning models for classification of human emotions using EEG signal

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ABSTRACT

Humans have the ability to portray different expressions contrary to the emotional state of mind. Therefore, it is difficult to judge the human's real emotional state simply by judging the physical appearance. Although researchers are working on facial expressions analysis, voice recognition, gesture recognition accuracy levels of such analysis are much less and the results are not reliable. Classifying the human emotions with machine learning models and extracting discrete wavelet features of Electroencephalogram (EEG) is proposed. The EEG data from Database for Emotion Analysis using Physiological signal (DEAP) online datasets is used for analysis and consists of peripheral biological signals as well as EEG recordings. EEG signal is collected from 32 subjects while watching 40 1-min-long music videos. Each video clip is rated by the participants in terms of the level of Valence, Arousal, Dominance. In the proposed work we have considered a significant band of EEG with a reduced frontal electrode (Fp1, F3, F4, Fp2) to get a comparable good result. The accuracy obtained from K- nearest neighbour (KNN), Fine KNN and Support Vector Machine (SVM) are 92.5%, 90% and 90% respectively for Valence, Arousal and Dominance.

1. Introduction

Emotion is one of the most physiological characteristics of human is associated with physical, mental and social health Human emotion can be described in many ways. In response to an external stimulus, changes of states taking place consciously or subconsciously [1]. Emotion play an important role in day-to-day life. Generally, an emotion is misinterpreted with the states like Mood and Affect [2]. Due to busy modern lifestyle and other factors people are more inclined to emotion related problems like Depression, Anxiety. Bipolar disorder and many more [3]. In recent years, an innovative field of computation, known as affective computing is persistently trying to make human-computer interaction (HCI) more natural [4]. The emotion types are indicated and described by the following models: Discrete emotion and two-dimensional valence-arousal model [5]. Physiological signals or/and emotional expressions of users are generally used for the recognition of emotional states. In recent years, lot of researchers are using physiological signals such as blood volume pulse, skin temperature, Electromyogram (EMG), Electrocardiogram (ECG), Galvanic skin Resistance (GSR) and Electroencephalogram (EEG) [6]. The EEG signals can be decomposed within 5 different frequency bands along with mental state associated with them are Delta(δ), Theta wave (θ), Alpha (α), Beta (β) and Gamma (γ). Researchers can use either discrete or dimensional emotion model. Ekman was proposed discrete model [7] with six basic emotions namely fear, sad, disgust, angry, happiness and surprise. The 2-dimensional bipolar model was proposed by Russell [8]. Based on Russell's 2-dimensional Valence-Arousal model was developed [9] and shown in Fig. 1.

A database for emotion analysis using physiological signals (DEAP) has been defined as a multi-modal directory that combines electroencephalography (EEG) data and other physiological signals from 32 individuals while they watch particular video clips to better understand how people react emotionally. The dataset includes 8 extra physiological markers in addition to 32-channel electroencephalogram readings. The 40 1-min music snippets that were selected have been rated according to their capacity to elicit emotions. Using 10–20 electrode positions and the 512 Hz frequency range, 32 electroencephalographic streams were collected as participants listened to the 40 music clips that were chosen [10].

The EEG signals from various electrodes in different scalp regions viz., frontal, parietal, temporal and occipital are studied. The region-

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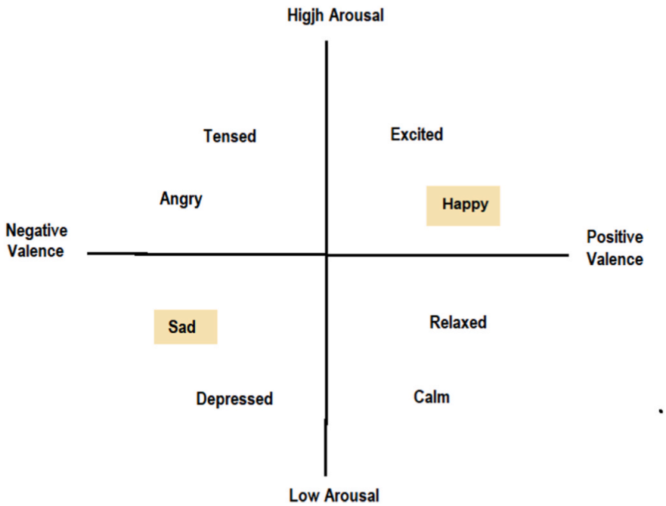

Fig. 1. Valence- arousal emotion model.

based classification is performed by considering each scalp region separately. Among all other scalp region electrodes, the frontal region electrodes performed better and gave the highest classification accuracy. The results indicate that the use of a set of frontal electrodes (Fp1, F3, F4, Fp2) for emotion recognition can simplify the acquisition and processing of EEG data.

The rest of the paper is categorized as follows: The literature review given under section 2 is based on the categorization of emotion into two emotion models. Section 3 describes the proposed methodology. Experiments and results are given in section 4, and concluding remarks are given under section 5.

2. Related work

Alhalaseh et al. [11] the study concentrates on a system that efficiently integrates the necessary phases of Electroencephalogram signal processing and extraction of necessity features. For signal analysis, this was accomplished via Empirical Mode Decomposition/Intrinsic Mode Functions (EMD/IMF) and Variational Mode Decomposition (VMD). The feature extraction technique was carried out using entropy and Higuchi's Fractal Dimension (HFD) technology. The DEAP database had been used to categorize emotions via naive Bayes, k-nearest neighbour (k-NN), convolutional neural network (CNN), and decision tree (DT). Using the CNN classifier, analysts were able to accomplish a 95.20% precision. Moshfeghi et al., [12] EEG data were collected from the frontal and central lobes of the brain using six electrodes. The retrieved variables were divided into three groups that are each categorized by using Waikato Environment for Knowledge Analysis (WEKA) machine learning technique with tenfold replication. When triple emotional states are utilized to categorize, the precision outcome was 54%, and when two emotional states were being used to categorize, the correctness result was 74%.

Vaishali M Joshi et al., [13] the Linear Formulation of Differential Entropy (LF-DfE) feature extractor and Bilinear Long Short-Term Memory (BiLSTM) network decoder were used to create a regime for recognizing emotions through Electroencephalogram signals. The suggested technique employed SEED database for distinguishing emotions into positive emotions, neutral emotions or negative emotions, using Database for emotion analysis using physiological signals (DEAP) to categories emotions using the valence and arousal scheme. The prediction accuracy of emotion categorization has enhanced by 4.12% for target dependent strategies, 4.5% for noncontingent strategies, and 1.3% for inter-dependent initiatives, according to the SEED database. In comparison to the DEAP dataset, the average result of participant noncontingent trials increased by 7.04%.

Demir et al., [14] during the pre-processing phase, the EEG signals were transformed into EEG rhythm pictures using the Continuous Wavelet Transform (CWT) and Wavelet Transform (WT). Such images were afterward used as input for various CNN models. According to the findings, AlexNet functionalities with Alpha rhythm produce greater valence discrimination accuracy scores than another deep features and MobilNetv2 features produce the highest arousal discrimination accuracy score (98.93% in Delta rhythm. Ghutke et al., [15] AI has been used by researchers to extract multiple aspects from EEG signal transcriptions. Maximum Relevance and Minimum Redundancy (MRMR) is used to reorganise features, while PCA is used to reduce extract features. When contrasted to K-NN, the Adaptive PSO precision seemed to be 10% higher. Mashael et al., [16] put forward various Deep Transfer Learning (DTL) schemes for sensing priorities via EEG signals Power Spectral Density was one of the features considered for retrieval. When contrasted to the DTL model created by the scholars using quintessential classifier, Random Forest (RF) achieved a comparable prediction performance as DTL for the DEAP test set. Gannouni et al., [17] the main research aim was to increase the potency of emotion detection using neural signals by implementing an innovative and adaptive channel selection approach that recognizes that neural activity has unique behaviour that varies based on one induvial to another, and from one psychological response to another. To precisely track the iterations in each psychological response, the zero-time windowing strategy was utilized. For the DEAP dataset, emotional responses were labelled using RNN and QDC classification model.

Placidi et al., [18] a lucrative machine learning-based methodology was used to compare Electroencephalography signals from various subjects in the DEAP data set. The SVM was implemented to a small number of features retrieved by Principle Component Analysis (PCA) based on the averaged values of the features calculated on the preferred 5 sub-trials. The prior results indicate that the proposed method could be efficaciously used to find the appropriate, optimised and limited amalgamation of channels/features for efficient classification of the three analysed emotional responses. The decision to leave isolated EEG channels in the classification stage was made after evaluating the impact of each channel to the overall classification process. Rahman et al., [19] propose a method that combines PCA and t-statistical method in extraction of features. Their work also contributes in process of reducing signal dimensions and selecting features that are more reliable for extraction of features using t-statistics. The above proposed scheme was applied on SEED dataset with four classifiers namely, SVM, Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA) and K-NN in which, ANN and SVM provided better accuracy of 84.3% and 77.1% respectively. From the above literature paper discussed we can infer that by reducing the number of electrodes that are subjected for recognizing emotions into different category yields better results. Shashikumar et al., [20] more than 30 features were extracted and backpropagation neural network was used for classifying the various emotional states resulting in an average accuracy above 92.45%.

Nawaz R et al., [21] used empirical mode decomposition (EMD) method to extract features for emotion recognition of EEG signal. Using SVM classifier, the classification accuracy obtained is 72.10% and 70.41% for valence and arousal dimensions respectively. Rab Nawaz et al., [22] frame work the statistical time domain features are extracted for emotion recognition. To improve the performance accuracy, the Principle Component Analysis is adopted. SVM is used for validate the efficacies of the features and achieved an overall best classification accuracy of 78.06%. Qinghua Zhonga et al., [23] proposed a method of EEG access for emotion recognition based on a deep hybrid network and applied to the DEAP dataset for emotion recognition experiments and the average accuracy for 3D emotion model (Arousal, Valence and Dominance) could achieve 79.77% on arousal, 83.09% on valence and 81.83% on dominance. Wei-Long Zheng et al., [24] adopted Deep Belief Networks (DNB's) for recognition of three emotions. The recognition considering 12 channels are relatively stable and obtained the best accuracy of 86.65% with SVM classifier, which is even better than that of the original 62 channels. Daksh Maheshwari et al., [25] used rhythm-specific multi-channel convolutional neural network (CNN) based approach for automated emotion recognition using multi-channel EEG signals. The EEG rhythms from the selected channels coupled with deep CNN are used for emotion classification and obtained the accuracy values for 3D model of 98.91%, 98.45%, and 98.69% for Low Valence v/s High Valence, Low Arousal v/s High Arousal and Low Dominance v/s High Dominance emotion classification strategies, respectively using DEAP database.

J. X. Chen et al., [26] proposed an improved deep CNN model to achieve better accuracy in emotion recognition for binary classification (valence and arousal dimensions) of emotions on DEAP dataset. When compared to the of 4 shallow classifiers, the deep CNN models showed 3.58% and 3.29% higher accuracy in valence and arousal dimension respectively. In the work of Yuling Luo et al., [27] three algorithms (DWT, Variance and FFT) for feature extraction is implemented on DEAP and SEED databases for four emotions (valence, arousal, dominance, liking) and three emotions (positive, negative and neutral) respectively. Hao Chao et al., [28] in their work employ DBN-GC models to obtain the high-level feature sequence of the multi-channel EEG signals on DEAP, AMIGOS and SEED datasets and CRF to deep belief networks for a 2D emotion classification. They obtained accuracies of 76.13% in Arousal & 77.02% in Valence dimension. The work of Hongli Zhong et al., [29] proposed an expression-EEG interaction multi-modal emotion recognition method using a deep automatic encoder. The model employed Decision tree for feature selection, facial expression recognition, BDAE for feature extraction and LIBSVM for emotion classification. 13 healthy participants were shown 30 video clips from a video library of 90 clips. The model achieved an average emotion recognition rate of s 85.71% for discrete emotion state type. G S Shashi Kumar et al., [30] obtained an accuracy of 90.25% considering the frontal electrodes. They also suggested time-frequency features to obtain better results.

Katsis et al., [31] created a wearable system to detect race car drivers emotional states. They attempted an automated approach to emotion recognition by using a variety of bio-signals. Sensors in the wearable system measured facial EMG, respiration, ECG, and skin conductance. When participants were exposed to visual stimuli using affective pictures from IAPS, EEG signals were recorded. The signals from 14 electrodes were split into alpha, beta and theta sub-bands utilizing the Fast Fourier Transform. Each sub-feature bands such as signal magnitude, maximum frequency, and spectral power, were extracted and fed into the designed neural network. S. Oh et al., [32] demonstrated that Hjorth parameters extracted from EEG signals can be extremely useful features because they contain data in both the time and frequency domains. Brennan et al., [33] examined this hypothesis by processing ERP signals. Then, significant differences among 2 groups were achieved through analysis of variance.

Hadjidimitriou, S. K et al., [34] planned new options supports a multi-wavelet remodel to reason human emotion as encephalogram signals. Rahnuma, K. S et al., [35] used SVM by scholars to categorize music preferences relying on brain waves. Nawasalkar, R. K et al., [36] used music to guesstimate psychological feature conditions based on differences not like effective frequency bands of graphical record signals; the authors used SVM as a classifier. Bajaj V et al., [37] employed SVM as a classifier, and proposed a method for identifying emotion rejoinders via a multimedia presentation of EEG signals. Punitha et al., [38] classified happy, disgusted, and surprised emotions by extracting textural features from an image taken from a facial expression database. They used the SVM classifier and achieved an accuracy of 87% in classification. Soleymani et al., [39] intended emotion classification from EEG by taking EEG recordings from 24 participants and using a linear discriminant criterion, they classified three emotions in the valence and arousal planes independently with a precision of 68.5% and 76.4%, respectively. Chanel et al., [40] the integration technique was used to incorporate the compiled peripheral signals with the ECG and accomplished a classification accuracy of 63%.

Frantzidis et al., [41] used the Mahalanobis classifier to classify four emotions elicited by images from the International Affective Picture System (IAPS). Meza-Kubo et al., [42] classified pleasant and unpleasant emotions in older adults using neural networks. Bhatti A. M. et al. [43] discovered that the rock and rap genres elicited happy and sad emotions in their subjects. Bastos-Filho et al., [44] aimed to categorize two emotional states calm and stress threshold values of Valence and Arousal. Three feature extraction methods were analysed and compared using the KNN classifier. Chung et al., [45] classified emotions using the Bayes classifier and the supervisory learning technique. Together with the 32 EEG channels in the DEAP dataset, they added 61 additional virtual channels via bipolar montage, yielding a total of 93 channels. For each channel, they extracted power spectral density from different frequency bands. When two affective states were considered, the accuracy of classification of valence and arousal was 66.6% and 66.4% respectively.

Adjabi I et al. [46], 2D facial recognition is still open to future technical and material developments for the acquisition of images to be analysed. The attention of researchers is increasingly attracted by 3D facial recognition. Veltmeijer EA et al. [47], have investigate automatic group emotion recognition and provided a comprehensive overview on group emotion estimation that covers a wide range of subjects, from group types and emotion models to performances. Methodological improvements, lies in improving the real-world applicability of current methods. Huang H et al. [48], proposed a Brain Computer Interface (BCI) for the patients with disorder of consciousness (DOC), such as coma, vegetative state, minimally conscious state and emergence minimally conscious state, suffer from motor impairment and generally cannot provide adequate emotion expressions. Conclude that, BCI system could be a promising tool to detect the emotional states of patients with DOC. El Morabit S et al. [49], comparing some popular and Off-the-Shell CNN architectures. Most of the used architectures achieved significantly better results compared to many state-of-the-art methods. Kumar GS S et al. [50], extracted the Power Spectral Density (PSD) of EEG signal. The features which provide better feature for positive and negative emotion classification is selected and classified using Long Short-Term Memory (LSTM) and Bi-Directional Long Short-Term Memory (Bi-LSTM) based on 2-D emotion model. Marriwala N et al. [51], proposed an approach that helps to classify different types of facial expressions using Convolutional Neural Network (CNN) algorithm. The proposed model is a Neural Network architecture that is based on sharing of weights and optimizing parameters using CNN algorithm.

3. Methodology

In this study, machine learning techniques are adopted to classify emotional states. Based on a 2-dimensional Russell's emotional model, states of emotion have been classified for each subject using EEG data. The DEAP dataset which was provided containing 32 subjects and each subject had 2 sets of datasets. One was named as "Data" which contained the EEG signal data, acquired for each subject, and the other was named as "label" which was the ratings on the scale of 1–9 for each emotion, i.e. Valence, Arousal and Dominance, given by each and every subject.

The proposed work uses DEAP dataset for EEG signals. The EEG data used is pre-processed by down sampling the signal to 128Hz, removing EOG artifacts. Bandpass filter has been applied to acquire signal between 4 and 45.0 Hz. The data is averaged for common reference and segmented for 60s to get EEG signal for each video. The EEG signals from various electrodes in different scalp regions viz., frontal, parietal, temporal, and occipital are studied. The region-based classification is performed by considering each scalp region separately. Among all other scalp region electrodes, the frontal region electrodes performed better and gave the highest classification accuracy. The results indicate that the use of a set of frontal electrodes (Fp1, F3, F4, Fp2) for emotion recognition can simplify the acquisition and processing of EEG data.

3.1. Feature extraction using Discrete Wavelet Transform

A major disadvantage of the Fourier Transform is it captures those frequencies that persist over an entire signal. Sometimes, this type of signal decomposition does not serve all applications well, for example Electroencephalogram (EEG) where signals have short intervals of characteristic oscillation. An alternative approach is the Wavelet Transform, which decomposes a function into a set of wavelets.

3.2. Wavelets

A Wavelet is a wave-like oscillation that is localized in time, an example is given in Fig. 2. Wavelets have two basic properties: scale and location. Scale (or dilation) defines how "stretched" or "squished" a wavelet is. This property is related to frequency as defined for waves. Location defines where the wavelet is positioned in time (or space).

3.3. Discrete Wavelet Transform

The wavelet transforms (WT) has broad application in the analysis of stationary and non-stationary signals. These applications include the removal of electrical noise from the signals, detection of abrupt discontinuities, and compression of large amounts of data. In WT, a signal is decomposed into a group of constituent signals, known as wavelets, each with well defined, dominant frequency, similar to the Fourier transform (FT) in which the representation of a signal is by sine and cosine functions of unlimited duration. When the signal is passed from the time domain to the frequency domain the information of time is lost in Fourier Transform. This is the main problem with FT. Unlike the FT, the WT allows an analysis in both time and frequency domains giving information on the evolution of the frequency content of a signal over time. The WT has been discretized and is known as Discrete Wavelet Transform (DWT). It exhibits an important advantage over traditional FT methods.

3.4. DWT for feature extraction

Since EEG time series signal includes much information with both, high and low, frequencies, it is considered to be non-stationary. Wavelet transform (WT) combines high- and low-frequency spectrums. It helps in dealing with raw signals which affect the accuracy results negatively. Therefore, WT identify noises and removes potential ones from EEG signals. The feature extraction step is used to choose the optimal group of attributes in the original data. The signal includes two kinds of EEG time-based frequencies, high-frequency information with short period and low-frequency information with long time periods. One of the disadvantages of Continuous Wavelet Transform is redundancy, whereas DWT is more efficient due to the frequency filter bank, which is used to remove the unwanted frequencies and decompose the signal into diverse levels using five levels of decomposition, each one contains the sample decomposed by two components. There are many types of DWT, which are considered as mathematical and statistical functions. These types were divided to families according to frequency components. Leading step in wavelet-based digital signal processing (DSP) depends on the choice of the appropriate mother wavelet. Multiple mother wavelets result in different degrees of DWT in the same EEG segment, which eventually leads to multiple detection results.

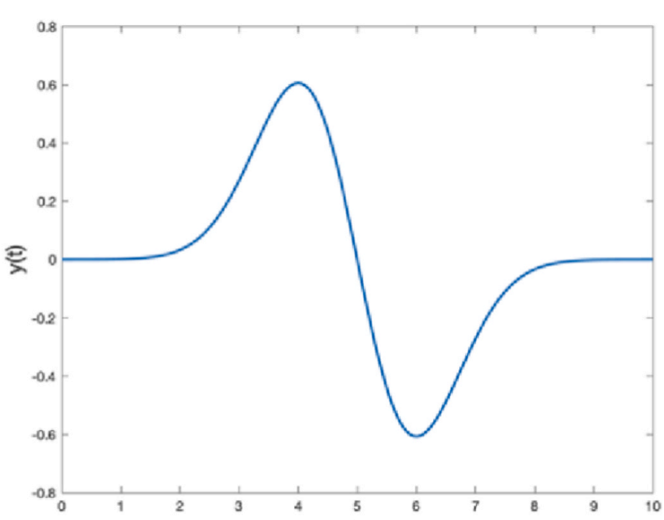

Fig. 2. Example wavelet.

3.5. Determination of feature matrix using DWT

Initial step is that, the signal is routed via band-pass filter. In order to get the desired outcome, band-pass filters combine high-band-pass filters (HPF) and low-band-pass filters (LPF). This process falls under the first level, which has two corresponding coefficients: Approximation (A) and Detailed (D). Since it falls under the first level, it will be referred to as A1 and D1, respectively. The process continues under various levels as a subsequent of coefficient from the first level within the approximation, for example (A2, D2) and (A3, D3). This process is illustrated through the flow diagram shown in Fig. 3. Utilizing filters, each procedure doubles the frequency resolution while halves the temporal complexity through decomposition. We used the DWT to three levels and the following features to extract features: D1, D2, D3, and A3.

This process was implemented using Wavelet analyzer app in MATLAB. The DWT is implemented by using numerous mother wavelets. Firstly, Haar wavelet was used and then, to improve the accuracy different mother wavelets were tried including Moore wavelet, Coiflet wavelet, Symlet wavelets and finally Daubhechies. The EEG signal was decomposed to 4 frequency bands by DWT and db4 was used for this decomposition. The parameters and decomposition window are shown in Fig. 4.

4. Results & discussion

The chapter discusses the results of classification of valence, arousal and dominance from EEG data. The performances of the classifiers are compared for the extracted feature vector. The input features are initially divided into k segments for k-fold validation. The cross-validation method involves (k = 5) iterations. For each iteration, the k^{th} fold is taken for testing and the rest of the k-1 folds are combined to train the classifier. Initially, Wavelet Analyzer app was used to decompose the data into 3 levels of decomposition and then the approximation coefficients were extracted from it. Mother wavelet used was

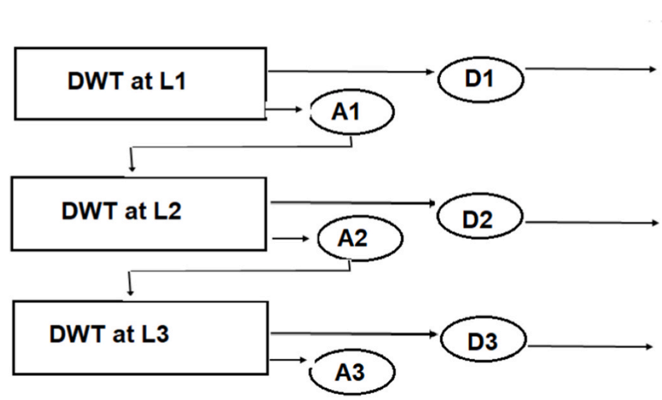

Fig. 3. Feature Extraction step.

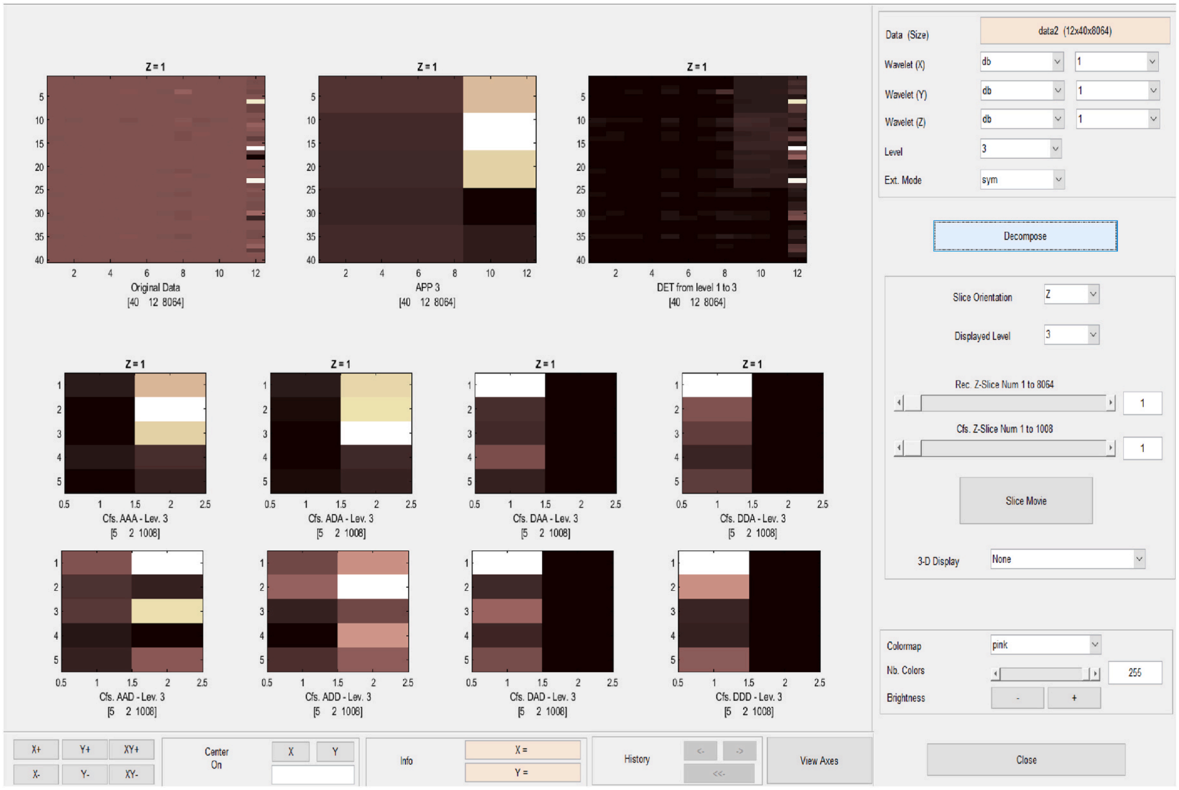

Fig. 4. Wavelet Decomposition window in Wavelet Analyzer app.

Daubechies and level of decomposition kept was 3. The next step was to use the 3 level approximation coefficients to form a feature matrix of mean, standard deviation, skewness and Shannon's entropy.

There are several types of classifiers available in R2022a MATLAB version. With the help of Classification Learner App classified and predicted the emotions (Arousal, Valence and Dominance) as High/Low. With the help of the participants ratings an excel sheet was made by combining the feature matrix with the ratings given by each participant and classified them high/low based on the value. If the value was greater than 5, then it was considered as a "High" class and when it was less than 5, then that value will go into the "Low" class. As the ratings given by each subject for each video trial was in the range 1–10, it became simpler to classify it into high/low classes based on their mid value, which is 5.

Mean, Standard Deviation, Skewness and Shannon entropy features from each frequency band are giving as the input to the multi classifier system in Classification Learner App such as Bagged Tree, SVM, KNN, Linear discriminant, Subspace discriminant. Logistic Regression. The best classifier was chosen depending on the accuracy it gives. The Classification learner app's window where it can be seen that Fine KNN gives 92.5%, Subspace discriminant gives 90% and Bagged tree gives 90% highest accuracy when trained for Valence, Arousal and Dominance respectively. Partitions of the input data are split for training, testing and validation as 80-10-10 ratio. The performance accuracy, confusion matrix and Region of convergence (ROC) for Valence, Arousal and Dominance using other classifiers are also shown from Figs. 7–12.

The results of recognition rate of emotion proved that EEG data comprises ample amount of information to differentiate among different emotional states. Time, frequency and nonlinear domain features are more suitable feature sets for emotion recognition. Comparison of our

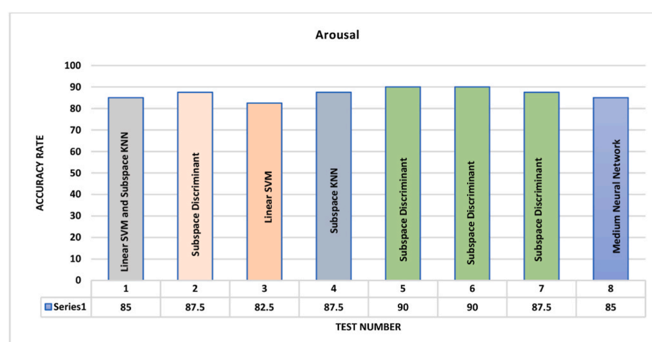

Fig. 7. Classifiers performance accuracy for Arousal emotion.

proposed method with latest study of emotion recognition that have also used DEAP dataset is given in Table 1.

The proposed methodology achieved the highest classification accuracy of 92.50% in valence-arousal dimension with improvement of the results obtained by Nawaz R et al. [21] which is 72.10%, Nawaz R et al. [22] which is 78.06%, Zheng Q et al. [23] which is 90.00%, Gannouni et al. [17] which is 91.22%. Regardless, the framework based on region-based classification achieved satisfactory results for EEG emotion recognition. Previous studies have reported that the emotional experiences are stored within the temporal region of the brain. The current evidence suggest that emotional response may also be influenced by different regions of the brain such as the parietal and frontal regions.

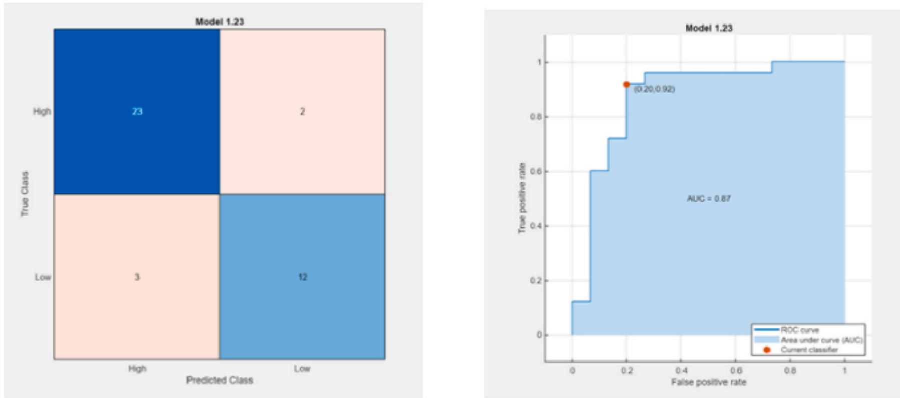

Fig. 8. Confusion matrix and ROC for Arousal emotion.

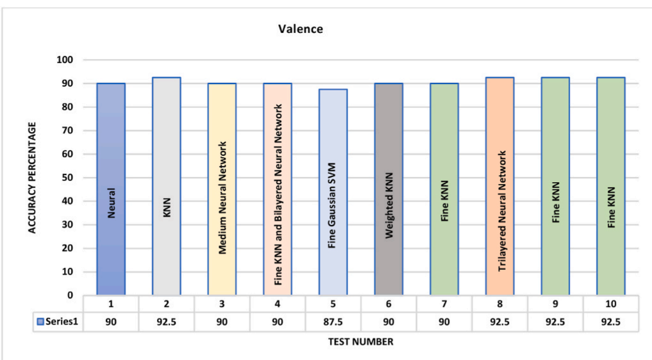

Fig. 9. Classifiers performance accuracy for Valence emotion.

In this study, 2-dimensional model (Arousal & Valance), minimum electrodes are considered. The experimental results demonstrate that the region-based classifications provide higher accuracy compared to selecting all 32 electrodes. In the recent development, a number of neurophysiological studies have reported that there is correlation between EEG signals and emotions. Studies showed that the frontal scalp seems to store more emotional activation compared to other regions of the brain such as temporal, parietal and occipital. From the experimental results of this study, frontal region gives higher classification accuracy. Also, among different brain regions, frontal region proved improved performance in classifying emotions.

5. Conclusions

In this paper, an emotion recognition system is proposed based on EEG signal. The results indicated that the extracted wavelet features are promising in recognizing human emotions. It is found that different classifiers using machine learning models such as Bagged Tree, SVM, KNN, Linear discriminant, subspace discriminant, Logistic Regression gave different accuracies. The performance of the KNN, Fine KNN and SVM classifier is studied based on the wavelet feature of EEG signal from frontal regions electrodes separately. KNN, Fine KNN and SVM provides highest classification accuracy from the frontal region electrodes (Fp1, F3, F4, Fp2) compared with all other scalp regions. It is observed that KNN gave 92.5%, Fine KNN gave 90% and SVM gave 90% highest accuracy when trained for Valence, Arousal and Dominance respectively using wavelet features and classification learner app. This improved accuracy enables us to use this system in different applications like, wearable sensors design, biofeedback applications for monitoring stress and psychological wellbeing.

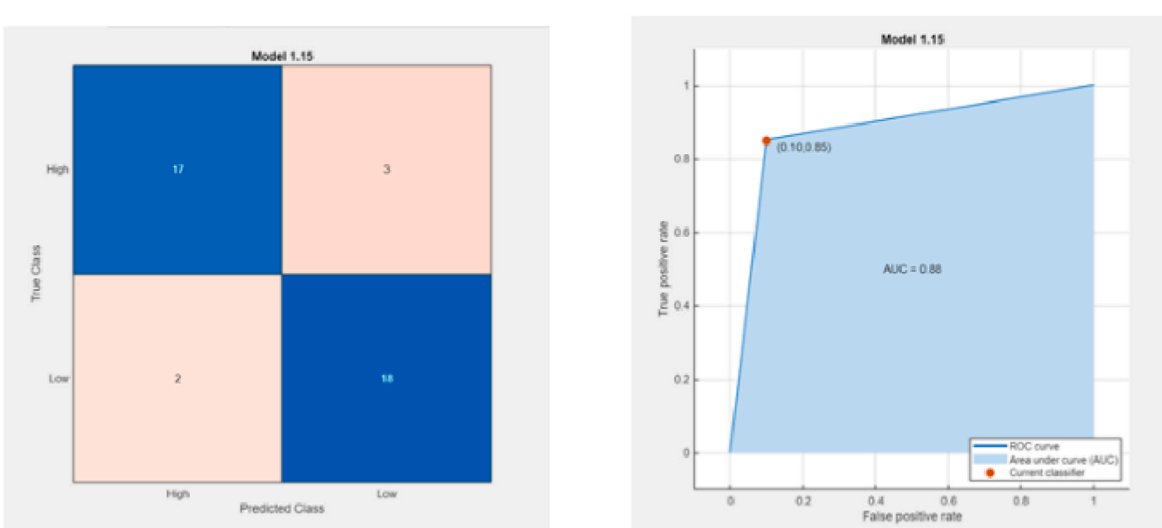

Fig. 10. Confusion matrix and ROC for Valence emotion.

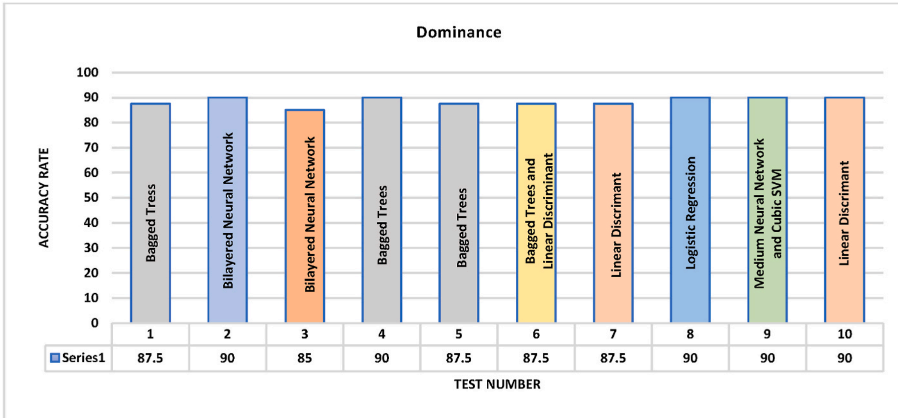

Fig. 11. Classifiers performance accuracy for Dominance emotion.

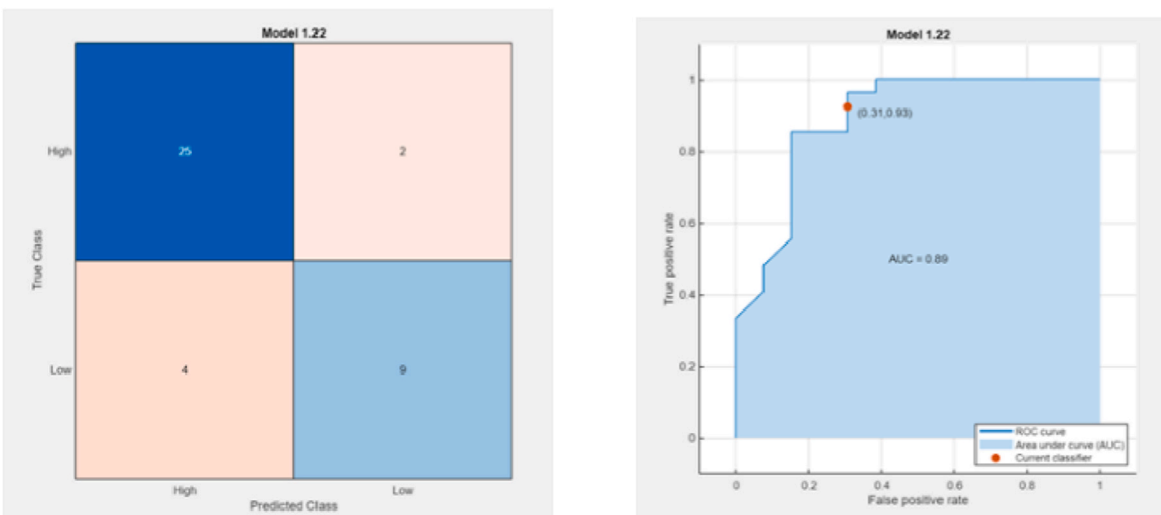

Fig. 12. Confusion matrix and ROC for Dominance emotion.

Table 1
Assessment of accuracy of different studied using DEAP data.

Papers	Emotion Model	Features	Classification	No. of EEG Channels	Accuracy (%)
Nawaz R et al. [21]	2D	Multiscale Sample Entropy (MSE)	SVM	32	72.10
Nawaz R et al. [22]	3D	Time & Frequency	SVM	14	78.06
Zheng Q [23]	2D	Time & Frequency	K-means	12	90.00
Gannouni S [17]	2D		QDN	6	85.64
			RNN	6	91.22
Proposed Method	2D	Wavelet	KNN	32	85.55
				Fp1,F3,F4, Fp2	92.50

CRediT authorship contribution statement

Shashi Kumar G S: Writing – original draft, Formal analysis, Data curation, performed all implementations, data analysis and wrote the paper. **Niranjana Sampathila:** Supervision, conceived the study and supervised. **Tanishq Tanmay:** Writing – review & editing, provides inputs for editing the paper. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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