Indonesian Journal of Electrical Engineering and Computer Science
Vol. 33, No. 2, February 2024, pp. 920~931
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i2.pp920-931

Electroencephalogram based human emotion classification for valence and arousal using machine learning approach

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Article Info

Article history:

Received Nov 6, 2023
Revised Nov 26, 2023
Accepted Nov 27, 2023

Keywords:

Discrete wavelet transforms
Electroencephalogram
Fast fourier transform
Human emotion classification
Power spectrum density
Valence and arousal

ABSTRACT

Humans have unique ability to express emotions and electroencephalogram (EEG) signals are one of the sought-after ways to analyze a person's emotional state. However, extracting proper emotion related features from EEG and finding corresponding emotion is challenging because of complex nature of emotions and underlying brain activities. The objective of this paper is to address this issue for more accurate emotion classification based on EEG. It also compares feature extraction methods namely fast fourier transform (FFT) and discrete wavelet transform (DWT). DEAP dataset is used for classification of human emotions through support vector machine (SVM) and K-nearest neighbor (KNN) algorithms by considering features such as standard deviation, mean, variance, power spectrum density (PSD) for FFT; and energy, entropy for DWT. It is observed that feature extraction from FFT yielded better results than DWT and KNN gave more accuracy of 96.61% for valence and 96.42% for arousal as compared to SVM. The proposed method based on PSD and FFT fared better than other existing ones in terms of accuracy when compared against different features and feature extraction techniques. This approach is expected to help researchers to understand feature extraction from EEG signals and decide proper features and techniques for better implementation.

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1. INTRODUCTION

Human emotion classification is indeed a very broad domain and there exists a plethora of features and methods for analysis. But there is a profound question regarding the selection of features and methods in human emotion classification, as the performance of the model is highly based upon these parameters. Emotions can be recognized through speech [1], [2], facial expressions [3]–[6], textual data [7], [8], body gestures, audio-visual features [9], human interaction with devices and physiological signals such as electroencephalogram (EEG), electrocardiogram [10], electromyogram, electrodermal activity, skin temperature, and respiration. Over the years, EEG has gained a lot of attraction as a powerful technique for exploring the study of emotions due to its inexpensiveness and portable nature. In addition to that, EEG signal is a physiological signal; hence, it provides accurate data for emotion recognition as compared to speech or facial expressions [11].

EEG offers the best promising avenue for human emotion classification, yet there exist several challenges that need to be addressed. Interpreting the complex patterns of various emotions requires sophisticated methods and improving their performance to capture suitable emotion related information from

EEG signals without any loss is a challenge. In recent developments, many research studies have worked on EEG signals and found that there exists strong connection between EEG signals and human emotions. EEG signal consists of various frequency ranges which reflect certain affective or cognitive states as mentioned in Figure 1. EEG provides valuable insights into the dynamic processes underlying emotional states. Hence, there is a need to identify how brain signals can reveal the emotional state of a human.

Delta (δ) [1-4 Hz]	Theta (θ) [4-7 Hz]	Alpha (α) [8-13 Hz]	Beta (β) [13-30 Hz]	Gamma (γ) [>30 Hz]
Deepest meditation and dreamless sleep state	Dreaming and sleeping state	Relaxed and calm state of mind	Attentive and alert state	Simultaneous processing of information from different areas of brain

Figure 1. Frequency bands in EEG signal

Emotions are very complex, and it is difficult to measure or quantify the emotion, like more happy or less happy, more angry or less angry. In literature, there exist some models for emotion. Psychologists modeled emotions into discrete and dimensional categories [12]. According to discrete emotion models, emotions are quantifiable and connected to physiology. Two models of this type are the Ekman model and Plutchik's wheel model. According to Ekman [13], basic emotions have common characteristics. Same emotions are exhibited by humans in the same situations in a similar way. According to him, the other emotions are the combinations of 6 basic emotions of happiness, sadness, anger, fear, surprise, and disgust. Plutchik [14] proposed an intensity based emotion model which considers 8 basic emotions of joy, trust, surprise, fear, sadness, anger, disgust, and anticipation. Each emotion can be less or more intense. As the research on emotion modeling is increased, psychologists observed that different emotions which indicate a certain degree of specific emotion e.g., happy and excited are different emotions. Hence, multi-dimensional emotion models were developed by psychologists. Emotions can be categorized in a 2 dimensional space of valence and arousal [12]. One such model is the circumplex model of affect proposed in 1980 by Russell [15], as portrayed in Figure 2. It specifies that all affective states of the human body arise from valence and arousal. These two bipolar and orthogonal dimensions define the affective space for emotion modeling [16].

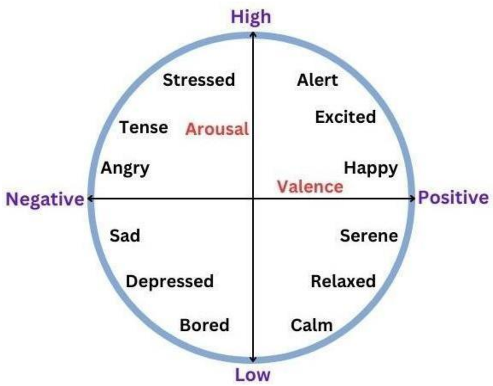


Figure 2. Circumplex model for valence and arousal [15]

Traditionally speaking, emotion classification from EEG includes various methods for artifacts removal from the captured signals, extracting appropriate features from time or frequency domain and ultimately, doing classification by training machine and deep learning models as shown in Figure 3. EEG signal preprocessing includes noise/artifact removal. Few of the methods used are finite impulse response (FIR), adaptive, and band pass filters. Once the signal is preprocessed, the next step includes feature extraction from time, frequency or both (wavelet) domains along with statistical features. The most popular time domain feature extraction methods are Hjorth Parameters (HP) and Higuchi Method; whereas FFT is a widely used frequency domain method and discrete wavelet transform (DWT) belongs to the wavelet domain. Literature survey mentions many classifiers such as support vector machine (SVM), K-nearest neighbor (KNN), decision tree (DT), random forest (RF), artificial neural network (ANN), and convolutional neural networks (CNN). Li *et al.* [17] used SVM and obtained 59.06% and 83.33% highest mean accuracy for DEAP and SEED datasets respectively with extracted features like variance, HP, maximum power spectrum density (PSD) and power sum. Another approach mentioned in [18] uses a tunable Q wavelet transform for extracting features from each sub-band like standard deviation (SD), absolute mean, average power, Kurtosis and Skewness; and achieved over 93% accuracy with rotation forest ensemble and SVM for SEED.

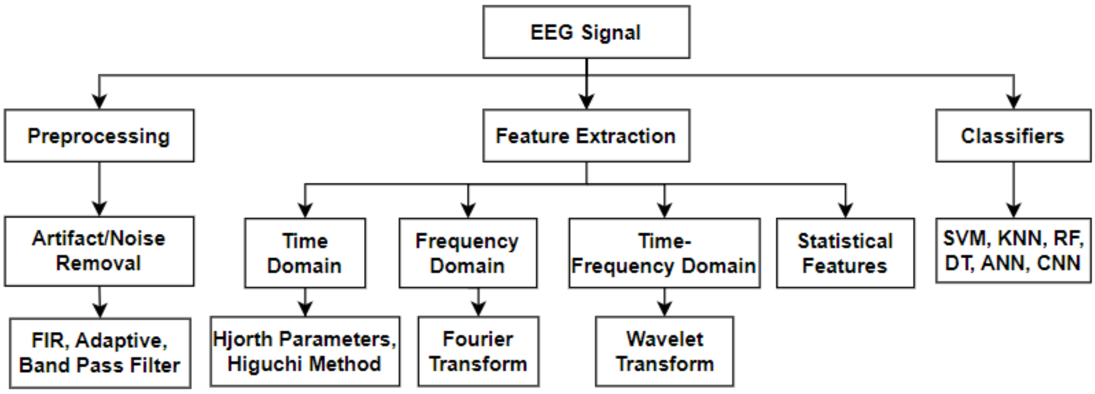


Figure 3. Taxonomy of methods used in EEG based emotion classification

Tong *et al.* [19] used the SEED dataset and extracted features such as PSD, differential entropy (DE), differential, and rational asymmetry. Classification was done by SVM, RF, and CNN. CNN gave classification accuracy of 85.27%. A method for emotion recognition from DEAP dataset was proposed by Qu and Zheng [20] based on long short-term memory (LSTM) and CNN. It considered temporal and spatial features that gave valence and arousal classification accuracies of 92.87% and 93.23% respectively. Kumar *et al.* [21] considered frontal channels named Fp1, F3, F4, Fp2 from DEAP dataset and got accuracy of 92.5% and 90% respectively for KNN, fine KNN and SVM for valence and arousal based on wavelet features. Kusumaningrum *et al.* [22] used an n-fold cross validation method on DEAP for SVM, RF, KNN, and weighted KNN using HP and PSD along with few other features. RF gave 62.58% accuracy. A model was proposed using KNN (K=1) with Manhattan distance for estimation of exact valence and arousal values for DEAP, AMIGOS, and DREAMER datasets. It can classify emotions into four classes with 84.4% accuracy through features named spectral entropy, HP, energy and entropy of wavelet, and intrinsic mode functions [23]. Wagh and Vasanth [24] used DWT on SEED dataset to get features like PSD, energy, SD, variance, as well as time domain features like HP, Kurtosis, Skewness. SVM, KNN, and DT were used out of which the maximum classification rate of DT was 71.52% and 60.19% for KNN. Fang *et al.* [25], used a multi-feature deep forest method to extract PSD and DE and obtained a mean accuracy of 71.05% for happy, angry, pleasant, sad, and neutral emotions for DEAP. The work carried out in [26] extracted PSD that was calculated using the welch method and used bi-directional LSTM resulting in 94.95% accuracy for DEAP. Alhalaseh and Alasasfeh [27] used entropy and Higuchi's fractal dimension (FD) as training features for Naive Bayes (NB), KNN, CNN, and DT. KNN yielded 93% accuracy with a value of k=3 and CNN gave 95.20% accuracy.

Gao *et al.* [28] collected EEG data using emotiv EPOC and extracted PSD and wavelet energy and entropy features. SVM gave an average accuracy of 89.17% for classification of three emotions named neutral, happy and sad. Time-frequency and spatial features were used in [29] to construct the symmetric positive definite matrix. KNN, RF, and SVM were employed and average valence and arousal accuracy of 91.86% and 91.84% were obtained for the DEAP dataset. George *et al.* [30] applied FFT on EEG and filtered α, β and γ bands using the butterworth band-pass filter. SVM exhibited 92.36% accuracy with extracted statistical features like minimum, maximum, SD, variance, skewness, kurtosis, entropy, and power bandwidth. Mehmood *et al.* [31] reduced feature set dimensions and employed Hjorth-activity for emotion recognition using RF that gave 69.01% accuracy for DEAP. Nawaz *et al.* [32] mentions use of SVM that had average accuracy of 77.62% for valence and 78.96% for arousal on DEAP with statistical features. Table 1 shows a list of various features that are identified after extensive literature review.

Table 1. Different features extracted from EEG signals

Reference	Considered features	Reference	Considered features
Li *et al.* [17]	Variance, HP, maximum PSD, power sum	Fang *et al.* [25]	PSD and DE
Subasi *et al.* [18]	SD, absolute mean, average power, Kurtosis and Skewness	Kumar *et al.* [26]	PSD
Tong *et al.* [19]	PSD, DE, differential and rational asymmetry	Alhalaseh and Alasasfeh [27]	Entropy and Higuchi's FD
Qu and Zheng [20]	Temporal and spatial features	Gao *et al.* [28]	PSD, energy, entropy
Kumar *et al.* [21]	Mean, SD, Skewness and shannon entropy	Gao *et al.* [29]	Time-frequency and spatial features
Kusumaningrum *et al.* [22]	HP and PSD	George *et al.* [30]	Minimum, maximum, SD, variance, Skewness, Kurtosis, entropy, power bandwidth
Galvão *et al.* [23]	Spectral entropy, HP, energy and entropy	Mehmood *et al.* [31]	Hjorth-activity
Wagh and Vasanth [24]	PSD, energy, SD, variance, HP, Kurtosis, Skewness	Nawaz *et al.* [32]	Power, entropy, FD, statistical features and wavelet energy

This paper attempts to identify the suitable features and methods and aims towards obtaining higher accuracy for EEG based emotion classification. Two research objectives are raised for this work: i) to extract and find appropriate features from EEG signals that can best relate to human emotions and analyze the relationships between EEG signals and human emotions for improving accuracy; and ii) to contribute in enhancement of emotion recognition technologies, that can be widely useful for applications like assessment of mental health, brain computer interfacing and responsive systems. Different sections of the paper are as follows: the method is explained in section 2. Section 3 throws light on analysis and interpretation of results and findings. Section 4 covers conclusion, contribution, limitations, and future work.

2. METHOD

The proposed methodology uses preprocessed DEAP dataset. The PSD feature is extracted using FFT; and energy and entropy features are considered from the wavelet domain. Supervised machine learning models named SVM and KNN are trained to categorize the emotion states into four classes of valence and arousal. The proposed system architecture for emotion classification is shown in Figure 4.

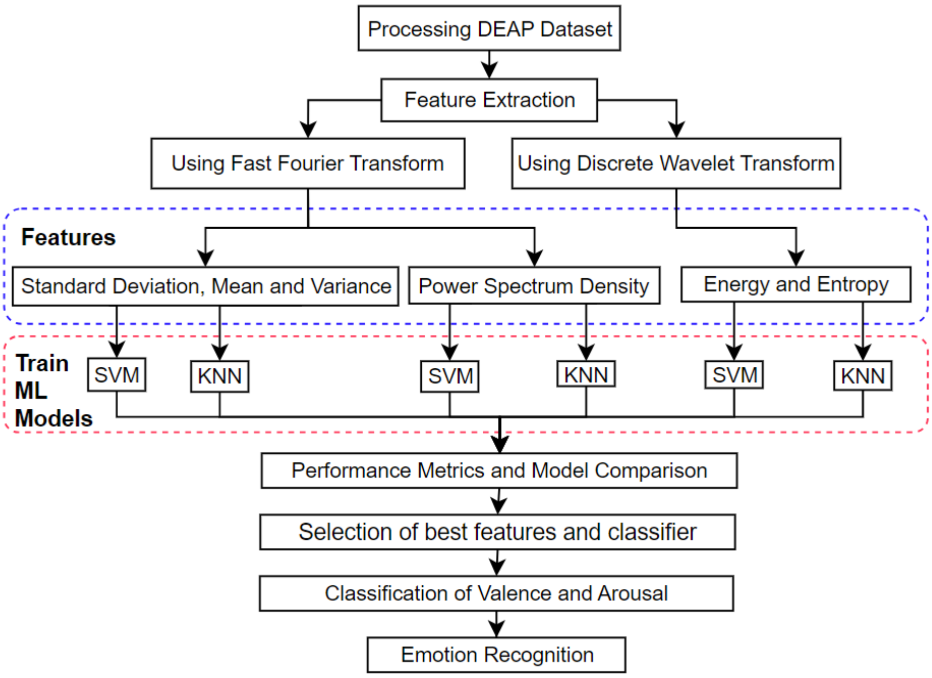


Figure 4. Proposed system architecture

2.1. Description of DEAP dataset

DEAP dataset is the most popular freely available EEG signal repository for human emotion analysis [33]. EEG signals were recorded along with physiological signals for 32 subjects while showing them 40 videos each of single-minute duration. Ratings of 1 to 9 were given by every subject to each video for arousal, valence, dominance, and liking; as described in Table 2.

Table 2. Description of DEAP

Array name	Array size
Data	40 videos×40 channels×8064 data values×32 subjects
Labels	40 videos×4 labels×32 subjects

2.2. Processing data from DEAP dataset and feature extraction methods

EEG signals data, valence and arousal ratings are extracted into separate files. Each file consists of 32 subjects×40 videos=1,280 values. Data from 32 channels is stored per person for each of the trails. The channels considered 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 [33]. Each user data consists of 8,064 rows×32 columns (1 column for each channel).

2.3. Fourier transform

Fourier transform (FT) means representing a signal in the frequency domain and decomposing it into its frequency components that provide valuable information for understanding brain activity related to different emotions. FT of a signal x(t) is given by (1);

$$F[x(t)] = X(f) = \int_{-\infty}^{\infty} x(t)\ e^{-2\pi i f t} dt \tag{1}$$

where, $i=\sqrt{-1}$
Inverse fourier transform gives x(t) back from X(f) as (2).

$$F^{-1}[X(f)] = x(t) = \int_{-\infty}^{\infty} X(f)\ e^{2\pi i f t} df \tag{2}$$

2.3.1. Fast fourier transform

FFT transforms time domain EEG signal into frequency domain [34]. FFT can analyze all frequencies in an EEG signal. The more the intensity of a particular frequency in EEG signal, the higher the possibility of the subject in a particular affective state associated with that frequency, e.g., if theta band frequency is dominant, the data would have been captured during sleep state and if alpha band is dominating, the subject would have been in calm/relaxed state during data capture. Power defines the strength of a particular frequency in the signal. Higher power of a particular frequency means that the EEG signal contains that frequency to a larger extent. The important characteristics of the EEG signals are contained in five frequency spectrums that can be analyzed after applying FFT [35].

2.3.2. Power spectrum density

PSD shows the distribution of signal's energy in the frequency domain. PSD of EEG data may be calculated by taking the FT of the autocorrelation which is the relation between present and time lagged values of a variable. Consider A(t) is an autocorrelation of signal x(t) [35]. Thus, PSD of x(t) is obtained by taking FT of A(t) and is shown by P(f) as given in (3). Figure 5 represents a sample PSD graph plot of EEG signal.

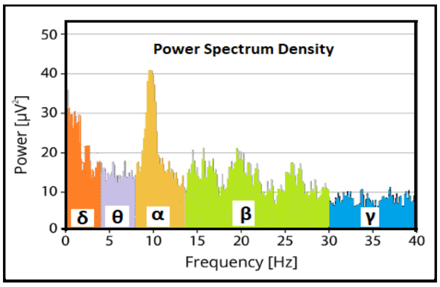


Figure 5. Power spectrum density of EEG

$$[P(f)] = F[A(t)] = \int_{-\infty}^{\infty} A(t)\ e^{-2\pi ift} dt \tag{3}$$

where, i=$\sqrt{-1}$

2.3.3. Algorithm

This section specifically describes the step-by-step algorithm for emotion classification using FFT and PSD.

1. Input: DEAP dataset
2. Processing: compute the FFT of pre-processed EEG signal as shown in (4):

$$X(f) = FFT[x(t)] \tag{4}$$

3. Feature extraction: extract features from the frequency spectrum X(f) to capture relevant information for emotion recognition. For example, calculate the PSD in specific frequency bands as (5) to (9):

$$Delta\ Power = \sum_{f=1}^{4}[P(f)] \tag{5}$$

$$Theta\ Power = \sum_{f=4}^{7}[P(f)] \tag{6}$$

$$Alpha\ Power = \sum_{f=8}^{13}[P(f)] \tag{7}$$

$$Beta\ Power = \sum_{f=13}^{30}[P(f)] \tag{8}$$

$$Gamma\ Power = \sum_{f=30}^{40}[P(f)] \tag{9}$$

4. Classification: train machine learning classifier (e.g., SVM, KNN) using the labelled dataset:
– Classifier= train classifier (features, labels)
– Classify the features into different emotional states using the trained classifier:
– Emotion= predict emotion (classifier, PSD features)
5. Output: predicted emotion based on the EEG features

2.4. Discrete wavelet transforms

EEG signal is a time series signal that has various frequency components. DWT is a method used to decompose a signal into coefficients that indicate approximate and detailed information [36]. The output of low and high pass filters (LPF, HPF) of DWT represents the approximation coefficients and the detail coefficients respectively. Wavelet transform of the next level is obtained by passing approximation coefficients through LPF again till desired level. There exist various families of wavelets. The db4 wavelet from Daubechies family is widely used for analysis of EEG signals. Figure 6 shows implementation of DWT using LPF and HPF. The decomposition of EEG signals gives us frequency spectrums [37] that are related to δ, θ, α, β and γ spectrums of EEG.

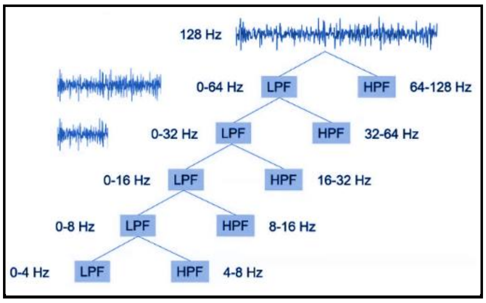


Figure 6. Discrete wavelet transformation

Once the DWT of an EEG signal is obtained, two important features are extracted from it. These are entropy and energy. Signal entropy gives the amount of information present in it. The entropy and energy of a signal in a particular frequency band is calculated as given in (10) and (11) respectively [38].

$$ENTROPY_i = -\sum_{k=1}^{n}(D_i\ (k)^2)\log(D_i\ (k)^2) \quad (10)$$

$$ENERGY_i = \sum_{k=1}^{n}(D_i\ (k)^2) \qquad \text{where } k = 1,2,\ldots,N \quad (11)$$

Where i is the decomposition level, and k indicates the number of coefficients within that level.

2.5. Implementation of feature extraction methods on DEAP

After applying FFT and DWT on the DEAP dataset for EEG signals, machine learning models are trained based on extracted features, namely, standard deviation, mean, variance, and PSD for FFT, similarly, energy and entropy for DWT. Training data and testing data is splitted into ratios of 70:30, 80:20 and 90:10 for each run. The actual ratings of valence and arousal are in the scale of 1 to 9. For classification purpose, these values are mapped into low and high. Values in the range of 1 to 4.5 are considered as low and 4.6 to 9 are considered as high. With reference to Figure 2, the four classes of valence and arousal can be represented in 2D space which is used for emotion classification. If valence and arousal both are high, it is falling under happy emotion. Low valence and low arousal relate to sad emotion. Similarly high valence and low arousal indicates calm/relaxed state and when valence is low with high arousal, it is categorized into angry emotion as depicted in Figure 7 that also shows mapping of valence and arousal scale values to labels named low and high.

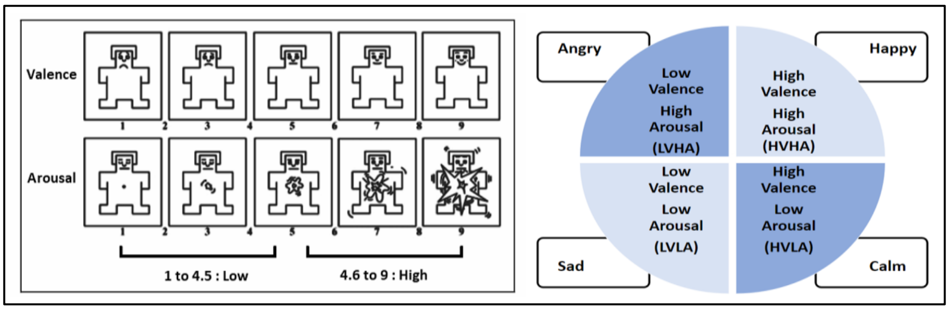


Figure 7. Mapping of valence and arousal scale values to labels (low, high)

3. RESULTS AND DISCUSSION

Firstly, results are obtained for FFT by training SVM and KNN over the SD, mean and variance features. The radial basis function (RBF) and linear kernels of SVM were implemented and out of experimentation, it is noticed that SVM with linear kernel achieved better performance than SVM, RBF, kernel, and KNN for 70:30, 80:20 and 90:10 splits of dataset. The mentioned performance metrics are described in Figure 8.

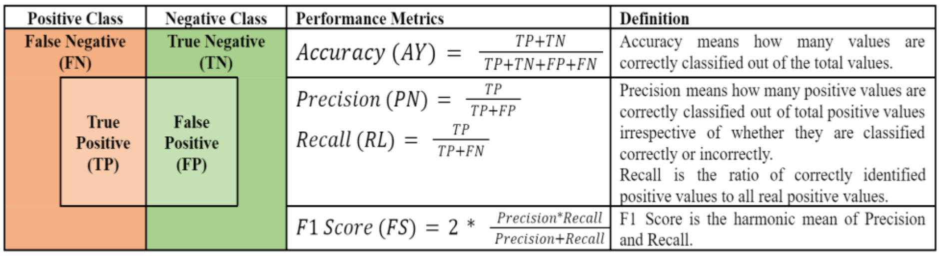


Figure 8. Performance metrics

Ideal values of precision and recall should be 1 which means that all actual positive values are correctly classified i.e., FP and FN are zero. If FP and FN are non zero, precision and recall values will decrease, which indicates that classification is not happening properly. To achieve good classification, there is a need to consider precision as well as recall, which is done by calculating F1-score. Table 3 shows result values of SVM and KNN for SD, mean and variance features extracted after applying FFT.

Table 3. Performance metrics of SVM (linear kernel) and KNN (n=3) for FFT: SD, mean and variance

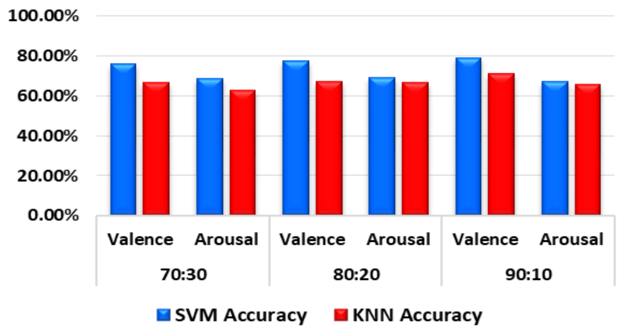
Dataset split	Label	SVM				KNN			
		AY	PN	RL	FS	AY	PN	RL	FS
70:30	Valence	76.04%	0.8000	0.7937	0.7968	66.66%	0.7259	0.8360	0.7771
	Arousal	68.75%	0.7118	0.8471	0.7735	62.50%	0.6581	0.7573	0.7042
80:20	Valence	77.34%	0.7784	0.8353	0.8058	67.18%	0.7340	0.8117	0.7709
	Arousal	69.14%	0.7076	0.8466	0.7709	66.40%	0.7243	0.7976	0.7592
90:10	Valence	78.90%	0.7956	0.8314	0.8131	71.09%	0.7752	0.8023	0.7885
	Arousal	67.18%	0.7128	0.8888	0.7912	65.62%	0.7422	0.7659	0.7539

The emotion related characteristics in EEG signals are more dominantly seen in terms of frequency bands. As a next step, the power spectrum density feature is extracted from EEG data. Each of the 32 channels is now divided into five spectrums of EEG signals as described in Figure 1. SVM and KNN were trained over the PSD feature. For SVM, it is observed that RBF kernel achieved better performance than linear kernel but KNN outperformed and gave highest accuracy for 70:30, 80:20 and 90:10 splits of dataset on PSD features extracted after applying FFT as mentioned in Table 4.

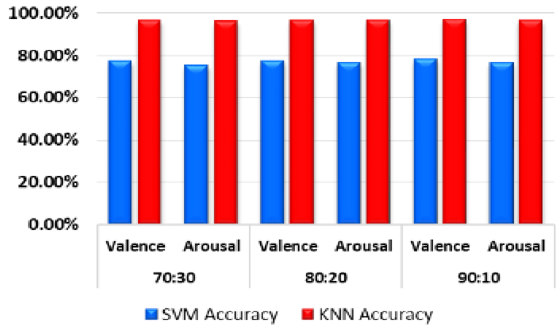
Table 4. Performance metrics of SVM (RBF kernel) and KNN (n=3) for FFT: power spectrum density

Dataset split	Label	SVM				KNN			
		AY	PN	RL	FS	AY	PN	RL	FS
70:30	Valence	77.06%	0.7591	0.7847	0.7717	96.51%	0.9597	0.9692	0.9644
	Arousal	75.06%	0.7416	0.9470	0.8318	96.23%	0.9713	0.9719	0.9716
80:20	Valence	77.11%	0.7674	0.8016	0.7841	96.54%	0.9607	0.9718	0.9662
	Arousal	76.22%	0.7522	0.9460	0.8381	96.40%	0.9736	0.9714	0.9725
90:10	Valence	78.02%	0.7626	0.7963	0.7791	96.78%	0.9639	0.9730	0.9684
	Arousal	76.53%	0.7653	0.9423	0.8446	96.65%	0.9724	0.9755	0.9739

The graph for comparison of SVM v/s KNN for FFT is shown in Figure 9 in which Figure 9(a) shows comparison for SD, mean, variance, and Figure 9(b) shows it for PSD feature. Table 5 shows performance metrics of SVM (RBF kernel) and KNN (n=3) for energy and entropy features extracted from DWT applied on EEG signals of DEAP dataset. Figure 10 shows the graph for comparison of SVM v/s KNN for DWT with energy and entropy features.



(a)



(b)

Figure 9. Comparison of SVM v/s KNN for FFT (a) SD, mean and variance and (b) power spectrum density

Table 5. Performance metrics of SVM (RBF kernel) and KNN (n=3) for DWT: energy and entropy

Dataset split	Label	SVM				KNN			
		AY	PN	RL	FS	AY	PN	RL	FS
70:30	Valence	65.88%	0.6703	0.9527	0.7869	60.41%	0.6916	0.6484	0.6693
	Arousal	64.06%	0.6260	0.9535	0.7558	61.19%	0.6814	0.7603	0.7187
80:20	Valence	66.40%	0.6188	0.9496	0.7493	59.76%	0.6892	0.7093	0.6991
	Arousal	65.23%	0.6480	0.9938	0.7845	61.32%	0.6540	0.7469	0.6974
90:10	Valence	65.62%	0.6355	0.9615	0.7653	55.46%	0.6867	0.7037	0.6951
	Arousal	64.84%	0.6446	0.9750	0.7761	64.06%	0.7472	0.7010	0.7234

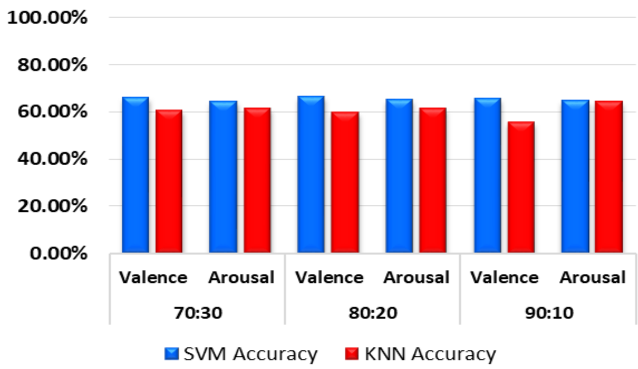
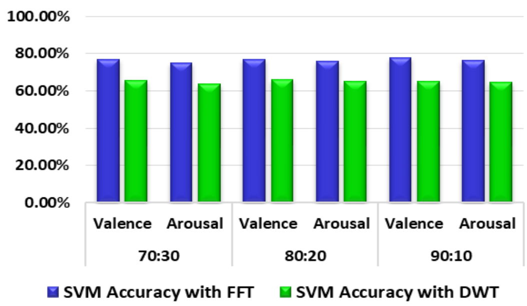


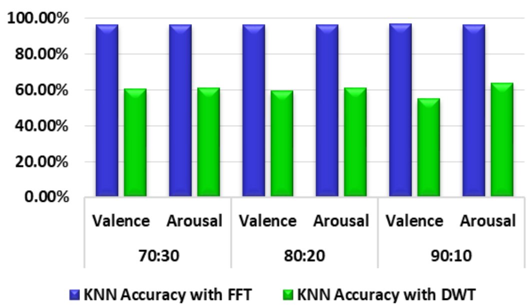
Figure 10. Comparison of SVM v/s KNN for DWT: energy and entropy

3.1. Findings

The overall result analysis reveals that in terms of feature extraction methods, FFT with PSD feature is performing better than DWT with energy and entropy feature. In terms of classifier comparison, KNN is giving better results than SVM. KNN classifier has achieved highest accuracy with the FFT method applied on EEG data and PSD feature as shown in Figure 11. Figure 11(a) represents accuracy comparison for SVM and Figure 11(b) for KNN.



(a)



(b)

Figure 11. Comparison of FFT v/s DWT for (a) SVM and (b) KNN

Precision and recall should ideally be 1 for a good classifier. The obtained values of precision and recall both are greater than 0.95 in all scenarios, which is an indication of a good classifier. As a result of this, the F1-score is also having good value. Mean classification accuracy of KNN for valence is 96.61% and for arousal it is 96.42%. Table 6 shows the comparison of obtained results with some of the previous similar work. The proposed method is implemented for PSD feature extraction using FFT. Table 7 shows the output of KNN for classifying emotions on the basis of predicted valence and arousal.

Table 6. Accuracy comparison for emotion recognition from DEAP dataset

Method	Classifier	Valence accuracy	Arousal accuracy
DWT: mean, SD, Skewness, and Shannon entropy [21]	KNN	85.55%	85.55%
Hjorth parameters, wavelet energy, and entropy [23]	KNN	89.83%	89.84%
Time-frequency and spatial features [29]	SVM	91.86%	91.81%
Temporal and spatial features [20]	LSTM-CNN	92.87%	93.23%
Entropy and Higuchi's fractal dimension [27]	KNN	93%	93%
Welch method: PSD [26]	Bi-directional LSTM	94.95%	94.95%
FFT: PSD [proposed method]	KNN	96.61%	96.42%

Table 7. Emotion classification output

Sr. No.	Output valence	Output arousal	Class	Emotion
1	6.97	6.04	HVHA	Happy
2	2.92	6.09	LVHA	Angry
3	2.03	3.04	LVLA	Sad
4	4.53	4.27	HVLA	Calm

4. CONCLUSION

In line with the research objectives raised, this paper represents a step forward in the domain of EEG based emotion classification. Several features can be extracted from EEG signals, so there comes the question which features should be considered and which ones to be excluded. Feature selection and extraction is very crucial in affective computing because the EEG signals are difficult to analyze in their original form. Feature extraction from frequency domain is one of the popular methods for EEG analysis. The obtained results indicate that PSD is an important feature related to emotion recognition. There exist many classification algorithms to classify high arousal to low arousal and positive valence to negative valence related to distinct emotional states. It is also observed from the literature review that the supervised machine learning algorithms are more preferable for detecting human emotion states. In terms of feature extraction, FFT performed better than DWT. The best accuracy is achieved for the PSD feature used with KNN. In terms of contributions, this paper primarily aims to address the problem of choosing appropriate features from EEG signals, and as a result, it significantly advances the implementation of accurate feature extraction techniques. This research work offers help to researchers for understanding the taxonomy and feature extraction methods for EEG signals. The findings of this analysis will be useful in determining the appropriate and proper methods, algorithms and procedures for EEG based emotion classification. The limitation of this work is that only one dataset is considered for the study. The same approach can be used with other datasets and results can be validated further. Future scope includes real time EEG data collection and classification of human emotions considering this research as a base and to build a robust emotion classification model. Further implementations also include applying various other feature extraction methods and studying its effect on model performance.

ACKNOWLEDGEMENTS

Authors wish to acknowledge the support and valuable guidance received from Prof. Dr. Dinesh Seth, Dean, Faculty of Engineering and Technology at Dr. Vishwanath Karad MIT World Peace University, Pune, India, for his help in refining this research paper.

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