EEG-Based Human Affective State Analysis for Emotion Recognition

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ABSTRACT

The human brain signals generated during emotional activities can be recorded and analyzed with the use of Electroencephalography (EEG) to understand the exact state of the brain. EEG has influenced the field of affective computing research since it can classify human emotions more precisely than facial expression, text, body gestures, or audio signal recognition. Emotion classification utilizing machine learning includes the selection and extraction of various emotion-related features taken from the EEG signals. This study addresses the challenge of proper feature selection and accurate emotion classification based on real-time EEG data. The proposed system considers frequency and wavelet domain features. The Random Forest (RF) classifier gave the highest accuracy of 97% for classifying four emotions, namely happiness, sadness, calm, and stress. K-Nearest Neighbors (KNN) performed quite well with 94% accuracy followed by Decision Tree (DT) with 93% accuracy. Wavelet domain features had 89% accuracy with RF, outperforming Support Vector Machine (SVM), KNN, Gradient Boosting (GB) and Decision Tree.

Keywords-Electroencephalography; affective computing; human emotion recognition; fast Fourier transform; band power; Emotiv EPOC X

I. INTRODUCTION

Emotion recognition technologies can be broadly classified as unimodal or multimodal, as shown in Figure 1. Human affective states can be understood via audio recordings, text, facial expressions, body gestures, and physiological signals [1, 2]. Human behaviors are affected by emotions, which result in physical and psychological changes in the human body. The brain waves are prominent physiological signals for understanding human emotions. Emotion models work as a base for emotion recognition technologies. In 1980, Russell proposed the 2-dimensional circumplex model of affect [3] based on valence and arousal. Valence represents how positive or negative a specific emotion is, and arousal represents how intense or calm an emotion is. EEG is a physiological signal consisting of Delta (δ: 1-4 Hz), Theta (θ: 4-7 Hz), Alpha (α: 8-13 Hz), Beta (β: 13-30 Hz) and Gamma (γ: >30 Hz) bands [4]. According to the existing study, alpha and beta bands can signify the affective and cognitive states of the human brain. Alpha waves are generated in a relaxed and calm state of mind, whereas Beta waves emanate during attentive and alert state [5]. The features required for recognizing emotional states can be obtained from EEG signals by applying Fast Fourier Transformation (FFT) and Discrete Wavelet Transform (DWT).

EEG and Electrocardiography (ECG) can provide reliable features for emotion recognition [6]. The deep learning approach based on combined features of EEG and ECG proposed in [7] achieved 94.25% accuracy for emotion detection. Authors in [8] yielded 92% accuracy for emotion recognition using data from the DREAMER dataset by proposing a hybrid fuzzy-deep learning approach. However, ECG signals are very sensitive to artifacts and have complex noise removal and processing.

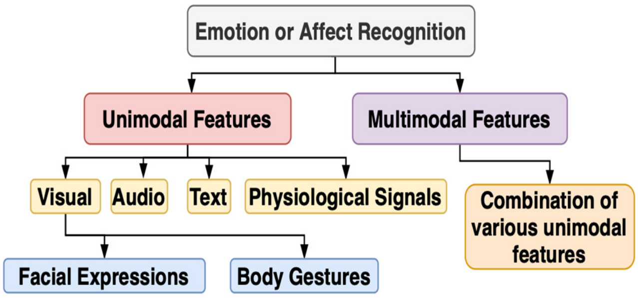

Fig. 1. Taxonomy of emotion recognition technologies.

TABLE I. EMOTION RECOGNITION USING EMOTIV EEG DEVICES

Sr. No.	Emotions	Data Collection	Features	Classifier and Accuracy
1	Neutrality, Joy, Sadness, Anger, Disgust, Fear, Surprise	Six subjects Age: 22 to 61 years (*14 channels)	α and β frequency bands	Fuzzy Logic Accuracy: 85.71% for Joy [11]
2	Happy, Pleasant, Frightened, Angry	4 males and 1 female Age: 24 to 28 years (FC5, F4, F7, AF3, and T7 channels)	Fractal Dimension (FD), 1st order HOC, Statistical Features, and Band Power (BP)	SVM Accuracy: 73.10% for classification of positive and negative emotions [12]
3	Valence and Arousal	20 males and 14 females Age: 18 to 22 years (*14 channels)	Mean, Standard Deviation (SD), Power	KNN Accuracy: 82.33% (valence) and 87.32% (arousal) [13]
4	Calm, Anger, and Happiness	10 users (*14 channels)	FD	SVM with RBF kernel Accuracy: 60% [14]
5	Happy and Sad	7 males and 5 females Age: 18 to 38 years (AF3, AF4, O1, and O2 channels)	Mean, SD, Number of peaks of α and β frequency bands	Naive Bayes Accuracy: 87.5% [15]
6	Neutral, Happy and Sad	5 males and 5 females Age: 21 to 24 years (*14 channels)	Power Spectral Density (PSD), Energy, Entropy	SVM Accuracy: 89.17% [16]
7	Calm, Angry, Sad, Happy	15 females and 7 males Age: 12 to 70 years (*14 channels)	Band Power and other Time domain features	KNN Accuracy: 70% for Sad emotion [17]

* (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4)

Emotions are directly connected to brain activity. EEG offers important insights into the dynamic mechanisms of emotions and cognitive states. The EEG gives true data for emotion detection because it is a physiological signal, and its falsification is not possible as can be done in voice or face expressions [9]. There are many EEG devices for data collection. EEG is frequently employed for emotion analysis due to its ease of acquisition, with Emotiv being one of the most widely used EEG devices [10]. This study emphasizes on emotion recognition for data collected using Emotiv EEG devices as shown in Table I.

II. PROPOSED METHODOLOGY

The proposed system architecture is shown in Figure 2. This work aims to classify human emotions using real-time EEG data. The detailed description of various steps is given in the following sub-sections.

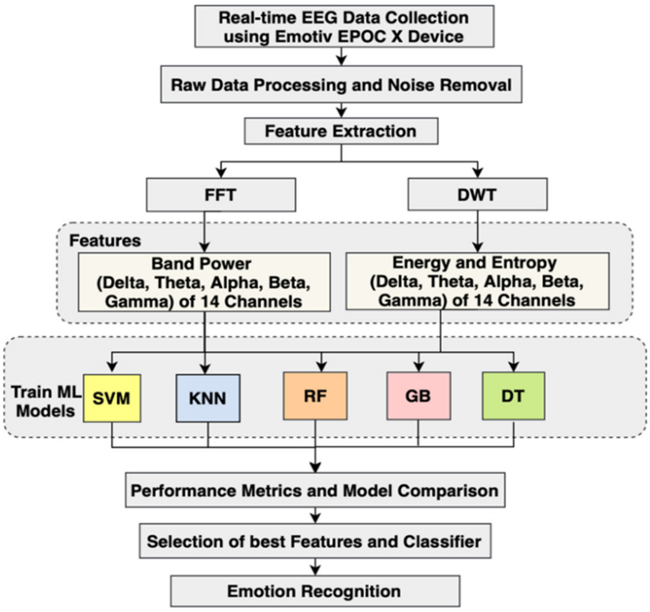

Fig. 2. Proposed system architecture.

A. Data Collection

Raw EEG data sampled at 128 Hz were collected using the EEG Emotiv EPOC X [18] device that has 14 channels (Table I). EEG data were collected from 20 healthy subjects (10 males and 10 females aged between 19 and 22 years) after obtaining their consent. Figure 3 shows the participants and the experimental setup. A total of 4 experiments were carried out for four separate categories of emotions as per Russell's Circumplex Model of Affect (Happy, Sad, Calm, Stressed). Participants rated their feelings on a scale of 1 to 9 based on the Self-Assessment Manikin system that represents the degree of valence and arousal.

B. EEG Raw Data Pre-Processing and Noise Removal

The EEG raw data consist of 4 categories of emotions for 14 channels of each of the 20 participants. The data dimensions are 32000 values × 20 participants × 14 channels per emotion (happy, sad, calm, and stressed). The correlation matrix is considered to ensure that the dataset does not exhibit any sort of bias. A slew limit of 30 mV was considered and a high-pass filter was applied with a cut-off frequency of 0.5 Hz to the raw EEG data for noise removal through EmotivPRO Analyzer.

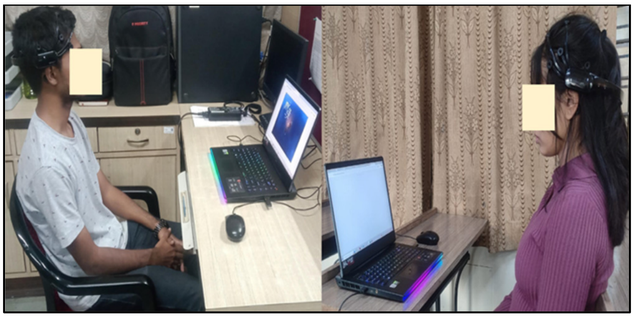

Fig. 3. Participants and Experimental Setup.

C. Feature Extraction

The following sections describe the feature extraction.

1) Frequency Domain Analysis of EEG Data

It is more closely associated with physiological processes and human brain, and hence it is specifically useful in studies of human emotion detection. Two prominent features obtained from EEG data are PSD and BP. PSD represents signal power distribution across different frequency bands. Band Power is the overall power contained within a particular frequency band of a signal. The algorithm for Frequency Domain Analysis using FFT is described below.

Input: Raw EEG Data collected from Emotiv EPOC X.

Output: Emotion Prediction based on EEG features.

Initialization:

Let $x(t) = [x_1, x_2, \dots, x_N]$ be the time domain EEG signal for a single channel after noise removal and X(f) be the frequency domain EEG signal obtained through FFT as shown in (1):

$$X(f) = FFT[x(t)] = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \quad (1)$$

where T is the total duration of the EEG signal, and

Features = Extracted EEG features for emotion classification.

Labels = Emotion Labels (Happy, Sad, Calm, Stressed).

Step 1: Preprocessing of the EEG Data

1: for i = 0; i < 14; i++ do // Loop over all 14 EEG channels

2: Remove noise through EmotivPRO Analyzer

3: Apply FFT on x(t) to obtain X(f) as formulated in (1).

4: Compute PSD(f) from X(f) using:

$PSD(f) = |X(f)|^2 / T$

Store PSD for every channel and band

5: end for

Step 2: Feature Extraction

6: for i = 0; i < 14; i++ do // Loop over all 14 EEG channels

7: for j = 0; j < 5; j++ do // Loop over all frequency bands (Delta, Theta, Alpha, Beta, Gamma)

8: if j == 0 then // Delta Band (1-4 Hz)

9: $P_\delta(f) = \int_1^4 PSD(f)\, df$

10: else if j == 1 then // Theta Band (4-7 Hz)

11: $P_\theta(f) = \int_4^7 PSD(f)\, df$

12: else if j == 2 then // Alpha Band (8-13 Hz)

13: $P_\alpha(f) = \int_8^{13} PSD(f)\, df$

14: else if j == 3 then // Beta Band (13-30 Hz)

15: $P_\beta(f) = \int_{13}^{30} PSD(f)\, df$

16: else if j == 4 then // Gamma Band (30-40 Hz)

17: $P_\gamma(f) = \int_{30}^{40} PSD(f)\, df$

18: end if

19: end for

20: Store extracted features (P_δ, P_θ, P_α, P_β, P_γ) for channel i

21: end for

Step 3: Classification

22: Dataset labelling for four emotion classes

23: Train ML models (SVM, KNN, RF, GB, DT):

Model = Train_Model (Features, Labels)

24: Use the trained model to classify features into specified emotional states:

Emotion = Predict_Emotion (Model, FFT Features)

2) Wavelet Domain Analysis of the EEG Data

DWT decomposes an EEG signal into approximate and detail coefficients that are represented by the output of low- and high-pass filters, respectively. This work uses db4 wavelet from the Daubechies family which is widely used for EEG analysis [19]. Energy and Entropy are most important features extracted after applying DWT on EEG data. Energy in the wavelet domain of the EEG signals identifies dominant frequency components. Entropy, on the other hand, quantifies the level of disorder or complexity in the distribution of wavelet coefficients. The Entropy and Energy for each band are calculated by:

$$ENTROPY_j = -\sum_{k=1}^{N} (D_j\ (k)^2) \log (D_j\ (k)^2) \quad (2)$$

$$ENERGY_j = \sum_{k=1}^{N} (D_j\ (k)^2) \quad (3)$$

where $D_j(k)$ represents the detail coefficient at the decomposition level j and k denotes the index of a coefficient within the detail coefficients for a given level (e.g., if there are 128 coefficients at level 2, k will range from 1 to 128).

The algorithm for Wavelet Domain Analysis using DWT is described below.

Input: Raw EEG data collected from the Emotiv EPOC X.

Output: Emotion prediction based on EEG features.

Initialization:

Let $x(t) = [x_1, x_2, \ldots, xN]$ be the time domain EEG signal for a single channel after noise removal.

Features = Extracted EEG features for emotion classification.

Labels = Emotion Labels (Happy, Sad, Calm, Stressed).

Step 1: EEG Data Preprocessing

1: for (i = 0; i < 14; i++) do // Loop over all 14 EEG channels

2: Remove noise with the EmotivPRO Analyzer

3: Perform wavelet decomposition on each EEG channel data $x_i(t)$ using the pywt.wavedec:

Coefficients = pywt.wavedec($x_i(t)$, 'db4', level=4) // Decompose the signal

4: Store the coefficients for further feature extraction

5: end for

Step 2: Feature Extraction

6: for (i = 0; i < 14; i++) do // Loop over all 14 EEG channels

7: for (j = 1; j ≤ 4; j++) do // Loop over all decomposition levels (1 to 4)

8: Dj = coefficients[i][j] // Extract detail coefficients at level j

9: Compute the Entropy for level j using (2):

$Entropy_j$ = compute_entropy(Dj)

10: Compute the Energy for level j using (3):

$Energy_j$ = compute_energy(Dj)

11: Store the computed Entropy and Energy values for each level as features

12: end for

13: Prepare the feature vector for classification using the Entropy and Energy values

14: end for

Step 3: Classification

15: Dataset labelling for four emotion classes: Happy, Sad, Calm, Stressed

16: Train ML models (SVM, KNN, RF, GB, DT):

Model = Train_Model (Features, Labels)

17: Use the trained model to classify features into the specified emotional states:

Emotion = Predict_Emotion (Model, DWT Features)

D. Emotion Labeling

The dataset is created and labeled with four emotion classes. The ratings given by participants during each experiment were recorded and stored against their data. The values between 1 to 4.5 were considered as low and 4.6 to 9 as high. The emotions were mapped according to the Circumplex Model. For example, if valence is 7 and arousal is 8, the status will be labeled as Happy. Table II shows the feature set and emotion labels. A total of 512 data instances were acquired for creating feature sets.

TABLE II. FEATURE SET

Features	Contents	Array Shape (Data values × Subjects × Features × Emotion Labels)	Size of Feature Set (Rows × Columns)	Emotion Labels
FFT: Band Power	14 channels × 5 bands = 70 features	512 × 20 × 70 × 4	40960 × 70	10240 per emotion label: 10240 × 4 labels = 40960
DWT: Energy and Entropy	14 channels × 5 bands × 2 features = 140 features	512 × 20 × 140 × 4	40960 × 140	10240 per emotion label: 10240 × 4 labels = 40960

E. Model Training and Emotion Classification

The ML algorithms SVM, KNN, RF, GB, and DT were trained on the feature set. Hyperparameter tuning was conducted for all classifiers on the training data using GridSearchCV with 5-fold cross-validation .

SVM with RBF kernel was tuned over regularization parameter $C \in \{0.1, 1, 10\}$ and gamma $\in \{0.001, 0.01, 0.1, 1\}$ and had optimal values C = 10 and gamma = 0.1. The KNN classifier was tuned for $k \in \{3, 4\}$, yielding the best performance at k = 3 using the Euclidean Distance. Similarly, the optimal hyperparameters for the other classifiers were: DT (max_depth = 10, min_samples_split = 2, min_samples_leaf = 1, criterion = gini); RF (n_estimators = 100, max_depth = 10, min_samples_split = 2, min_samples_leaf = 1, max_features = sqrt); and GB (n_estimators = 100, learning_rate = 0.1, max_depth = 5, subsample = 1.0).

The best model of each classifier was saved for further testing. The final trained model was fed with unseen EEG data to predict emotional states.

III. RESULTS AND DISCUSSION

The results of Frequency and Wavelet Domain Features are discussed in this section. The train-test dataset split ratio values were 70:30, 80:20, and 90:10. Precision (PN), Recall (RL), F1 Score (F1S), and Accuracy (AY) were calculated for every classifier. A total of 70 FFT and 140 DWT features from 14 channel data of 20 participants were considered. Results for 512 values × 70 features × 20 subjects are shown in Tables III and IV for frequency and wavelet domains, respectively. Figure 4 shows the testing accuracy comparison for band power features.

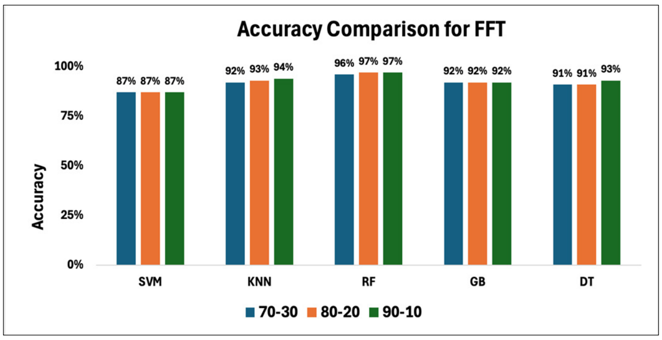

Fig. 4. Accuracy comparison for FFT Features: Band Power.

With frequency domain band power features, RF gave a consistent and highest accuracy of 97% for 80:20 and 90:10 dataset splits, which is the highest recorded among all combinations. KNN, GB, and DT also performed well and gave accuracy above 90%. SVM had an accuracy of 87% for different splits. Figure 5 shows the accuracy comparison for energy and entropy features. With wavelet domain features, again RF fared better than the other classifiers. It gave 89% accuracy for the 90:10 dataset split, whereas DT had 78% accuracy. SVM and KNN obtained less accuracy values for Energy and Entropy features. Frequency domain features of the EEG signal gave the highest accuracy as compared to other features. The highest recorded accuracy of 97% on real-time EEG data was achieved by RF for the band power of five bands of each of the 14 EEG channels after applying FFT. It should be mentioned that FFT gave better results as compared to DWT.

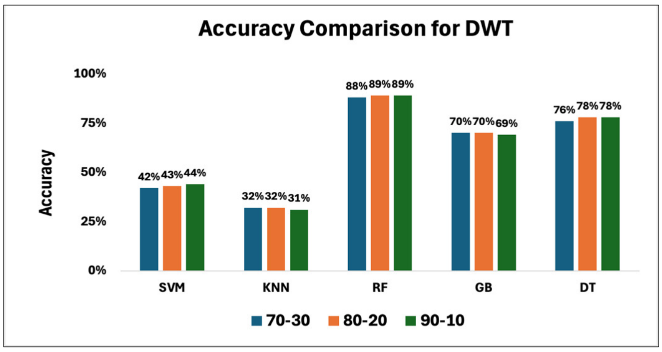

Fig. 5. Accuracy comparison for DWT Features: Energy and Entropy.

Figure 6 shows the accuracy comparison of the current work with existing studies related to emotion recognition using Emotiv EEG devices. The proposed approach outperformed the existing approaches mentioned in Table I.

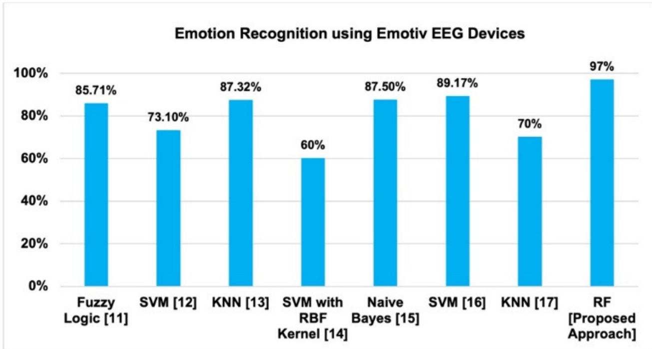

Fig. 6. Accuracy comparison.

TABLE III. RESULTS FOR FREQUENCY DOMAIN FEATURES: BAND POWER

Dataset Split		70:30				80:20				90:10			
Classifier	Metric	Happy	Sad	Calm	Stressed	Happy	Sad	Calm	Stressed	Happy	Sad	Calm	Stressed
SVM	PN (%)	83	89	86	89	84	89	86	89	84	90	85	89
	RL (%)	84	88	87	87	85	89	88	88	85	89	88	87
	F1S	0.84	0.9	0.87	0.88	0.84	0.9	0.87	0.88	0.85	0.9	0.86	0.88
	AY (%)	87				87				87			
KNN	PN (%)	91	93	92	93	92	94	93	93	94	95	94	95
	RL (%)	91	94	92	93	92	95	92	95	93	95	94	96
	F1S	0.91	0.9	0.92	0.93	0.92	0.95	0.93	0.94	0.94	0.95	0.94	0.95
	AY (%)	92				93				94			
RF	PN (%)	97	97	95	95	97	97	97	95	97	98	97	97
	RL (%)	96	96	96	97	97	96	97	97	97	97	97	98
	F1S	0.96	0.96	0.96	0.96	0.97	0.97	0.97	0.96	0.97	0.98	0.97	0.97
	AY (%)	96				97				97			
GB	PN (%)	91	94	91	91	90	94	92	92	92	94	90	93
	RL (%)	92	91	93	91	92	92	93	92	93	92	93	92
	F1S	0.91	0.9	0.92	0.91	0.91	0.9	0.92	0.92	0.92	0.9	0.91	0.93
	AY (%)	92				92				92			
DT	PN (%)	92	90	91	90	93	92	91	89	94	94	93	92
	RL (%)	92	91	89	90	93	91	90	91	94	94	93	92
	F1S	0.92	0.9	0.9	0.9	0.93	0.9	0.91	0.9	0.94	0.9	0.93	0.92
	AY (%)	91				91				93			

TABLE IV. RESULTS FOR WAVELET DOMAIN FEATURES: ENERGY AND ENTROPY

Dataset Split		**70:30**				**80:20**				**90:10**			
Classifier	**Metric**	**Happy**	**Sad**	**Calm**	**Stressed**	**Happy**	**Sad**	**Calm**	**Stressed**	**Happy**	**Sad**	**Calm**	**Stressed**
SVM	**PN (%)**	42	38	40	54	42	40	40	54	42	40	40	57
	RL (%)	44	49	41	36	44	49	42	37	41	49	46	38
	F1S	0.43	0.43	0.41	0.43	0.43	0.44	0.41	0.44	0.42	0.44	0.43	0.46
	AY (%)	42				43				44			
KNN	**PN (%)**	31	32	29	41	31	32	29	42	32	31	27	43
	RL (%)	31	23	48	24	32	22	49	25	33	21	49	23
	F1S	0.31	0.27	0.36	0.3	0.32	0.26	0.36	0.31	0.32	0.25	0.35	0.3
	AY (%)	32				32				31			
RF	**PN (%)**	85	83	89	94	87	86	89	95	88	86	89	96
	RL (%)	87	90	88	85	89	91	89	87	89	92	90	87
	F1S	0.86	0.86	0.88	0.89	0.88	0.89	0.89	0.91	0.89	0.89	0.9	0.91
	AY (%)	88				89				89			
GB	**PN (%)**	65	63	71	87	65	64	70	88	66	63	64	89
	RL (%)	67	78	68	66	68	78	68	66	67	77	69	63
	F1S	0.66	0.69	0.7	0.75	0.67	0.66	0.69	0.75	0.67	0.69	0.67	0.74
	AY (%)	70				70				69			
DT	**PN (%)**	73	74	78	80	76	77	78	81	77	77	76	81
	RL (%)	74	75	77	79	74	78	79	81	76	75	81	80
	F1S	0.73	0.75	0.77	0.8	0.75	0.77	0.79	0.81	0.76	0.76	0.78	0.81
	AY (%)	76				78				78			

IV. CONCLUSION AND FUTURE SCOPE

Study of human emotions using EEG has grabbed huge attention because of its relevance in Affective Computing domain. This work adds contribution in terms of addressing the challenge of proper feature selection. The creation of a new and self-curated emotion dataset based on EEG signals and making an attempt towards accurate emotion recognition makes this work novel with enhancement of existing technologies. Various features were extracted from raw EEG and compared for finding best features suitable for recognizing emotions. It is found that Band Power is an important feature for identifying emotions because it has direct relation to the various frequency bands of an EEG signal. Considering feature extraction, FFT outperformed DWT. Random Forest achieved the highest accuracy of 97% for test-train dataset split in the ratio of 80:20 and 90:10 with band power as a prominent feature as compared to SVM, KNN, GB and DT. RF performed best with both wavelet and frequency domain features, but it achieves significantly higher accuracy with frequency domain features (96% - 97%) compared to wavelet domain features (88% - 89%). Frequency domain features are the most effective for EEG based emotion classification, as they had consistently provided the highest accuracy across all classifiers. Future scope will include real-time EEG based classification of more complicated human emotions.

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