Predicting Human Emotions through Time and Frequency Feature Extraction using EEG Emotional Database Analysis

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ABSTRACT

Emotion recognition is a technique to identify the emotion of an individual by using facial expressions, behavior, and neuroimaging techniques. Electroencephalography (EEG) is a non-invasive technique mainly used to recognize emotions. To study variations in human emotions, the authors created an EEG dataset, named EEG Emotional Database Analysis (EEDA), by conducting a study with the help of an EEG technician on 10 healthy participants. The participants were asked to watch video clips representing five emotions with a 60-second gap between clips. The emotional responses were collected simultaneously through EEG across five trials, utilizing a 32-channel system. The EEG data were preprocessed to remove artifacts using a band-pass filter and Independent Component Analysis (ICA). Subsequently, signal features were extracted in three domains: time, frequency, and time-frequency. The data were segregated into five classes: Relaxed-Happy-Excitement (RHE), Relaxed-Fear-Sad (RFS), Relaxed-Happy-Fear (RHF), Relaxed-Excitement-Sad (RES), and Relaxed-Happy-Sad (RHS) for training and testing purposes. After feature extraction, feature selection was performed using Principal Component Analysis (PCA), mutual information, Recursive Feature Elimination (RFE), and Least Absolute Shrinkage and Selection Operator (LASSO) regularization to calculate the accuracy with the Bidirectional Long Short-Term Memory (BiLSTM) model. The highest classification accuracies obtained on the EEDA dataset were 84.27% for the RHS class in the time domain, 61.81% for the RES class in the frequency domain, and 84.37% in the time-frequency domain for the RHS and RHF classes.

Keywords-emotions; EEG; BiLSTM; feature extraction

I. INTRODUCTION

Emotions are a captivating interaction of psychological and physiological processes, each influencing the other. Emotions mainly arise due to thoughts, feelings, and surrounding environments and at the same time are reflected in the body in terms of human behavior [1, 2]. Emotions affect human behavior, cognition, mood, decision making, and have an impact on personal connections [3, 4].

In this contemporary era, prediction of emotion recognition through Electroencephalography (EEG) has become more popular among researchers due to its interdisciplinary approach, human computer interaction, and its relation to human psychology [5-7]. Lack of emotional imbalance is the major reason for various psychological and mental disorders [8]. EEGs make it easy to measure brain activity. EEGs are noninvasive, inexpensive, and fast; therefore, they are the researchers' choice for studying the human brain and behavior

[9, 10]. Thus, an emotional model needs to be developed to recognize emotions [11-13].

Various researchers are working on this topic using two types of principal models and approaches to evaluate emotions: 'discrete and dimensional models' and 'subject-dependent and subject-independent approaches'. In the subject-dependent approach, the same data are used for training and testing purposes, whereas in the subject-independent approach, the whole dataset is combined and analyzed [14]. The discrete model mainly focuses on specific emotions like happiness, anger, etc. The dimensional model mainly focuses on complex emotions or mixed emotions [15, 16].

In this study, have created an EEG dataset called the EEG Emotional Database for Analysis (EEDA) to analyze human emotions based on five emotion classes, i.e., relaxed, happy, excitement, sad, and fear. In this work, the subject-independent approach is applied for the analysis of emotions. The study captured the EEG data of participants in various scenarios. After preprocessing the data, feature extraction was applied for the classification and prediction of the results.

Authors in [17] proposed a Convolutional Fuzzy Neural Network (CFNN) and achieved 98.21% accuracy. In this study, the authors worked with the DEAP dataset of 32 participants. After preprocessing, they extracted features using Fast Fourier Transform (FFT) and Discrete Fourier Transform (DFT). They then assigned the extracted features to the CFNN for training and testing purposes, achieving an average accuracy of 98.21% and 98.08% accuracy for valence.

In [18], the authors proposed their own dataset, the Intellect Database for Emotion Analysis (IDEA), which is based on subject-dependent and subject-independent approaches. They collected EEG data from 14 participants, related to positive and negative emotions and classified the data based on individual feature extraction parameters. Accuracy was evaluated for both dependent and independent settings using the Bidirectional Long Short-Term Memory (BiLSTM) model. They achieved better results using Modified Differential Entropy (MD-DE) features as compared to other feature extraction parameters.

Authors in [19] classified EEG data using a Graph Convolutional Neural Network (GCNN) for three emotions: positive, negative, and relaxed. In this study, they used the public SEED dataset. Fifteen participants watched four-minute Chinese movie clips representing three emotions and had their brain activity recorded. Five features—Differential Entropy (DE), Power Spectral Density (PSD), Differential Asymmetry (DASM), rational asymmetry, and differential causality—were extracted based on frequency bands. The authors applied support vector machine, logistic regression, and k-nearest neighbors classifiers and received accuracy results for the subject-dependent approach. DE achieved the highest accuracy of 82.46%, 75.23%, and 84.44% across the machine learning classifiers. Similarly, the GCNN achieved an accuracy of 89.97%.

In [20], the authors used EEG brain activity during online shopping scenarios to predict participants' purchase selections. For this study, they collected data over the past 3 years from around 12 batches of participants recorded in realistic scenarios. The participants primarily focused on product types such as hygiene products, cosmetics, nutritional products, and household products. A machine learning algorithm applied to these data achieved 82% accuracy with two classes and 86% accuracy with three classes. Table I provides an overview of the aforementioned studies, highlighting differences in datasets, feature extraction methods, classification techniques, and achieved accuracies.

II. METHODOLOGY

This work focused primarily on creating an EEG dataset of five types of emotions: relaxed, happy, excitement, fear, and sad. Brain activity was measured using a portable EEG machine with 32 electrode channels. The electrodes were placed on the scalp to cover the frontal, occipital, parietal, and central regions of the brain. Figure 1 illustrates the proposed study's workflow, which includes EEG data collection, feature extraction (time, frequency, and time-frequency domains), and classification using BiLSTM. To predict accuracy, the data were classified into five classes: Relaxed-Happy-Excitement (RHE), Relaxed-Fear-Sad (RFS), Relaxed-Happy-Fear (RHF), Relaxed-Excitement-Sad (RES), and Relaxed-Happy-Sad (RHS).

A. Dataset

Ten participants took part in this research study. All of the participants were either working professionals or students with an average age of 38. All of them agreed to and signed the consent form, providing written approval for the study.

TABLE I. COMPARATIVE ANALYSIS OF RECENT EEG-BASED EMOTION RECOGNITION STUDIES

Ref.	Dataset	Feature extraction	Classification	Accuracy	Emotions
[17]	DEAP dataset (32 participants, 16 male & 16 female)	FFT, DFT	CFNN	98.21% (avg. accuracy), 98.08% for valance	Valence and arousal
[18]	Own dataset (14 participants)	MD-DE	BiLSTM	99.8% (subject dependent), 88.5% (subject independent)	Positive and negative
[19]	SEED dataset (15 participants)	DE, PSD, DASM, rational asymmetry, differential causality	GCNN	89.97% (subject dependent)	Positive, negative, and relaxed
[20]	Own dataset	Hijorth mobility and complexity	Random forest	82% (2 classes), 86% (3 classes)	Bought, put on cart, and not bought

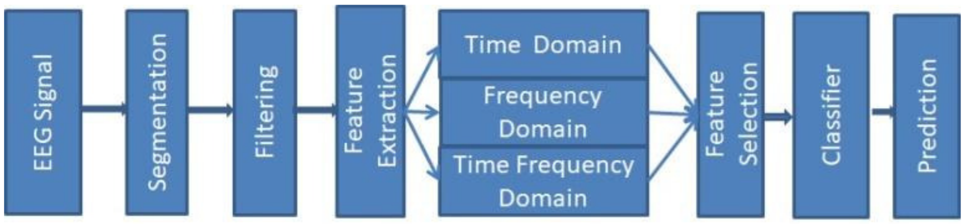

Fig. 1. Workflow of the proposed EEG-based emotion recognition system.

For this study, the data were collected using an IMPL-make digital EEG machine operating at 256 Hz with 32 channels or electrodes. The whole process was performed under the supervision of a technical expert. During EEG recording, all electrodes were attached to the scalp to collect the brain signals. This arrangement of electrodes is called a montage and collects data in two ways: bipolar and referential. In this study, the EEG machine captured brain activity and transferred the data using the bipolar montage with 32 channels. During recording, the system measured the potential difference between adjacent electrodes. The electrodes were placed in 21 positions on the scalp according to the international 10-20 system [21], such as F3, T7, AF3, FC5, P8, P7, O1, O2, F4, T8, FC6, F4, and AF4. The electrodes were placed on the frontal, parietal, occipital, and central lobes of the brain.

The procedure for data collection was demonstrated to all participants before the EEG test. Participants were informed about the scanning process and were asked to minimize head movement and other activity to reduce artifacts and noise in the signal. During EEG recording, participants were asked to keep their eyes closed and remain relaxed. Brain signals for the resting state were collected simultaneously. The participants then watched four different videos, each corresponding to an emotional state: relaxed, happy, excitement, fear, and sad. Figure 2 shows participants watching a video clip during EEG signal capture and Figure 3 shows the EEG channel plotting.

Russell's emotion model represents the valence and arousal system. On the arousal axis, low to high values represent the relaxed to excited states. On the valance axis, negative to positive values indicate unpleasant to pleasant states [22]. Figure 4 illustrates the emotional classes used in this study.

After collecting the brain activity data from all the participants, they were segmented according to emotional classes. EEG data from 16 channels were using a bipolar montage.

B. Segmentation and Preprocessing

Each participant watched 4 emotional videos of 4 m each, with relaxing intervals of 2 m between each video. EEG recording took approximately 30 m to 35 m per participant. In addition, we calculated the time stamps of the emotional video clips and resting states while collecting EEG recordings for each participant. Based on these time stamps we segmented each emotional time window for all the participants. The full EEG recording ($61\times2{,}563 = 156{,}343$ samples per participant) was divided into five segments corresponding to the emotional classes. For each emotional class, approximately 2 m of EEG data were segmented and stored separately per participant. With 10 participants and 5 emotional classes, a total of $10 \times 5 = 50$ data files were created. Table II shows a sample of EEG data after segmentation. Each EEG output file contains 17 columns: 16 for bipolar montage ECG data and one for time (per second). Each second of EEG data consists of 60×17 rows and columns, respectively.

Fig. 2. Participant watching emotional video during EEG recording.

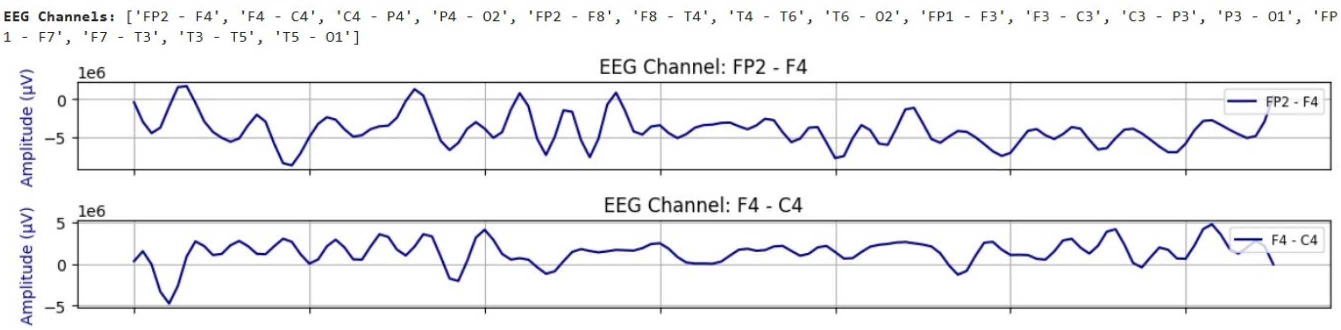

Fig. 3. Channel-wise EEG signals.

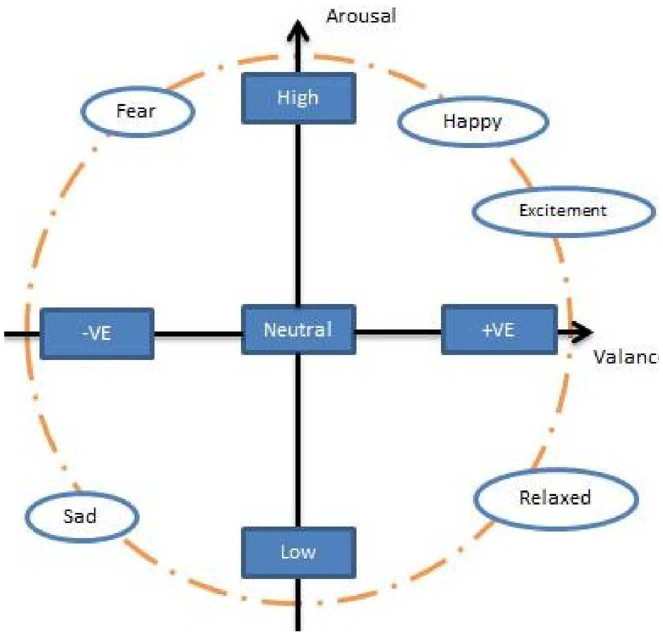

Fig. 4. Emotional classes mapped on the arousal and valence space based on Russell's model.

TABLE II. SAMPLE EEG DATA SHOWING 10 ROWS ACROSS 16 BIPOLAR CHANNELS

Time	FP2-F4	F4-C4	C4-P4	P4-O2	FP2-F8	F8-T4	T4-T6	T6-O2	FP1-F3
60	3	-1	-3	-5	0	1	1	-12	-4
61	-4	-1	-2	5	-1	-1	2	-4	-4
62	2	-2	3	-8	-1	0	-1	-2	6
63	1	0	0	1	-3	1	-1	4	4
64	2	-12	6	-15	-2	-3	-5	-13	0
65	0	-1	2	-1	-3	0	-1	2	-5
66	13	1	2	-5	9	8	2	-3	25
67	0	-1	-1	-1	-2	1	-3	-2	0
68	-2	1	-1	-2	-1	-3	0	-1	0
69	1	1	-1	4	4	0	-1	-5	-7

After segmenting, all EEG signal data were stored in .csv files according to emotional classes and participants. Then, preprocessing was performed by applying a band-pass filter, a notch filter, and Principal Component Analysis (PCA) to remove artifacts and noise from the signals. The filtered data were stored in different .csv files.

C. Feature Extraction

Feature extraction is the process of converting raw data into numerical features. It provides better results than direct classification of raw data by a machine learning algorithm [19]. Extracting features from EEG signals is a complex task, and the quality of feature extraction directly affects classification accuracy.

The features were extracted from the filtered EEG signals in three ways: time domain, frequency domain, and time-frequency domain:

- Time domain: A total of 18 features were extracted, including statistical features (mean, variance, kurtosis, skewness), Hjorth parameters (activity, mobility, complexity), Teager Energy Operator (TEO), wavelength, line length and zero crossing.
- Frequency domain: A total of 8 features were extracted based on PSD & FFT across frequency bands (gamma, beta, alpha, theta).
- Time-frequency domain: Features were extracted from the filtered EEG signals using Discrete Wavelet Transform (DWT), based on mean, variance, and entropy.

D. Data Analysis and Classification

In this research work, the authors first collected the raw EEG signal data and then segregated them into different emotional classes for each participant. After segmentation, preprocessing was applied to remove the artifacts and noise from the EEG signals using a band-pass filter, notch filter, and PCA. The band-pass filter removed low-frequency artifacts (0-3 Hz) caused by body movement. The high-pass filter removed high-frequency noise above 50 Hz. The notch filter removed eliminated narrow-band interference, whereas PCA was used to identify and remove eye-blinking and other movement artifacts. Following preprocessing, EEG data were segmented according to emotional class time stamps, and features were extracted from the filtered signals.

The best features were selected by applying a feature selection method to the time and frequency domain features. BiLSTM was used to classify these features and determine emotion class accuracy. Similarly, for time-frequency domain analysis, BiLSTM classification was applied to the best features across all three domains. Highly correlated features were removed.

III. RESULTS AND DISCUSSION

In this experimental study, we extracted features in the time and frequency domains, applied a feature selection method, and classified the data separately by domain. Prior to classification, feature selection methods such as PCA, mutual information, Recursive Feature Elimination (RFE), and Least Absolute Shrinkage and Selection Operator (LASSO) regularization were applied to reduce dimensionality and retain the most relevant features. BiLSTM classification was then applied to the selected features, and the accuracy was obtained based on three combinations of emotional classes.

A. Time Domain Results

Table III presents the classification performance using time domain features. Emotions such as excitement, fear, and sad were classified with high accuracy. However, happy emotion showed overlapping patterns with other positive emotions, resulting in lower classification performance in some combinations.

B. Frequency Domain Results

Table IV presents the classification performance using frequency domain features. The results show that excitement emotion is consistently well-identified by the model across all combinations. Similarly, fear emotion is also recognized effectively. However, the detection of happy and sad emotions varies, performing well in some combinations but not in others.

C. Time-Frequency Domain Results

Time-frequency features were extracted using DWT, including mean, variance, and energy. These features were then combined with all time and frequency domain features and optimized through feature selection. Table V presents the final results after BiLSTM classification on the selected combined feature set. The time-frequency domain achieved the best overall performance across all emotional classes. The fusion of multi-domain features combined with BiLSTM classification significantly enhanced emotion discrimination.

TABLE III. CLASSIFICATION PERFORMANCE USING TIME DOMAIN FEATURES

Emotion combination	Accuracy (%)	Class	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
RHE	71.53	Relaxed	67.29	80.22	66.67	67.29
		Happy	45.71	79.82	42.11	43.84
		Excitement	91.07	98.86	98.08	94.44
RFS	81.25	Relaxed	65.71	86.24	60.53	63.01
		Fear	100	100	100	100
		Sad	71.70	86.81	76	73.79
RHF	73.61	Relaxed	90.57	67.03	61.54	73.28
		Happy	11.43	94.50	40	17.78
		Fear	96.43	97.73	96.43	96.43
RES	81.94	Relaxed	48.57	92.66	68	56.67
		Excitement	100	100	100	100
		Sad	84.91	80.22	71.43	77.59
RHS	84.72	Relaxed	65.71	90.83	69.70	67.65
		Happy	96.43	97.73	96.43	96.43
		Sad	84.91	89.01	81.82	83.33

TABLE IV. CLASSIFICATION PERFORMANCE USING FREQUENCY DOMAIN FEATURES

Emotion combination	Accuracy (%)	Class	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
RHE	54.86	Relaxed	60.38	70.33	54.24	57.14
		Happy	14.29	86.24	25	18.18
		Excitement	75.00	73.86	64.62	69.42
RFS	58.33	Relaxed	65.71	86.24	60.53	63.01
		Fear	100	100	100	100
		Sad	71.70	86.81	76.00	73.79
RHF	49.13	Relaxed	50.94	70.33	50.00	50.47
		Happy	34.29	69.72	26.67	30.00
		Fear	57.14	85.23	71.11	63.37
RES	61.81	Relaxed	51.43	77.06	41.86	46.15
		Excitement	71.43	87.50	78.43	74.77
		Sad	58.49	79.12	62	60.19
RHS	59.72	Relaxed	20	87.16	33.33	25
		Happy	92.86	63.64	61.90	74.29
		Sad	50.94	86.81	96.23	58.70

TABLE V. CLASSIFICATION PERFORMANCE USING TIME-FREQUENCY DOMAIN FEATURES

Emotion combination	Accuracy (%)	Class	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
RHE	66.66	Relaxed	34.38	89.06	61.11	44
		Happy	71.88	65.62	51.11	59.74
		Excitement	93.75	95.31	90.91	92.1
RFS	66.66	Relaxed	50	82.81	59.26	54.24
		Fear	56.25	71.88	50	52.94
		Sad	93.75	95.31	90.91	92.31
RHF	84.37	Relaxed	81.25	85.94	74.29	77.61
		Happy	100	98.44	96.97	98.46
		Fear	71.88	92.19	82.14	76.67
RES	80.20	Relaxed	87.50	76.56	65.12	74.67
		Excitement	100	100	100	100
		Sad	53.12	93.75	80.95	64.15
RHS	84.37	Relaxed	84.38	84.38	72.97	78.26
		Happy	100	100	100	100
		Sad	68.75	92.19	81.48	74.58

IV. CONCLUSION

This study explores the use of Bidirectional Long Short-Term Memory (BiLSTM) networks for emotion detection using Electroencephalography (EEG) signals. For this study, a new dataset called the EEG Emotional Database Analysis (EEDA) was created to predict human emotions. After segmentation and preprocessing, the EEG data were stored in .csv files according to emotion classes.

Feature extraction was performed using three techniques: time domain, frequency domain, and time-frequency domain. Feature selection methods such as Principal Component Analysis (PCA), mutual information, Recursive Feature Elimination (RFE), and Least Absolute Shrinkage and Selection Operator (LASSO) were applied to select the most relevant features from the extracted sets.

The selected features were then classified using the BiLSTM algorithm. This experimental work analyzed classification performance based on five combinations of emotional classes: Relaxed-Happy-Excitement (RHE), Relaxed-Fear-Sad (RFS), Relaxed-Happy-Fear (RHF), Relaxed-Excitement-Sad (RES), and Relaxed-Happy-Sad (RHS). The highest classification accuracies on the EEDA dataset were 84.37% in the time-frequency domain for the RHS and RHF classes, 84.27% in the time domain for the RHS class, and 61.81% in the frequency domain for the RES class.

Future work includes expanding the study to include multiple emotional classes with a larger sample size to further improve the model's performance.

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