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Dual-Domain Experiment for EEG Emotion Recognition

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***Abstract*— Electroencephalography (EEG) is a pivotal tool for emotion recognition in computing and neuroscience fields. This study proposes a dual-method investigation by utilizing frequency-domain and time-domain EEG features. In the first experiment, EEG signals of 24 young adults were recorded when they listened to Kannada music had to evoke sad, relaxing, and enjoyable states. The data were band-pass filtered for 0.5–45 Hz which was trans-formed into frequency domain using Fast Fourier Transform (FFT), and features like band power, spectral centroid, spectral spread, spectral flux, and spectral flatness were extracted by utilizing the Power Spectral Density (PSD). Random Forest (RF) and KNN classifiers gained comparable accuracies of 73.33% (Channel 1) and 53.33% (Channel 2). In the second experiment, emotions such as funny, sad, and scary were classified while watching the advertisements by using time-domain statistical features like mean, variance, standard deviation, skewness, and kurtosis from the pre-processed EEG. The dataset was improved with subject-to-subject distance measures and clustering before classification by utilizing Multi-Layer Perceptron (MLP) neural network which achieved 83.33% accuracy on both Channel 1 and Channel 2. These results shows the distinct advantages of frequency-domain and time-domain analyses for culture-based emotion studies and consumer-neuroscience applications, respectively.**

***Keywords*— Electroencephalography (EEG), Frequency domain features, Time domain features, Emotion recognition, Multi-Layer Perceptron, Random Forest, KNN.**

I. INTRODUCTION

Emotions influence choices, behavior, and how situations around us are under-stood. It influences human behavior and how they respond to others. Emotion recognition is useful in different fields like healthcare, education systems, entertainment and Human Computer Interaction (HCI). Many techniques which de-pend on facial expressions or speech are not reliable as they often fail when a person fakes the emotions intentionally. Even though EEG collects the brain's electrical activity, it consists of noisy and multiple variations when people respond differently for different situations. Most of the existing systems depend on multiple channels and also they do not use the stimuli that are culturally relevant, which reduces how naturally participants react. To overcome these limitations, this paper utilizes a simple dual channel EEG setup and analyzed two types of emotional responses, those evoked by kannada musical clips using frequency-domain features and commercial advertisement videos using time-domain features and refined through distance measure computation. This study aims to show that reliable emotion recognition is possible even with basic hardware, culturally familiar stimuli, and minimal yet meaningful signal features.

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Prior studies observed that EEG-based emotion recognition benefits from non-invasive signals and that frontal-region features such as bandpower and PSD effectively separate emotional dimensions like arousal and valence [1][2]. Ad-vanced studies showed that frequency-domain features are more resilient to noise and subject variabilities [3]. Random Forest model outperformed deep net-works on smaller datasets by utilizing spectral measures like Flux and Flatness [4]. Few studies showed clear emotional shifts across Alpha, Beta, and Gamma bands during auditory stimuli and stressed the importance of culturally relevant EEG datasets [5][6]. A residual graph attention networks for multi-channel EEG emotion recognition and Random Forest demonstrated that multi-feature EEGs improved the performance, while CNN and quantum-based models highlighted the value of advanced feature transformations [7][8]. DEAP and SEED datasets were applied on ANN, SVM, and KNN with time-domain features showed frontal–temporal regions as strong predictors of emotional states [9][10]. Bi-LSTM models utilized energy-based and differential features and achieved strong results on SEED and DEAP datasets, and broader reviews confirmed that simple time-domain measures (ZCR, SSC, WA) with models such as SVM, RF, CNN, and LSTM consistently achieve high accuracy, with frontal–temporal re-gions remaining the most informative for emotion recognition [11][12].

II. Dataset Description

The study utilized the MindData for Enhanced Entertainment EEG data collec-tion, consisting recordings from 46 participants. The first experiment includes EEG data from 24 Kannada-speaking subjects who listened to music clips de-signed to stimulate emotions like sadness, relaxation, and enjoyment. EEG was recorded using a BIOPAC 2-channel system positioned over the Fp1–Fp2 frontal regions, with each stimulus lasting 60–90 seconds. The signals were sampled at 2000 Hz, band-pass filtered to 0.1–50 Hz, cleaned for artifacts, and stored in CSV data format. This resulted in approximately 60,000 samples per channel. The second study utilizes EEG recordings from 22 participants who viewed three 10-second commercials (funny, sad, scary), with a 60-second rest period between clips using the same BIOPAC setup with electrodes over the medial prefrontal cortex and left hemisphere. The recordings for each advertisement produced approximately 20,000 samples per channel. The overall dataset has two main folders Commercial Advertisements and Kannada Music Clips containing a total of 12 CSV files, where the columns represent the subjects and the rows represent the sample values.

III. Methodology

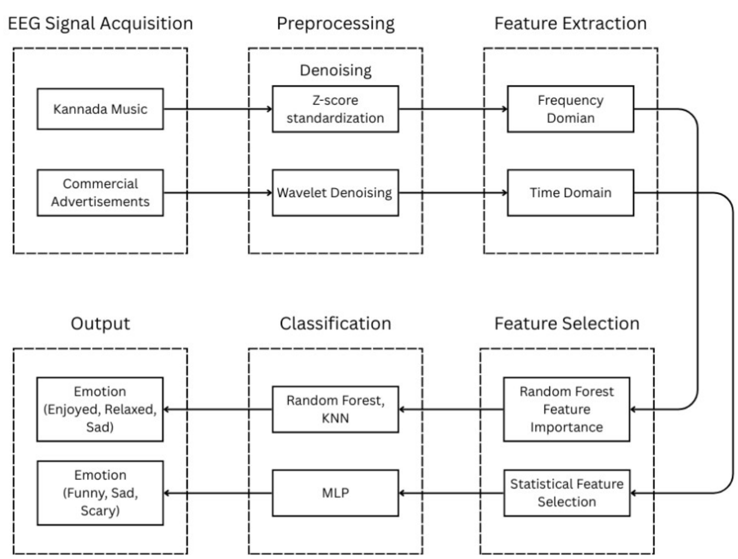


Fig. 1. Proposed Methodology

To explore different approaches to emotion recognition, the study designed a methodological pipeline, summarized in Figure 1, that processes raw EEG signals into emotion predictions via two distinct experiments. One experiment investi-gates frequency-domain features derived from EEG recorded as participants lis-tened to stimulative Kannada music. The other experiment focuses on time-domain features from EEG collected during the viewing of commercials. Despite their different focuses, both pathways share a common structure involving pre-processing, feature extraction, feature selection, and classification. This dual-stream architecture provides a clear basis for determining how time and frequen-cy-based representations contribute to classification.

A. Experiment on Frequency Domain Features

Pre-processing. The aim of pre-processing is to keep the signals clear enough for analysis, and it involves band-pass filtering (0.5–45 Hz) to eliminate DC drift and power-line noise. Fast rejection of noise caused by eye blinks and muscle movements is performed using threshold-based removal. Normalization is done using Z-score standardization, where each feature is transformed to zero mean and unit variance to reduce subject-to-subject amplitude differences.

$$\mathrm{Zi} = \frac{\mathrm{xi}-\mu}{\sigma} \tag{1}$$

Where x_i is the original value, μ is the mean of the data, σ is the standard deviation

Frequency Domain Analysis. This part of the EEG is Fourier transformed:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\Pi k \ /N} \tag{2}$$

Where: X(k) is DFT of the signal at frequency bin k, x(n) is EEG signal in the time domain at sample n, N is the total number of samples in the signal. K is the frequency index (ranging from 0 to N−1), j is the imaginary unit (\sqrt{−1}) from these frequencies, the PSD was calculated with Welch split energy algorithms for the bands.

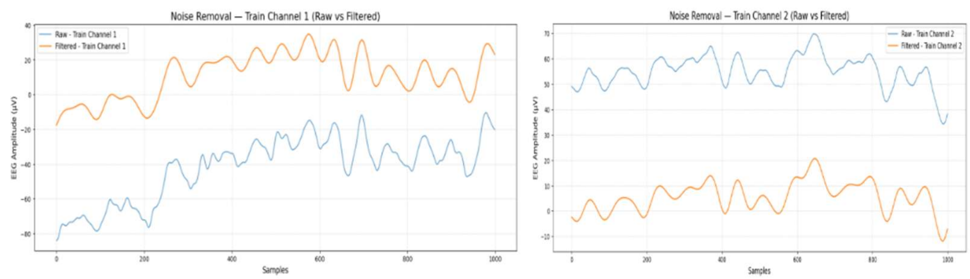


Fig. 2. Representation of raw versus filtered data channel 1 and channel 2 respectively

Feature Extraction. Five frequency-domain characteristics were extracted from each PSD segment:

Band Power (P). The extent of energy present in a certain frequency band of a signal.

Spectral Centroid (C). Where most of the spectral energy is concentrated.

Spectral Spread (S). The spreading of energy across the frequencies.

Spectral Flux (F). How individual or rapid changes in energy occur over time in the psychoacoustic spectrum, with most changes relating to emotional arousal.

Spectral Flatness (Ff). Rank the noisiness of EEG activity.

Classification Models. This involves pre-processing EEG signals via filtering and Z-score normalization and proceeding to extracting of important frequency-domain features such as Band Power, Spectral Centroid, Spectral Spread, Spectral Flux, and Spectral Flatness. These acquired features were employed in classify-ing emotions using two standard machine learning classification algorithms, Random Forest (RF), and K-Nearest Neighbours (KNN). To ensure fair and unbi-ased learning, participant-wise cross-validation with an 80-20 train-test split was documented, whereby all data from a given participant was exclusively kept in either training or testing. By preventing leakage related to specific subjects, this practice increases the model generalizability in the presence of substantial inter-subject variability.

Random Forest. The Random Forest (RF) model utilizes a combination of 200 dependent trees, each trained by sampling a bootstrap from training data, while splits at the nodes are based on randomly selected feature subsets. In this way, the model is capable of capturing very complex non-linear relationships between EEG features and emotional states while remaining quite robust to noise and out-liers. For any test sample, the final predicted class is arrived at by taking the ma-jority votes from all trees, mathematically expressed as:

$$\hat{y}_{i=}\ mode\{\widehat{y_i^1}, \widehat{y_i^2}, \ldots .\widehat{y_i^{200}}\} \tag{3}$$

Where: $\hat{y}_i$(t)is the prediction of t-th tree for sample I, T is the total number of trees (e.g., 200), $\hat{y}_i$= final predicted emotion label

Apart from high accuracy on classification, RF also provides feature importance where the most discriminative EEG features contributing to emotion recognition can be identified. It is this interpretability that is particularly important for understanding the neural correlates of emotional processing. The multi-class classification flexibility of the RF model is also advantageous in distinguishing emotions such as humorous, sad, and scary.

K-Nearest Neighbours. This algorithm assigns classes based on the majority rule, as the test example is placed within the k=5 nearest neighbours in the multi-dimensional feature space. Distance measurement in the Euclidean space forms the basis for similarity between instances according to the following rule:

$$d(x_i, x_j) = \sqrt{\sum_{f=1}^{F}(x_{i,f} - x_{j,f})^2} \quad (4)$$

Where F is the total number of features, $x_{i,f}$ is the value of feature f for sample i.

It is a simple and intuitive algorithm, so KNN can serve as an appropriate baseline for EEG emotion classification. Its efficacy is highly reliant on the very local distribution of the feature vectors, marginally distinguishing among sub-jects and emotions. Being sensitive to noise and irrelevant features, KNN com-plements RF by bringing into perspective the distance-based paradigm and so capturing the local structure in the data.

Both these models were evaluated using the same standard metrics - accuracy, precision, recall and F1-score, which serve the purpose of comparative analysis in terms of the effectiveness of models for classifying emotions from EEG sig-nals. Thus, a framework expected to combine ensemble learning and distance-based approaches is anticipated to yield a robust, interpretable solution of emo-tion recognition independent of participant variability.

B. Experiment on Time Domain Features

Pre-processing. It was common for EEG signals collected using the BIOPAC 2-channel acquisition system to be tainted by noise from muscular activity, blink-ing artifacts, and line interferences. Wavelet Denoising was applied as a filtering technique to retain only the bona fide brain-related activity. Wavelet denoising finds precedence over standard filtering methods because it is localized in both time and frequency, thereby allowing for the removal of non-stationary noise components without distorting the information in the EEG of interest. The proce-dure consists of three stages: decomposition, thresholding, and reconstruction.

Decomposition. The raw EEG signal (t) decomposes DWT into approximation coefficients and detail coefficients:

$$x(t) = \sum_k c_{J,k}\,\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_k d_{j,k}\,\psi_{j,k}(t) \quad (5)$$

Where: $\phi_{J,k}(t)$ = scaling (approximation) function, $\psi_{j,k}(t)$= wavelet (detail) function, $c_{J,k}$ = approximation coefficients, $d_{j,k}$ = detail coefficients These coefficients represent the components of the EEG recorded at low tension and at high frequency.

Thresholding. This step removes coefficients lower than the threshold, assuming they are representing noise. T is added on the detail coefficients through soft thresholding, in order to suppress noise:

$$d_{j,k} = \begin{cases} \text{sign}(d_{j,k})\,(|d_{j,k}| - T), & \text{if}\,|d_{j,k}| > T \\ 0, & \text{if}\,|d_{j,k}| \le T \end{cases} \quad (6)$$

Where: d(j,k) = original detail coefficient at scale j and position k, T = threshold value used to suppress noise, sign () = sign function that keeps the polarity of the coefficient

Reconstruction. After thresholding, the clean EEG signal is reconstructed through the Inverse Discrete Wavelet Transform (IDWT):

$$\hat{x}(t) = \sum_k \hat{c}_{J,k}\,\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_k \hat{d}_{j,k}\,\psi_{j,k}(t) \quad (7)$$

Where: $\hat{x}(t)$ = reconstructed clean EEG signal, $\hat{c}_{J,k}$= approximation coefficients at the final level J, $\hat{d}_{j,k}$= denoised detail coefficients, $\phi_{J,k}(t)$= scaling function (low-frequency component), $\psi(j,k)(t)$ = wavelet function (high-frequency component), J = decomposition level.

Feature Extraction. The process of feature extraction is very valuable because it reduces a complex representation of EEG signal data into a more meaningful representation while still maintaining the essential information regarding brain activity. In this research, time-domain features have been used because these features are computationally inexpensive and support a strong discriminative capability for EEG-based emotion

recognition. Time-domain features help ana-lyse the varying degrees of EEG amplitude through time and statistically charac-terize the signal in terms of average energy, dispersion, asymmetry, and sharp-ness.
Mean (μ). Central tendency of signal, measures overall brain activation.
Variance (σ^2). Signal fluctuation. Reflects emotional arousal level.
Standard Deviation (σ). Deviation from mean indicates signal consistency.
Skewness. Asymmetry of signal detects emotional imbalance.
Kurtosis (Ku). Sharpness of peaks identifies extreme neural responses.

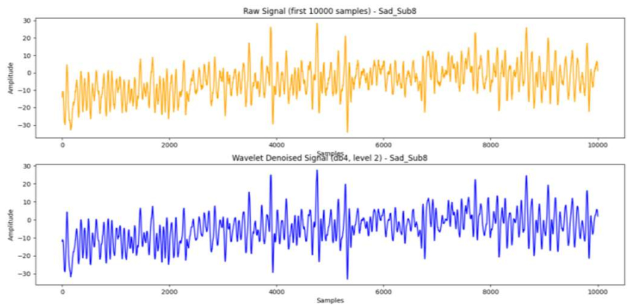


Fig. 3. Representation of raw versus filtered data

Distance Measure Calculation. Following the extraction of time-domain fea-tures from the EEG signals, the next level involved the computation of distance measures to assess how related the emotional responses were from different sub-jects. Each subject's EEG feature data (mean, variance, Skewness, kurtosis, and standard deviation) was represented as a feature vector, and the distances be-tween all pairs of subjects were computed to generate a distance matrix. With this, emotions can now be quantified in terms of similarities and dissimilarities across participants. Distance measure was implemented in this project Euclidean distance was calculated.
Euclidean Distance: Euclidean distance is used because it provides a clear geo-metric measure of similarity between two emotional EEG feature vectors. It helps determine how closely two subjects emotional responses align in overall magni-tude.

$$D_{euclidean}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (8)$$

Where: x_i = feature iii of subject 1, y_i = feature iii of subject 2, n = total number of extracted features, $D_{euclidean}$ = similarity measure based on straight line distance.
Clustering- Based Dimensionality Reduction. Once the distance-based matrices were evaluated, clustering methods were implemented to identify subjects whose EEG responses were indeed consistent and meaningful. Any subject for whom any extreme or inconsistent distance value was assigned was classified as an outlier and was cleared off the records, to ensure a reasonably valid dataset. Through this clustering-based filtering, the dataset was filtered from the original 22 subjects to a refined 18 subjects, which were preserved for having consistent emotional response patterns. This process actually reduced dimensionality, not in terms of number of features but rather by filtering away very unreliable sources of data (subjects).

C. Classification Model

Multi-Layer Perceptron (MLP). An emotion classification using MLP architec-ture involves a simple feed-forward fully connected neural network structure, which comprises an input layer, two hidden layers, and an output layer. Each of the neurons performs a weighted summation of inputs, followed by a nonlinear activation function, which enables the model to learn complex decision bounda-ries. This input layer is the subject's distance-feature-based feature vector, and all the neurons in hidden layers are fully connected to all other neurons in the previous layer. The output of each neuron is computed using:

$$h_{j=}f\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right) \quad (9)$$

Where: x_i= input features, w_{ij} = weight connecting input i to neuron j, b_j= bias term, f() = activation function (ReLU)
The last layer uses the softmax function to produce probabilities for the three emotional categories:

$$\widehat{y_k} = \frac{e^{z_k}}{\sum_{m=1}^{3} e^{z_m}} \quad (10)$$

Where: z_k= activation of output neuron for class k, $\widehat{\boldsymbol{y}_k}$= predicted probability of class k
The learning of the network occurs by minimizing the cross-entropy loss:

$$L = -\sum_{k=1}^{3} y_k \ \ log(\hat{y}_k) \qquad (11)$$

Where yk is the actual class label.

IV. EXPERIMENTAL RESULTS

A. Frequency Domain Features

Random Forest has 73.33% accuracy for channel 1and 53.33% for channel 2, the best overall and the most affirmative towards the noise. KNN has 73.33% accura-cy for channel 1 and 53.33% accuracy for channel 2.

TABLE I. EVALUATION METRICS OF RANDOM FOREST

Channel 1				
Classes	Accuracy	Precision	Recall	F1-score
Enjoyed	100	0.71	1.00	0.83
Relaxed	40	0.67	0.40	0.50
Sad	80	0.80	0.80	0.80
Channel 2				
Classes	Accuracy	Precision	Recall	F1-score
Enjoyed	20	1.00	0.20	0.33
Relaxed	60	0.60	0.60	0.60
Sad	80	0.44	0.80	0.57

TABLE II. EVALUATION METRICS OF CHANNEL 1 KNN

Channel 1				
Classes	Accuracy	Precision	Recall	F1-score
Enjoyed	100	0.62	1.00	0.77
Relaxed	40	0.67	0.40	0.50
Sad	80	1.00	0.80	0.89
Channel 2				
Classes	Accuracy	Precision	Recall	F1-score
Enjoyed	60	0.60	0.60	0.60
Relaxed	40	0.50	0.40	0.44
Sad	60	0.50	0.60	0.55

Random Forest shows higher resistance against noise compared to KNN and pro-vides stable feature importance results. It consistently named Spectral Centroid and Band Power as the highly discriminating features between Enjoyed and Re-laxed responses while identifying Spectral Flatness as an important feature to separate Sad responses. This stability suggests reliable discrimination capability of the model, even with a small number of EEG channel. PSD graphs also highly depict emotion differences; higher Alpha is present in relaxed states; higher Be-ta/Gamma in Enjoyed states; lower Beta together with higher Theta in Sad states. These reflective patterns are known EEG characteristics giving further evidence that a small number of EEG channels can also discriminate among the emotions

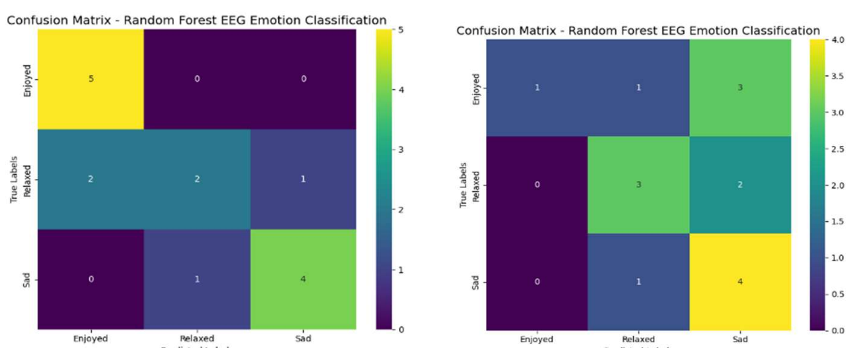


Fig. 4. Confusion Matrix for Channel 1 and Channel 2 trained using Random Forest

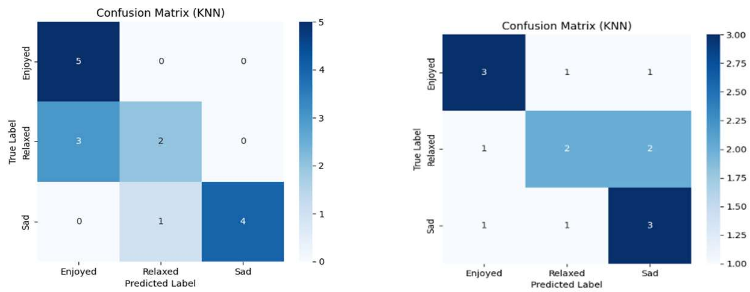


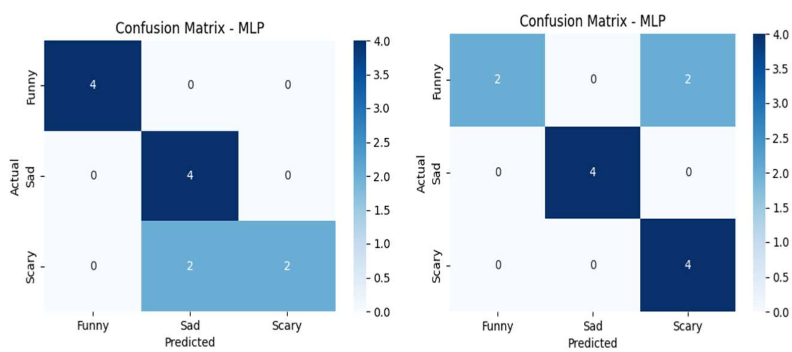
Fig. 5. Confusion Matrix for Channel 1 and Channel 2 trained using KNN

B. Time Domain Features

The MLP classifier reached an accuracy of 83.33% for Channel 1 and Channel 2 through the use of only a two-feature combination involving Variance and Skewness. Emotion classification is quite effective with an even low feature set.

TABLE III

Channel 1				
Classes	Accuracy	Precision	Recall	F1-score
Funny	100	1.00	1.00	1.00
Sad	100	0.67	1.00	0.80
Scary	50	1.00	0.50	0.67
Channel 2				
Classes	Accuracy	Precision	Recall	F1-score
Funny	50	1.00	0.50	0.67
Sad	100	1.00	1.00	1.00
Scary	100	0.67	1.00	0.80



V. CONCLUSION

This work demonstrates that emotions can effectively be recognized with a sim-ple two-channel EEG setup combined with frequency and time features. For in-stance, frequency-based features such as Band Power, Spectral Centroid, Spread, Flux, and Flatness captured and brought out the salient neural responses formed in relation to Kannada music stimuli, while statistical features in the time domain provided reliability for emotion detection in advertisement-based EEG record-ings. The use of distance-measure refinement further improved class separability, and both multilayer perceptron and RBF neural network classifiers gave good and stable performance results. This leads to the conclusion that even the small-est EEG hardware could yield significant patterns in real time and reliably asso-ciate them with emotions.

Future studies should evaluate multi-channel EEG configurations that could yield much richer spatial information, while feature extraction could then be automated by deep learning models and real-time implementations could also become more flexible for interactive BCI applications. Generalization would be improved if more subjects and different types of stimuli were added to the data. Other modalities, such as facial expressions or physiological signals, can be in-corporated into this quite robust and powerful emotion-aware system.

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