Novel EEG Features for Consumer Emotion Prediction using Correlation-Based Subset Selection

MAYUR JARTARKAR, BITS Pilani, K. K. Birla Goa Campus, India
ASHISH SINHA, BITS Pilani, K. K. Birla Goa Campus, India
RIDDHESH SAWANT, BITS Pilani, K. K. Birla Goa Campus, India
MAHAK KOTHARI, BITS Pilani, K. K. Birla Goa Campus, India
VEEKY BATHS*, BITS Pilani, K. K. Birla Goa Campus, India

Affective neuroscience research can help in detecting emotions when a consumer responds to an advertisement. Successful emotional elicitation is a verification of the effectiveness of an advertisement. Affective neuroscience using EEG provides a cost-effective alternative to measure advertisement effectiveness while eliminating several drawbacks of the existing market research tools, which depend on self- reporting. Affective neuroscience research has also provided several techniques to classify and predict emotions. In our study, we collected EEG data from 13 participants while commercial video advertisements were shown to them. We used the "correlation-based subset selection" and "asymmetry of hemispheric channels" to create our feature set, using pearson-coefficient based significance validation. From the correlation analysis, we found that EEG channels in the central region (C3/C4) are strong predictors of emotions when elicited from a video advertisement. We find that hemispheric asymmetry-based features improved the performance of ML-based models as compared to commonly used power spectral density-based features. This study shows that EEG activations in the central region can predict consumer emotional response to commercial video advertisements and are also consistently elicited uniformly across consumers.

Additional Key Words and Phrases: Affective Neuroscience, Neuromarketing, Electroencephalography (EEG), Feature Engineering, Frontal Asymmetry

1 INTRODUCTION

Affective neuroscience is a special discipline within Cognitive Neuropsychology that discusses all the cognitive and neural processes that give rise to emotions in the brain [32]. The last few decades have seen significant research attempting to detect and classify emotions using various inputs from a person like their facial expressions [11, 16, 31, 36], gait analysis [42], voice [37]. All these external features can be controlled through conscious effort, and thus these features cannot be a reliable representation of one's emotions. Research that compared the person's facial expressions to the electrophysiological (EEG) activity produced in the brain [9] found cerebral symmetries when emotions are elicited and can be used to classify positive from negative emotions. In recent years, research in emotion recognition using EEG has increased manifold [1, 6, 27, 41, 50, 53].

Research studies employ different methods to elicit emotions, processing of EEG data is done in various ways, and various classification tools are used for emotion detection and identification. The field of Consumer neuroscience [19] has directly benefited due to advancements in Affective neuroscience. Capturing honest consumer responses to marketing stimulus has been a consistent challenge for traditional marketing research methods since they depend on self-reporting, which can be biased, influenced, and unreliable. Affective neuroscience using EEG has made it possible to identify emotions elicited while being exposed to advertising [26, 27]. EEG datasets like the DEAP (Database for Emotion Analysis using Physiological Signals) [21] and the SEED (SJTU Emotion EEG Dataset) [44, 54] have been analyzed by many research groups to find novel techniques to classify

*Corresponding Author

IMX '22 - Emotion, 2022, Portugal

emotions using EEG.

Electroencephalography (EEG) is a neuroimaging technique to collect electrical signals from various scalp locations using highly sensitive electrodes designed to record extremely small voltages (μV). Among the various neuroimaging techniques like fMRI, PET, MEG, fNIRS, etc., EEG provides several advantages. Using EEG is economical, easy to set up, and provides excellent temporal resolution. In addition, it takes a very short period of time to set up the participant for EEG collection. Finally, with the advent of mobile EEG headsets, we can now collect brain information at a location that simulates the real world. This becomes very important for the marketing industry because of the extremely narrow timelines for conducting product reviews and budget limitations. Thus, using EEG allows for Neuromarketing research to be done at a fraction of the cost compared to other neuroimaging techniques. However, using EEG does not provide sufficient spatial resolution for us to measure brain activity in the brain's cortical regions. Thus, EEG should be used for drawing general assumptions about brain response but not to identify specific activations within the cortices.

Several novel methods have been proposed to classify emotions using EEG data. [8]Gated Recurrent Unit (GRU) network with attention for human emotion classification. They evaluated their model by classifying emotions using the DEAP dataset. Another research group implemented a SincNet-R based classifier [51] (used for speaker recognition), which consisted of three convolutional layers and three deep neural networks (DNN) layers. An alternative approach proposed the use of conditional Transfer Learning (cTL) [24], which allows results acquired from some participants to be used in analyzing the data of other participants. This reduces the amount of effort and time expended on collecting EEG data from a participant. Sparse discriminative ensemble [40] can also be created for computing the most discriminative subset of EEG channels for Emotion recognition. This solves the objective function via sparse non-negative Principal Component Analysis (PCA). "correlation-based subset selection" [7] was used for dimensionality reduction and the DEAP dataset was analyzed. A survey [14] of over a hundred research articles on Emotion classification found that 39% of the research focus on Machine Learning algorithms, 21% focused on the EEG techniques, 8% referred mainly to the process of feature extraction.

There is significantly less research for EEG based feature set selection for commercial advertisement. Emotion detection and emotion prediction help in creating a model to predict consumer behavior without the necessity to get conscious feedback. Band-power one-minute features [45] of 10 channels provided the best accuracy on the DEAP dataset in a particular research. Deep Belief Networks [23] were used to show that learned features perform comparably to manually generated features for emotion recognition.
For a product manufacturer, knowing the consumer preference for the product is very important, and neuromarketing aims to understand the same. This study [48] tries to establish a method that can better understand consumer emotions in response to advertisements, helping the sellers understand whether their goals are aligned with consumer emotions. As discussed in [43], how in social networks, where social network advertising content that directly appeals to the emotions of consumers has better effectiveness than the ones that have simple messages. A similar theory can be applied to visual advertisements as well, and this study proposes metrics that marketers can use to analyze their video advertisements and scale the emotionality accordingly, with the help of EEG analysis. Specifically, we explored the frontal asymmetry of the brain, using time-frequency domain features to help us identify the region of the brain as well as the frequency ranges in which the EEG signals are elicited and correlate to human emotions highly when given a visual stimulus.

1.1 Current Study

In the proposed approach, we aim to evaluate how effectively emotion prediction can work for a Neuromarketing stimulus. Since the emotions are fully elicited towards the end of the advertisement, the final thirty seconds of each advertisement were considered for EEG analysis. We are also interested to know the most discriminative subset of EEG channels that affect emotion recognition [40] because the cost of the EEG headset and the time to set up is proportional to the number of channels, therefore using a minimal number of channels without affecting the decoding performance is much desired by the companies. We have used correlation-based subset selection [7] to create our feature set. In addition, we also created features that capture the effect of emotions on cerebral asymmetries. This feature set was then used in various Machine Learning algorithms to identify the emotions of the viewer. To evaluate the effectiveness of our feature set, we also generated features using power spectral density [25]. We then compared the performance of both the feature sets when fed into the ML models and found that the proposed feature set performed better.

2 METHOD

2.1 Neurophysiology of Emotion

Extensive research in the study of the human brain in the last century showed that the limbic system of the brain containing that of the amygdala, the hypothalamus, and the hippocampus governs emotion and memory. The amygdala is primarily responsible for regulating our perceptions and reactions to aggression and fear. The hypothalamus interacts with various systems in the brain to create feelings of pleasure. Hypothalamus [29] is known to play a role in the feeling of reward when rats are stimulated. The limbic system also modulates the secretion of neuromodulators like dopamine, serotonin, norepinephrine, and acetylcholine, each of which causes a specific emotional response in a person. Neuroanatomical components of emotion were reviewed [5] and the term hippocampal-diencephalic-cingulate network was used to explain the key components participating in emotion. They propose that although the hippocampus is seen as the start and finish points in the limbic subsystem, other components also play crucial roles in emotional activation. The hippocampus plays interfacing and integrating roles between emotion and memory retrieval/formation.

Several studies have attempted to develop brain networks to show that different network configurations represent different emotions. Convolutional Neural Networks [30] use brain connectivity metrics to create network representations for different emotions. Functional connectivity network and local activations can be used to classify emotions [22]. Emotion can then be describes as a large network with large-scale network interactions [35]. This introduces the concept of "functionally integrated systems" that control the organizing of emotions in the brain. Several systems interact with each other through complex pathways to create the cocktail that emotions are.

To summarize, we know the brain regions which modulate emotion. These brain regions are located in the inner brain, thus requiring alternative methods to capture data and recognize emotion. Using neurological tools of EEG, MEG, and fMRI, several models of emotion recognition have been proposed. Most of the proposed models rely heavily on Deep learning tools. Deep learning methodology hides the inner layers of its computation, hiding the aspects of computation that are more critical than others. In our study, we choose scalp locations that several studies have consistently reported. This includes all EEG channels along the central midline and adjacent EEG channels on either side of the midline. We have engineered features using the electrodes that are symmetrically opposite to each other.

2.2 Participants and Procedure

Thirteen voluntary participants (1 female, 12 male) were recruited from the university campus for the study who watched the advertisements in random order. EEG data from 2 participants were rejected due to excessive

Table 1. Advertisement details and description

(Index -Index Number of the Ad, Duration (in seconds) - Time duration of the advertisement, Is there background music - 'No' if there is no background music in the ad, else 'Yes', Average rating - average of user rating given by users, Language - the language in which the advertisement is delivered, Theme - the key ideology or topic represented by the advertisement)

Index	Duration (in sec)	Is there background music	Average Rating	Language	Theme
1	60	No	2.680088	Hindi	Educative, Motivational
2	120	No	3.100415	Hindi	Gender Bias, Woman equality
3	60	Yes	2.196925	English	Circus
4	61	Yes	2.440337	English	Dance, Song, Colorful
5	108	Yes	3.235237	English	Self-change, Motivational
6	60	No	1.843399	English	Car, Imagination
7	60	Yes	1.931552	Music Only	Attraction, Pool, Cold drink
8	60	No	2.163982	Hindi	Gifts, Festival

artifacts. All participants were well versed in English and Hindi, allowing them to understand the speech in the majority of the advertisements. We do not test for gender-associated emotional activation as existing research has not found significant differences in cross-gender studies [55]. Informed and written consent was taken from all participants. It was also ensured that the participants had no history of brain trauma/illness. They were also advised to be well-rested before the day of the EEG data acquisition. After the recording session, remuneration was provided in the form of coupons. The study was approved by the Institution Human Ethics Committee (IHEC) vide. Approval No. IHEC 40/16-1. In this study, we analyze multiple features created using different EEG channels that highly correlate to the consumer's emotions recorded to provide a comprehensive set of EEG channels and features that can be fed into a machine learning model to predict human emotions for consumer advertising videos. The study was approved by the Institutional Human Ethics committee. The EEG data were stripped of all personal information before being shared with the researchers for analysis.

2.3 Experimental Design

The stimulus presentation was designed using Psychopy [34] software. Commercial advertisements shown were of entertaining nature and only communicated the brand features to the viewer. After each advertisement, questions pertinent to the advertisement were asked to the participant, for which the answers were provided through a Likert scale. One of the questions, "What were your emotions while watching the video?" had responses ranging from 1 to 6, where 1 represents positive while 6 represents negative emotion. We analyzed the emotional response towards the commercial ads to identify the features derived from EEG channels that exhibit high co-variance to the emotional response. The experimental design and all the questions are given in Figure 1

In each session, participants were shown eight advertisements (average advertisement time: 73.6 seconds, Shortest Advertisement: 60 s, Longest advertisement: 120 s). The advertisements were all unfamiliar and not seen by the participants before. The advertisements belong to different product categories, viz. approach, avoidance, and utilitarian products [49]. According to the immediacy principle [28], people are attracted to things they like and move away from the ones they dislike or the ones they do not prefer. Each advertisement has been assigned to broad classes that they fit in. (Table 1)

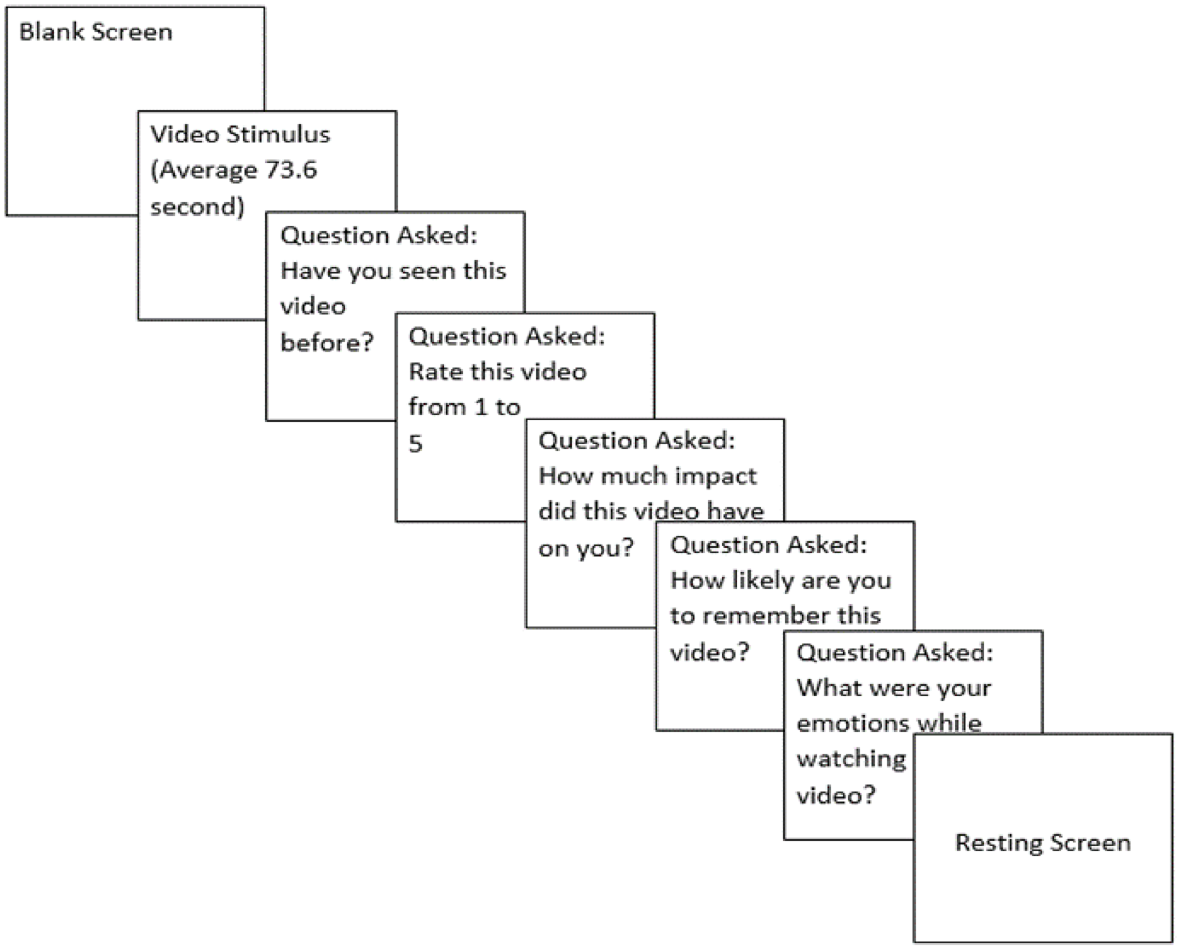

Fig. 1. Schematic of the Stimulus Design including the questions asked post stimulus

2.4 Data Collection

EEG data were acquired using the 32-channel EGI Netstation system (Magstim EGI). The appropriate electrode net size (small, medium, and large sizes) was chosen depending on the participant's head size. All the electrodes were placed in accordance with the 10-20 International system of electrode placement [17]. Each participant was seated comfortably in the recording room with no electrical interference. All electrodes on the EEG net were brought to an impedance level below the accepted threshold of 50 $k\Omega$. The stimulus was shown on a 21.5" screen and was placed at a distance of approximately 70 cm from the participant. Advertisement sounds were provided via an audio headset, and the EEG data were collected at a sampling rate of 1000 Hz.

2.5 EEG Analysis

EEG data was first imported into the EEGLab software [10]. The data was then band-pass filtered between 0.1 Hz to 30 Hz. Bad/Noisy EEG channels were interpolated and EEG was average referenced. Further, ICA components were used to eliminate eye blink and muscle artifacts. For automatic component removal, the MARA algorithm was employed [47]. The data was then epoched with each epoch indicating neurological response to an advertisement. Every advertisement always has an emotional arc culminating into a strong emotional elicitation at the end. Thus, the EEG data at the beginning of an advertisement does not convey concrete, well-formed emotions. To recognize emotions effectively, we need EEG data that represents fully formed emotions elicited by the advertisement; thus, we extracted the last 30 seconds of the advertisement to create our training and testing benchmarks.

2.6 Feature Engineering and Correlation-Based Subset Selection

Several studies have used a combination of time and frequency features for classification on EEG data [18, 52]. These studies try to identify epileptic seizures or a cognitive command in a stream of EEG data. Such analysis techniques will be required if the recognition task is to be done on the EEG data in real-time. For the purpose of Neuromarketing research, such analysis is not necessary as the system is not a time-critical system. In view of this, our study mainly focused on constructing the feature vector using frequency components only. The frequency components were powers for the EEG frequency bands of theta θ (4-8 Hz), alpha α (8 - 13 Hz), lower beta βl (13 − 21 Hz), and upper beta βu (21 − 30 Hz).

As discussed earlier, EEG studies have reported several scalp locations used by emotion identification algorithms [38]. Further, brain asymmetry plays a crucial role in demonstrating the likability towards the stimulus [4, 9]. Thus, our feature vector is constituted of individual frequency properties at various scalp locations and derived properties extracted by combining data from opposite scalp locations.

The derived features are the difference between the power values between two opposite scalp sites. We identified eight opposite regions to extract the derived features for our study. Figure 2 shows the various channels from which the derived features were extracted. Opposite channels in the prefrontal, frontal, central, parietal, temporal and occipital regions were selected. We get these hemispheric differences in all the 4 frequency bands mentioned above.

For the naming convention of these derived features, we use delta (Δ) notations with channel names and frequency band information being provided as subscript information. Thus $\Delta_{(Fp1-Fp2,\alpha)}$ is the derived feature extracted from the pre-frontal electrodes Fp1 and Fp2 in the alpha frequency band. Other features contained the name of the channel and the frequency band in the subscript.

This provided us with an initial feature set consisting of 164 values (33 features (one from each electrode) + 8 derived features (from hemispheric differences) per frequency band, making a total of 41 features across 4 frequency bands, which is $41 * 4 = 164$). Correlation values between the spectral power and the emotion label were calculated for all the features. We then selected all the values and EEG channels that were known to participate in emotion elicitation and had high correlation values. We also confirm that the correlation values were statistically significant by extracting their p-values (discussed below in the Results section). The Pearson correlation coefficient was calculated using the formula.

$$\rho(X, Y) = cov(X, Y) * \sigma(X) * \sigma(Y) \tag{1}$$

In our study, X is the values of the feature set, and Y is the emotion label assigned by the participant in response to the advertisement [12].

2.7 Validating feature set using machine learning

A Deep learning strategy involves feeding the entire feature set into the neural network, which learns the important features and predicting emotions. However, this presents a drawback that it is impossible to identify the features that contributed the most to the prediction. From a consumer neuroscience perspective, it is often economical to have minimum electrodes placed on the focus group members. Thus, we use correlation-based

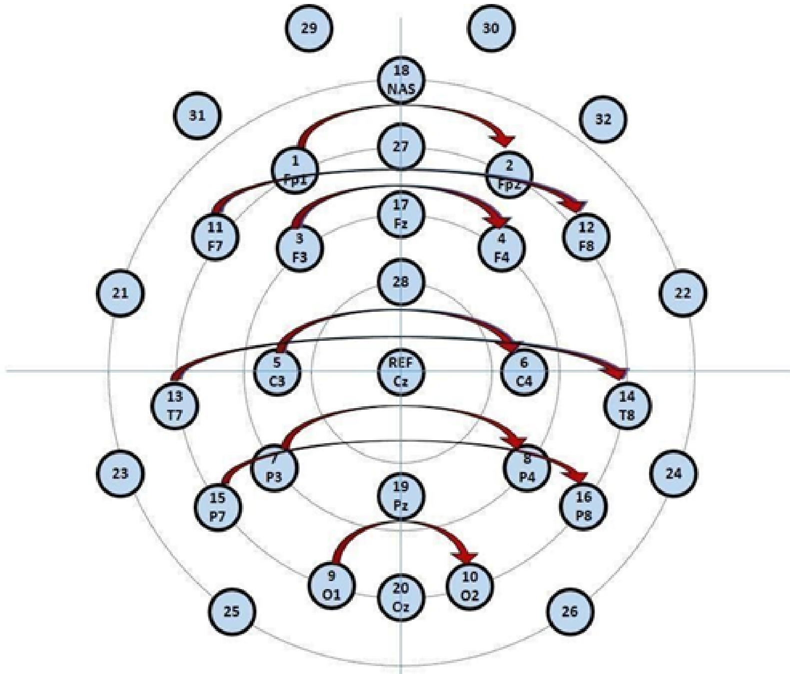

Fig. 2. The EEG scalp electrodes used to extract the derived features for emotion detection.

subset construction to identify the features exhibiting the highest Pearson's correlation values [15].
To further concrete our hypothesis of the feature set selected, we use machine learning to validate our feature set, and test its predictive capabilities. Each entry consisted of the feature set followed by the emotion label that the viewer provided. On a scale of 1 to 6, lower values represented positive emotions while higher values represented negative emotions. Please note that for regression the prediction value that is the emotional response values were normalized between 0 and 1. To ensure that the models did not suffer from overfitting on participant specific aspects, the testing data was from a participant who was never seen by the learning models during training.
To achieve normalization of the results, we used k-fold cross-validation [33]. Thus, for our dataset containing 11 participants (88 data points, i.e., 11 participants × 8 videos/participant), data from 10 participants formed the training data for every iteration, while data from 1 participant formed our testing data. We tested our feature set performance on three commonly used regression models, viz. Linear Regression [2], Bayesian Ridge [3], and Random Forest Regression [13]. Figure 3 provides a graphical representation of the EEG feature extraction pipeline. The process of k-fold cross-validation is done in all the regression ML models that we used.

The performance of the Regression models was calculated using Mean Absolute Error (MAE), which is defined as the arithmetic mean of the absolute errors of the actual and predicted values. Mathematically,

$$MAE = \sum_{t=1}^{n} |y_i - x_i| \tag{2}$$

where y represents all the predicted values while x represents all the actual values and n represents the total number of data points. MAE is found to be a better measure to show model performance than Root Mean Square

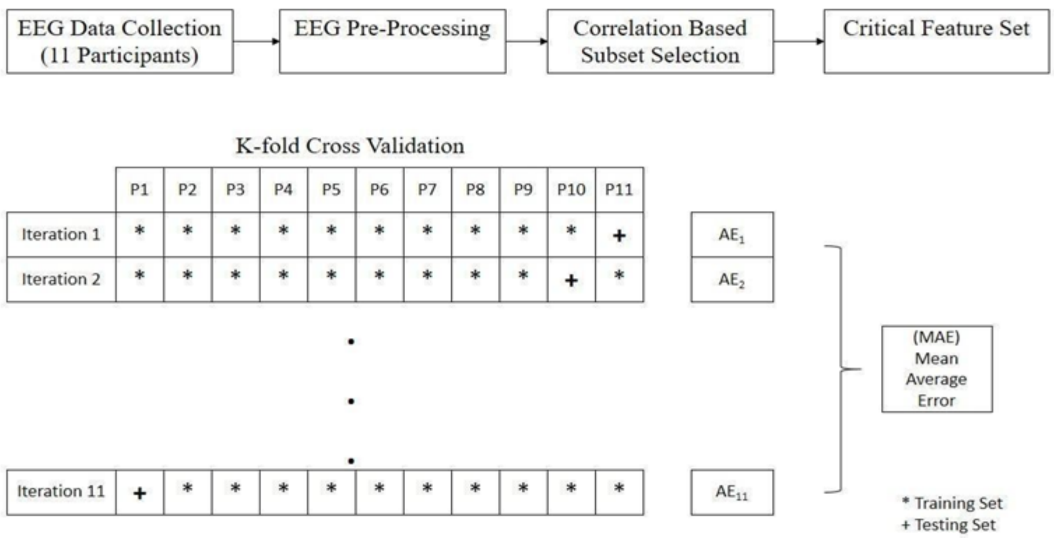

Fig. 3. EEG Processing Pipeline for feature construction and outline of k-fold cross validation for all ML regression algorithms.

Error (RMSE) [46] since RMSE data is dependent on three factors and could be ambiguous, unlike MAE, which is a more natural measure of average error.

3 RESULTS

3.1 Feature Engineering and Correlation-Based Subset Selection

After selecting the features with higher correlation values, we found that electrodes in the central brain region (C3 and C4) provided the highest correlation values in multiple frequency bands. In addition, we also found a high correlation for the derived features between the two EEG channels. The role of central electrodes in emotion is reported in exist[1]. Table 2 shows all the features that showed high correlation values with corresponding p-values (refer to the appendix 4 for all the correlations with insignificant p-value).

3.2 Validating feature set using machine learning

We used the reduced subset of features and implemented models for emotion prediction. A comparison of Mean Absolute Error (MAE) values using Power Spectral Density and Proposed Feature set is given in Table 3.

A comparison of the MAE values is shown in Figure 4, as shown below. We observed that using a reduced correlation-based subset reduced the MAE values compared to Power Spectrum Density based features. We can see that using linear regression leads to a 28.57% increase in test losses when we use power spectral density features as opposed to the proposed feature set, using Bayesian Ridge Regression leads to a 20.58% increase in test losses, and random forest regression increases the test losses by 12.52%.

From the analysis of model performance, it is clear that extracting hemispheric differences and adding them into the feature set improves model performance in predicting emotional response as reported by the consumer.

Table 2. Correlation values of channels C3 and C4 for all frequency bands and also the derived features from the EEG channels. (in increasing order of p-values

(Feature - Feature used for the work, Correlation value with Emotion label -Pearson correlation coefficient of the feature with the emotional labels, P-Value - the corresponding p-value for the concerned feature and emotional labels)

Feature	Correlation value with Emotion label	P-Value
$C3_{\theta}$	0.512677	3.280108e-07
$C3_{\alpha}$	0.429349	2.991254e-05
$C3_{\beta u}$	0.426374	3.441681e-05
$\Delta_{C3-C4,\theta}$	0.417782	5.122844e-05
$C3_{\beta l}$	0.407479	8.138808e-05
$\Delta_{C3-C4,\beta u}$	0.367269	4.317329e-04
$\Delta_{C3-C4,\alpha}$	0.344033	1.030886e-03
$\Delta_{C3-C4,\beta l}$	0.330762	1.646461e-03

Table 3. Performance of the Predictive Models in Training and Testing data sets

(Regression Model - Machine learning model used, Model Performance - Model performance for specific machine learning models for a particular feature set, PSD - Feature set based on power spectral density, Proposed Feature Set - Feature set propose by this study)

Sl No	Regression Model	Model Performance			
		PSD		Proposed Feature Set	
		Train Loss	Test Loss	Train Loss	Test Loss
1	Linear Regression	0.08612	0.13703	0.09004	0.10695
2	Bayesian Ridge Regression	0.09706	0.12715	0.09407	0.10584
3	Random Forest Regression	0.10235	0.11910	0.09272	0.10303

We can also see that our proposed feature set performs better when compared to the feature set containing the power spectral density.

4 DISCUSSION

In the field of Consumer neuroscience, we often take inspiration from research done in primary cognitive research fields and test if similar behavior can be observed with marketing stimulus. Findings in the field of Affective neurosciences lend nicely to test several hypotheses regarding consumer behavior.

In the survey [1], key recommendations are provided to avoid common pitfalls in using signals that reflect Affective states. The research also lists recent literature in affective neuroscience and evaluates how many of the recommendations were adhered to. The survey also describes the more commonly used datasets for EEG analysis and what are the emotion classes that the research articles classify. Finally, they also list all the various measures that are extracted from the EEG signals and used in the feature set.

To identify emotions using EEG signals, various features are extracted from raw EEG data. Most of the features are based on the frequency and power related properties of the EEG signal. EEG based emotion classification is then done using the features and machine learning models. The results of such studies are using the measures of accuracy, sensitivity, and specificity. Also, some studies use deep learning techniques allowing the model to learn

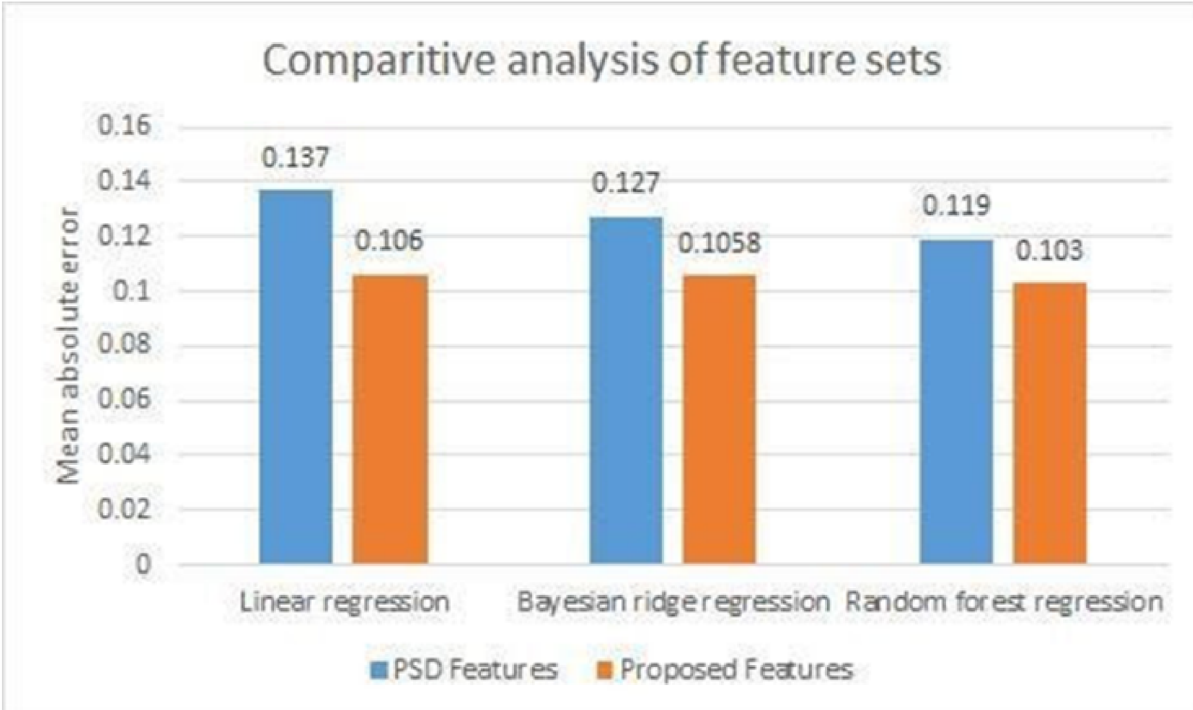

Fig. 4. Model performance and comparison for different feature sets

the important features and then use the learned characteristics to classify emotion.

Research shows that the features extracted were relative power values in the five frequency bands of the delta, theta, alpha, beta, and gamma [20]. Further, Bayesian networks are for classification. Alternative approaches [39] involve using a feature set of Russel's Circumplex model, Higuchi's Fractal Dimension (HFD), and Power Spectral Density (PSD) and using Support Vector Machine for machine learning.

In this study, we use correlation-based subset selection to use EEG channels and features to model and predict consumer emotional behavior. We find that EEG activity in the central region is consistent and predictive of the emotion score response given by the consumer. We also find that the models implemented thereof are not subject dependent and can be used across the participant group.

Most of the existing literature presents their findings using the measures of accuracy in classification. However, the participants in our study provided a real values response against the typical binary response. Thus, it is not possible to present our results using accuracy measures. We have used Mean Average Error (MAE) to show the deviation between the predicted score using the regression models and the actual response provided by the consumer. We have also shown that using the asymmetry-based features improves the MAE against using power spectral features. With such a small amount of data, the ML models were able to generalize very well and have shown very little overfitting.

5 CONCLUSION

In this study, we have proposed a way of exploring the relationship between emotions felt by the viewer while watching a commercial advertisement. We have implemented our methodology to help us gain insights into the activation regions in the brain, which may directly be impacted by the emotions of the consumer. We use correlation-based subset selection for identifying the critical features. We also evaluated different regression techniques to see if any of them could accurately identify this emotional state. Alternatively, unsupervised machine learning techniques can be used to see how these features combine to provide insights on their own, paving the way for more unsupervised research in this field and hence proving the genuineness of these statistical techniques in predicting human emotions.

Currently, the research is based on the dataset which utilizes commercial advertisements as a stimulus, hence application of the same metric to different datasets not based upon the same stimuli has not been explored, this study solely focuses on commercial advertisements, which are of high impact and of short time duration in nature.

The research in affective neuroscience has allowed for several applications in the field of Neuromarketing. Affective neuroscience research has shown several brain regions to be responsible for emotional elicitation. Machine learning techniques have also enabled us to classify emotions as positive, negative, and neutral. Our study aims to contribute in two ways. The first contribution is to show that EEG asymmetry is a vital feature in a consumer's emotional elicitation. Secondly, we also showed that emotional classification could be done with reasonable accuracies for advertising stimulus. This study should encourage more research groups to conduct affective neuroscience studies that have direct applications to the real world while also identifying the cognitive processes behind the emotion being elicited.

ACKNOWLEDGMENTS

We would like to thank all the members of the Cognitive Neuroscience Lab whose contribution made this research possible. We also thank the Dept. of Science and Technology who made this research possible by providing research funding provided through the Cognitive Science Research Initiative (CSRI), vide research grant No: SR/CSRI/50/2014(G). The authors also thank the Junior Research Fellowship (JRF) Scheme of the University Grants Commission (UGC) for supporting the research vide Award No: F. 15-6(DEC.2015)/2016(NET) and Ref No: 3409/(OBC)(NET-DEC. 2015).

REFERENCES

[1] Soraia M. Alarcao and Manuel J. Fonseca. 2019. Emotions Recognition Using EEG Signals: A Survey. *IEEE Transactions on Affective Computing* 10, 3 (July 2019), 374–393. https://doi.org/10.1109/TAFFC.2017.2714671

[2] Javier M. Antelis, Luis Montesano, Ander Ramos-Murguialday, Niels Birbaumer, and Javier Minguez. 2013. On the Usage of Linear Regression Models to Reconstruct Limb Kinematics from Low Frequency EEG Signals. *PLoS ONE* 8, 4 (April 2013), e61976. https://doi.org/10.1371/journal.pone.0061976

[3] Scott A. Baldwin and Michael J. Larson. 2017. An introduction to using Bayesian linear regression with clinical data. *Behaviour Research and Therapy* 98 (Nov. 2017), 58–75. https://doi.org/10.1016/j.brat.2016.12.016

[4] Hanna Becker, Julien Fleureau, Philippe Guillotel, Fabrice Wendling, Isabelle Merlet, and Laurent Albera. 2020. Emotion Recognition Based on High-Resolution EEG Recordings and Reconstructed Brain Sources. *IEEE Transactions on Affective Computing* 11, 2 (April 2020), 244–257. https://doi.org/10.1109/TAFFC.2017.2768030

[5] Emma J. Bubb, Lisa Kinnavane, and John P. Aggleton. 2017. Hippocampal–diencephalic–cingulate networks for memory and emotion: An anatomical guide. *Brain and Neuroscience Advances* 1 (Jan. 2017), 239821281772344. https://doi.org/10.1177/2398212817723443

[6] John T Cacioppo. 2004. Feelings and emotions: roles for electrophysiological markers. *Biological Psychology* 67, 1-2 (Oct. 2004), 235–243. https://doi.org/10.1016/j.biopsycho.2004.03.009

[7] Debashis Das Chakladar and Sanjay Chakraborty. 2018. EEG based emotion classification using "Correlation Based Subset Selection". *Biologically Inspired Cognitive Architectures* 24 (April 2018), 98–106. https://doi.org/10.1016/j.bica.2018.04.012

[8] J. X. Chen, D. M. Jiang, and Y. N. Zhang. 2019. A Hierarchical Bidirectional GRU Model With Attention for EEG-Based Emotion Classification. *IEEE Access* 7 (2019), 118530–118540. https://doi.org/10.1109/ACCESS.2019.2936817

[9] Richard J. Davidson, Paul Ekman, Clifford D. Saron, Joseph A. Senulis, and Wallace V. Friesen. 1990. Approach-withdrawal and cerebral asymmetry: Emotional expression and brain physiology: I. *Journal of Personality and Social Psychology* 58, 2 (1990), 330–341. https://doi.org/10.1037/0022-3514.58.2.330

[10] Arnaud Delorme and Scott Makeig. 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods* 134, 1 (March 2004), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

[11] Paul Ekman. 1993. Facial expression and emotion. *American Psychologist* 48, 4 (1993), 384–392. https://doi.org/10.1037/0003-066X.48.4.384

[12] David Freedman, Robert Pisani, and Roger Purves. 2007. *Statistics* (4th ed ed.). W.W. Norton & Co, New York. OCLC: ocm76142955.

[13] Himaanshu Gauba, Pradeep Kumar, Partha Pratim Roy, Priyanka Singh, Debi Prosad Dogra, and Balasubramanian Raman. 2017. Prediction of advertisement preference by fusing EEG response and sentiment analysis. *Neural Networks* 92 (Aug. 2017), 77–88. https://doi.org/10.1016/j.neunet.2017.01.013

[14] Mohamed Hamada, B. B. Zaidan, and A. A. Zaidan. 2018. A Systematic Review for Human EEG Brain Signals Based Emotion Classification, Feature Extraction, Brain Condition, Group Comparison. *Journal of Medical Systems* 42, 9 (Sept. 2018), 162. https://doi.org/10.1007/s10916-018-1020-8

[15] Mustafa A. H. Hasan, Muhammad U. Khan, and Deepti Mishra. 2020. A Computationally Efficient Method for Hybrid EEG-fNIRS BCI Based on the Pearson Correlation. *BioMed Research International* 2020 (Aug. 2020), 1–13. https://doi.org/10.1155/2020/1838140

[16] Ursula Hess, Reginald B. Adams, and Robert E. Kleck. 2004. Facial Appearance, Gender, and Emotion Expression. *Emotion* 4, 4 (2004), 378–388. https://doi.org/10.1037/1528-3542.4.4.378

[17] Richard W Homan, John Herman, and Phillip Purdy. 1987. Cerebral location of international 10–20 system electrode placement. *Electroencephalography and Clinical Neurophysiology* 66, 4 (April 1987), 376–382. https://doi.org/10.1016/0013-4694(87)90206-9

[18] Zafer Iscan, Zümray Dokur, and Tamer Demiralp. 2011. Classification of electroencephalogram signals with combined time and frequency features. *Expert Systems with Applications* 38, 8 (Aug. 2011), 10499–10505. https://doi.org/10.1016/j.eswa.2011.02.110

[19] Bernadette Kamleitner. 2012. Handbook of Developments in Consumer Behaviour, Victoria Wells, Gordon Foxall (Eds.). Edward Elgar Publishing Ltd, Cheltenham Glos (2012). 606 pp.(Hardcover), ISBN: 978-1-84980-244-4.

[20] Kwang-Eun Ko, Hyun-Chang Yang, and Kwee-Bo Sim. 2009. Emotion recognition using EEG signals with relative power values and Bayesian network. *International Journal of Control, Automation and Systems* 7, 5 (Oct. 2009), 865–870. https://doi.org/10.1007/s12555-009-0521-0

[21] S. Koelstra, C. Muhl, M. Soleymani, Jong-Seok Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras. 2012. DEAP: A Database for Emotion Analysis ;Using Physiological Signals. *IEEE Transactions on Affective Computing* 3, 1 (Jan. 2012), 18–31. https://doi.org/10.1109/T-AFFC.2011.15

[22] Peiyang Li, Huan Liu, Yajing Si, Cunbo Li, Fali Li, Xuyang Zhu, Xiaoye Huang, Ying Zeng, Dezhong Yao, Yangsong Zhang, and Peng Xu. 2019. EEG Based Emotion Recognition by Combining Functional Connectivity Network and Local Activations. *IEEE Transactions on Biomedical Engineering* 66, 10 (Oct. 2019), 2869–2881. https://doi.org/10.1109/TBME.2019.2897651

[23] Xiang Li, Peng Zhang, Dawei Song, Guangliang Yu, Yuexian Hou, and Bin Hu. 2015. EEG Based Emotion Identification Using Unsupervised Deep Feature Learning. Santiago, Chile.

[24] Yuan-Pin Lin and Tzyy-Ping Jung. 2017. Improving EEG-Based Emotion Classification Using Conditional Transfer Learning. *Frontiers in Human Neuroscience* 11 (June 2017), 334. https://doi.org/10.3389/fnhum.2017.00334

[25] Jingxin Liu, Hongying Meng, Asoke Nandi, and Maozhen Li. 2016. Emotion detection from EEG recordings. In *2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*. IEEE, Changsha, China, 1722–1727. https://doi.org/10.1109/FSKD.2016.7603437

[26] Yisi Liu, Olga Sourina, and Mohammad Rizqi Hafiyyandi. 2013. EEG-Based Emotion-Adaptive Advertising. In *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*. 843–848. https://doi.org/10.1109/ACII.2013.158

[27] Yisi Liu, Olga Sourina, and Minh Khoa Nguyen. 2010. Real-Time EEG-Based Human Emotion Recognition and Visualization. In *2010 International Conference on Cyberworlds*. 262–269. https://doi.org/10.1109/CW.2010.37

[28] Albert Mehrabian. 1981. Silent messages: implicit communication of emotions and attitudes, Wadsworth Pub.

[29] Peter M. Milner. 1991. Brain-stimulation reward: A review. *Canadian Journal of Psychology/Revue canadienne de psychologie* 45, 1 (1991), 1–36. https://doi.org/10.1037/h0084275

[30] Seong-Eun Moon, Soobeom Jang, and Jong-Seok Lee. 2018. Convolutional Neural Network Approach for Eeg-Based Emotion Recognition Using Brain Connectivity and its Spatial Information. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, Calgary, AB, 2556–2560. https://doi.org/10.1109/ICASSP.2018.8461315

[31] Paula M. Niedenthal, Martial Mermillod, Marcus Maringer, and Ursula Hess. 2010. The Simulation of Smiles (SIMS) model: Embodied simulation and the meaning of facial expression. *Behavioral and Brain Sciences* 33, 6 (Dec. 2010), 417–433. https://doi.org/10.1017/S0140525X10000865

[32] Sergio Paradiso. 2002. Affective Neuroscience: The Foundations of Human and Animal Emotions. *American Journal of Psychiatry* 159, 10 (Oct. 2002), 1805–1805. https://doi.org/10.1176/appi.ajp.159.10.1805

[33] CK Park and DG Kim. 2012. K-FOLD cross-validation. *Prog. Neurol. Surg.* (2012).

[34] Jonathan W. Peirce. 2007. PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods* 162, 1-2 (May 2007), 8–13. https://doi.org/10.1016/j.jneumeth.2006.11.017

[35] Luiz Pessoa. 2017. A Network Model of the Emotional Brain. *Trends in Cognitive Sciences* 21, 5 (May 2017), 357–371. https://doi.org/10.1016/j.tics.2017.03.002

[36] James A. Russell. 1994. Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. *Psychological Bulletin* 115, 1 (1994), 102–141. https://doi.org/10.1037/0033-2909.115.1.102

[37] James A. Russell, Jo-Anne Bachorowski, and José-Miguel Fernández-Dols. 2003. Facial and Vocal Expressions of Emotion. *Annual Review of Psychology* 54, 1 (Feb. 2003), 329–349. https://doi.org/10.1146/annurev.psych.54.101601.145102

[38] Louis A. Schmidt and Laurel J. Trainor. 2001. Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions. *Cognition & Emotion* 15, 4 (July 2001), 487–500. https://doi.org/10.1080/02699930126048

[39] Gokul Sidarth Thirunavukkarasu, Hamid Abdi, and Navid Mohajer. 2016. A smart HMI for driving safety using emotion prediction of EEG signals. In *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, Budapest, Hungary, 004148–004153. https://doi.org/10.1109/SMC.2016.7844882

[40] Habib Ullah, Muhammad Uzair, Arif Mahmood, Mohib Ullah, Sultan Daud Khan, and Faouzi Alaya Cheikh. 2019. Internal Emotion Classification Using EEG Signal With Sparse Discriminative Ensemble. *IEEE Access* 7 (2019), 40144–40153. https://doi.org/10.1109/ACCESS.2019.2904400

[41] Stefano Valenzi, Tanvir Islam, Peter Jurica, and Andrzej Cichocki. 2014. Individual Classification of Emotions Using EEG. *Journal of Biomedical Science and Engineering* 07, 08 (2014), 604–620. https://doi.org/10.4236/jbise.2014.78061

[42] Jan Van den Stock, Ruthger Righart, and Beatrice de Gelder. 2007. Body expressions influence recognition of emotions in the face and voice. *Emotion* 7, 3 (Aug. 2007), 487–494. https://doi.org/10.1037/1528-3542.7.3.487

[43] Natalia Abuín Vences, Jesús Díaz-Campo, and Daniel Francisco García Rosales. 2020. Neuromarketing as an Emotional Connection Tool Between Organizations and Audiences in Social Networks. A Theoretical Review. *Frontiers in Psychology* 11 (July 2020), 1787. https://doi.org/10.3389/fpsyg.2020.01787

[44] Wei-Long Zheng and Bao-Liang Lu. 2015. Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks. *IEEE Transactions on Autonomous Mental Development* 7, 3 (Sept. 2015), 162–175. https://doi.org/10.1109/TAMD.2015.2431497

[45] Itsara Wichakam and Peerapon Vateekul. 2014. An evaluation of feature extraction in EEG-based emotion prediction with support vector machines. In *2014 11th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. IEEE, Chon Buri, 106–110. https://doi.org/10.1109/JCSSE.2014.6841851

[46] Cj Willmott and K Matsuura. 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research* 30 (2005), 79–82. https://doi.org/10.3354/cr030079

[47] Irene Winkler, Stefan Haufe, and Michael Tangermann. 2011. Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals. *Behavioral and Brain Functions* 7, 1 (2011), 30. https://doi.org/10.1186/1744-9081-7-30

[48] Mahendra Yadava, Pradeep Kumar, Rajkumar Saini, Partha Pratim Roy, and Debi Prosad Dogra. 2017. Analysis of EEG signals and its application to neuromarketing. *Multimedia Tools and Applications* 76, 18 (Sept. 2017), 19087–19111. https://doi.org/10.1007/s11042-017-4580-6

[49] Seounmi Youn, Tao Sun, William D. Wells, and Xinshu Zhao. 2001. Commercial Liking and Memory: Moderating Effects of Product Categories. *Journal of Advertising Research* 41, 3 (May 2001), 7–13. https://doi.org/10.2501/JAR-41-3-7-13

[50] Morteza Zangeneh Soroush, Keivan Maghooli, Seyed Kamaledin Setarehdan, and Ali Motie Nasrabadi. 2017. A Review on EEG Signals Based Emotion Recognition. *International Clinical Neuroscience Journal* 4, 4 (Oct. 2017), 118–129. https://doi.org/10.15171/icnj.2017.01

[51] Hong Zeng, Zhenhua Wu, Jiaming Zhang, Chen Yang, Hua Zhang, Guojun Dai, and Wanzeng Kong. 2019. EEG Emotion Classification Using an Improved SincNet-Based Deep Learning Model. *Brain Sciences* 9, 11 (Nov. 2019), 326. https://doi.org/10.3390/brainsci9110326

[52] Dongye Zhao, Fengzhen Tang, Bailu Si, and Xisheng Feng. 2019. Learning joint space–time–frequency features for EEG decoding on small labeled data. *Neural Networks* 114 (June 2019), 67–77. https://doi.org/10.1016/j.neunet.2019.02.009

[53] Wei-Long Zheng, Wei Liu, Yifei Lu, Bao-Liang Lu, and Andrzej Cichocki. 2019. EmotionMeter: A Multimodal Framework for Recognizing Human Emotions. *IEEE Transactions on Cybernetics* 49, 3 (March 2019), 1110–1122. https://doi.org/10.1109/TCYB.2018.2797176

[54] Wei-Long Zheng, Jia-Yi Zhu, Yong Peng, and Bao-Liang Lu. 2014. EEG-based emotion classification using deep belief networks. In *2014 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE, Chengdu, China, 1–6. https://doi.org/10.1109/ICME.2014.6890166

[55] Jia-Yi Zhu, Wei-Long Zheng, and Bao-Liang Lu. 2015. Cross-subject and Cross-gender Emotion Classification from EEG. In *World Congress on Medical Physics and Biomedical Engineering, June 7-12, 2015, Toronto, Canada*, David A. Jaffray (Ed.). Springer International Publishing, Cham, 1188–1191.

A CORRELATION VALUES FOR EEG FEATURES WITH INSIGNIFICANT P-VALUE

Feature	Correlation value with Emotion label
$C3_{\theta}$	0.512677
$C3_{\alpha}$	0.429349
$C3_{\beta u}$	0.426374
$\Delta_{C3-C4,\theta}$	0.417782
$C3_{\beta l}$	0.407479
$\Delta_{C3-C4,\beta u}$	0.367269
$\Delta_{C3-C4,\alpha}$	0.344033
$\Delta_{C3-C4,\beta l}$	0.330762
$C4_{\theta}$	0.325954
$F3_{\theta}$	0.279428
$\Delta_{F3-F4,\theta}$	0.278996
$C4_{\beta u}$	0.278964
$C4_{\alpha}$	0.275871
$C4_{\beta l}$	0.248706
$P7_{\theta}$	0.234398
$F7_{\theta}$	0.230637
$F4_{\theta}$	0.229198
$\Delta_{P7-P8,\theta}$	0.219021
Fz_{θ}	0.217823
$F3_{\alpha}$	0.214373
$T7_{\theta}$	0.213708
$Fp2_{\theta}$	0.205513
NAS_{α}	0.205354
$\Delta_{F3-F4,\alpha}$	0.204753
$NAS_{\beta u}$	0.203809
$NAS_{\beta l}$	0.203371
$P8_{\theta}$	0.197937
$Fz_{\beta l}$	0.196078
$F3_{\beta u}$	0.192619
$\Delta_{F3-F4,\beta u}$	0.191816
NAS_{θ}	0.191382
$Fz_{\beta u}$	0.188224
Fz_{α}	0.186636
$P7_{\alpha}$	0.181465
$\Delta_{T7-T8,\theta}$	0.177952
$F4_{\alpha}$	0.177017
$Fp2_{\beta u}$	0.170411
$O1_{\theta}$	0.169183
$F7_{\alpha}$	0.166839
$F4_{\beta u}$	0.166676
$\Delta_{P7-P8,\alpha}$	0.166179
$F3_{\beta l}$	0.159131

$Fp2_{\beta l}$	0.158251
$\Delta_{F3-F4,\beta l}$	0.156407
$P8_{\alpha}$	0.155682
$P7_{\beta u}$	0.153422
$P3_{\theta}$	0.151652
$\Delta_{O1-O2,\theta}$	0.15004
$T7_{\alpha}$	0.149545
$Fp2_{\alpha}$	0.144389
$F4_{\beta l}$	0.142905
$F33_{\theta}$	0.141646
$T8_{\theta}$	0.13799
$F7_{\beta u}$	0.136874
$\Delta_{P7-P8,\beta u}$	0.136162
$P7_{\beta l}$	0.136084
$O1_{\alpha}$	0.131233
$P4_{\theta}$	0.131152
$\Delta_{P3-P4,\theta}$	0.128671
$P3_{\alpha}$	0.125805
$O2_{\theta}$	0.124383
$\Delta_{P7-P8,\beta l}$	0.123035
$T7_{\beta u}$	0.12295
$\Delta_{T7-T8,\alpha}$	0.122358
$\Delta_{F7-F8,\theta}$	0.121691
$F33_{\alpha}$	0.121289
$P8_{\beta u}$	0.120806
$F7_{\beta l}$	0.117721
$P4_{\alpha}$	0.116922
$P8_{\beta l}$	0.116625
$\Delta_{Fp1-Fp2,\theta}$	0.116522
$T7_{\beta l}$	0.113599
$\Delta_{Fp1-Fp2,\beta l}$	0.113202
$\Delta_{O1-O2,\alpha}$	0.111141
$\Delta_{P3-P4,\alpha}$	0.109164
$\Delta_{T7-T8,\beta u}$	0.108185
Oz_{θ}	0.103774
$P3_{\beta u}$	0.099563
Pz_{θ}	0.099535
$\Delta_{T7-T8,\beta l}$	0.095903
$T8_{\alpha}$	0.095828
$O1_{\beta u}$	0.093634
$\Delta_{O1-O2,\beta u}$	0.090646
$O1_{\beta l}$	0.090534
Pz_{α}	0.089937
$P3_{\beta l}$	0.089012
$T8_{\beta u}$	0.089007
$O2_{\alpha}$	0.088251

$\Delta_{Fp1-Fp2,\beta u}$	0.088165
$\Delta_{Fp1-Fp2,\alpha}$	0.087257
$\Delta_{F7-F8,\alpha}$	0.084268
Oz_{α}	0.083008
$P4_{\beta u}$	0.082538
$\Delta_{O1-O2,\beta l}$	0.082096
$F33_{\beta l}$	0.081322
$\Delta_{P3-P4,\beta u}$	0.08102
$O2_{\beta u}$	0.078031
$P4_{\beta l}$	0.077809
$T8_{\beta l}$	0.076628
$\Delta_{P3-P4,\beta l}$	0.073666
$O2_{\beta l}$	0.068697
$F33_{\beta u}$	0.068412
$Oz_{\beta u}$	0.065294
$Oz_{\beta l}$	0.062945
$Pz_{\beta l}$	0.058942
$Pz_{\beta u}$	0.055765
$\Delta_{F7-F8,\beta u}$	0.055586
$\Delta_{F7-F8,\beta l}$	0.049763
$F8_{\theta}$	0.046281
$Fp1_{\beta l}$	0.034029
$F8_{\alpha}$	0.028263
$Fp1_{\theta}$	0.019041
$F8_{\beta l}$	0.007732
$Fp1_{\alpha}$	0.004753
$F8_{\beta u}$	0.001783
$Fp1_{\beta u}$	0.001517

Table 4. Correlation values of EEG channels for all frequency bands and also the derived features from the EEG channels with insignificant p-values.