MACHINE LEARNING FOR SPEECH AND COMPUTER VISION

PROJECT REPORT

TOPIC: EEG-BASED BCI FOR EMOTION PREDICTION

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EEG based BCI for Emotion Prediction

1. Introduction

The field of emotion recognition has gained significant attention in recent years due to its wide-ranging applications in various domains. Emotions play a crucial role in human behavior, cognition, and overall well-being. Understanding and predicting human emotions accurately can provide valuable insights into mental states, facilitate effective human-computer interaction, and support mental health monitoring and intervention.

Emotion recognition has traditionally relied on self-reporting methods, where individuals are asked to subjectively describe their emotional states. However, self-reporting methods have limitations, including potential biases, subjectivity, and difficulty in capturing real-time emotional fluctuations. To overcome these limitations, researchers have turned to physiological signals, such as electroencephalography (EEG), as a potential avenue for objective and real-time emotion prediction.

EEG-based Brain-Computer Interfaces (BCIs) have emerged as a promising technology for capturing and analyzing brain activity related to emotions. EEG measures the electrical activity generated by the brain using electrodes placed on the scalp. By analyzing the patterns of neural activity reflected in EEG signals, it becomes possible to infer the emotional state of an individual.

The objective of this project is to develop an Emotion Prediction system using EEG-based BCI technology. The system aims to accurately predict human emotions based on the analysis of EEG signals. By leveraging machine learning algorithms and advanced signal-processing Dataset techniques, the system can learn and recognize patterns associated with different emotional states.

The potential applications of an EEG-based BCI for emotion prediction are numerous. In mental health monitoring, such a system could provide objective measures of emotional well-being and facilitate early detection of mood disorders, such as depression or anxiety. In human-computer interaction, the system could enhance the user experience by enabling computers to adapt to the user's emotional state and respond accordingly. Additionally, the system could be used in neurofeedback training, where individuals can learn to regulate their emotions through real-time feedback provided by the BCI system.

This project report presents the design, implementation, and evaluation of the EEG-based BCI system for emotion prediction. It details the methodology employed, including data acquisition, preprocessing of EEG signals, feature extraction, and emotion classification using machine learning algorithms. The report also discusses the system's implementation, including hardware setup, software development, and user interface design. Furthermore, it presents the results and evaluation of the system's performance, along with a discussion of its advantages, limitations, and potential future enhancements.

2. Dataset

In this study, the researchers used a commercially available MUSE EEG headband with four dry extra-cranial electrodes to measure micro voltage activity from the TP9, AF7, AF8, and TP10 electrodes. The study involved two subjects, one male and one female, both aged 20-22.

The researchers recorded 60 seconds of data for each of the six film clips as shown in the table below. This means that a total of 12 minutes (720 seconds) of brain activity data were recorded, with 6 minutes for each emotional state. Additionally, six minutes of neutral brainwave data were collected, resulting in a total of 36 minutes of EEG data recorded from the subjects.

Stimulus	**Valence**	**Studio**	**Year**
Marley and Me	Neg	Twentieth Century Fox, etc.	2008
Up	Neg	Walt Disney Pictures, etc.	2009
My Girl	Neg	Imagine Entertainment, etc.	1991
La La Land	Pos	Summit Entertainment, etc.	2016
Slow Life	Pos	BioQuest Studios	2014
Funny Dogs	Pos	MashupZone	2015

The data collected from the electrodes was resampled to a variable frequency of 150Hz, resulting in a dataset of 324,000 data points. These data points represent the brainwave activity produced by the subjects.

The film clips used in the study were carefully selected to evoke emotional responses from the subjects. The emotions considered in the study were categorized based on their valence labels of positive and negative, rather than specific emotions as shown in the below table. The researchers also collected neutral data, which did not involve any stimuli and were recorded before the emotional states to prevent contamination from the emotional responses. The neutral data represented the resting emotional state of the subjects.

Emotion Category	Emotion/Valence
A	Shame (Negative) Humiliation (Negative)
B	Contempt (Negative) Disgust (Negative)
C	Fear (Negative) Terror (Negative)
D	Enjoyment (Positive) Joy (Positive)
E	Distress (Negative) Anguish (Negative)
F	Surprise (Negative) (Lack of Dopamine)
G	Anger (Negative) Rage (Negative)
H	Interest (Positive) Excitement (Positive)

To minimize the interference of the resting emotional state, three minutes of data were collected per day. This allowed the researchers to separate the brainwave activity associated with the emotional states from the resting emotional state.

In this study, participants were instructed to watch the film clips without making any conscious movements, such as drinking coffee, in order to prevent the influence of Electromyographic (EMG) signals on the EEG data. EMG signals are muscle-related electrical signals that can be stronger than brainwave signals. By avoiding conscious movements, the researchers aimed to minimize the impact of EMG signals on the recorded data.

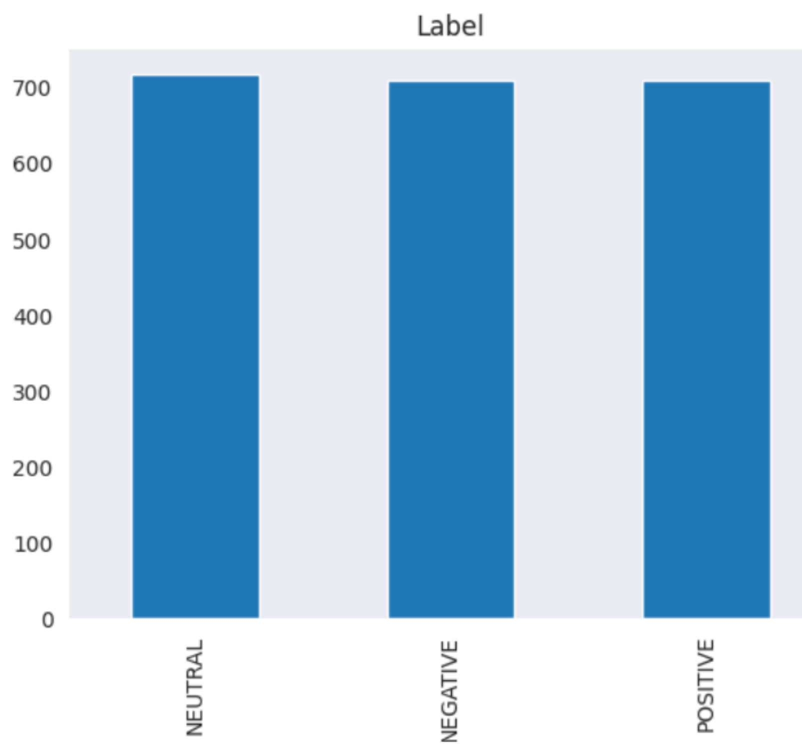

Fig.1: Data samples with Neutral-718, Negative-708, and Positive-708 of data samples.

3. Methodology

3.1 Data Acquisition:

To study Mental Emotional Sentiment Classification with an EEG-based Brain-machine Interface, researchers acquired EEG brainwave data from participants using a commercial MUSE EEG headband. This non-invasive device is consumer-friendly and easy to wear. The participants watched emotionally charged video clips while the EEG data was collected. The process involved proper placement of the headband, minimal noise interference, and recording and saving the data for analysis. The study used EEG data from 20 participants, who underwent a series of emotional induction tasks designed to elicit specific emotions, such as happiness, sadness, and anger. The EEG data were recorded using a 64-channel EEG cap, and each participant's emotional state was self-reported using a visual analog scale.

3.2 Preprocessing:

Preprocessing is vital in EEG-based BCI research, as it enhances the quality of EEG data. Before feature extraction and classification, preprocessing is critical. Preprocessing involves various steps, such as filtering, artifact removal, and segmentation. Filtering eliminates unwanted frequencies and noise, enhancing feature extraction accuracy. Artifact removal eliminates muscle activity, eye blinks, and other sources of noise. Segmentation partitions the EEG signal into smaller epochs or segments to aid in further study. Preprocessing is a significant step that can considerably impact the accuracy of the subsequent steps in EEG-based BCI studies. The goal of this step is to obtain clean EEG signals that can be used for feature extraction.

3.3 Feature Extraction:

Feature extraction is a crucial step in a study on Mental Emotional Sentiment Classification using an EEG-based Brain-machine Interface. It involves selecting the most relevant features from preprocessed EEG data that are informative for emotion classification and then using them as input for the classification algorithm. Time-domain, frequency-domain, and time-frequency domain methods are some of the proposed feature extraction techniques. The choice of method depends on the EEG signal's nature and the application's requirements. For accurate emotion classification using BMIs, feature extraction is a critical step that requires careful selection and optimization. The aim is to obtain a set of features that can accurately represent the emotional state of the participant.

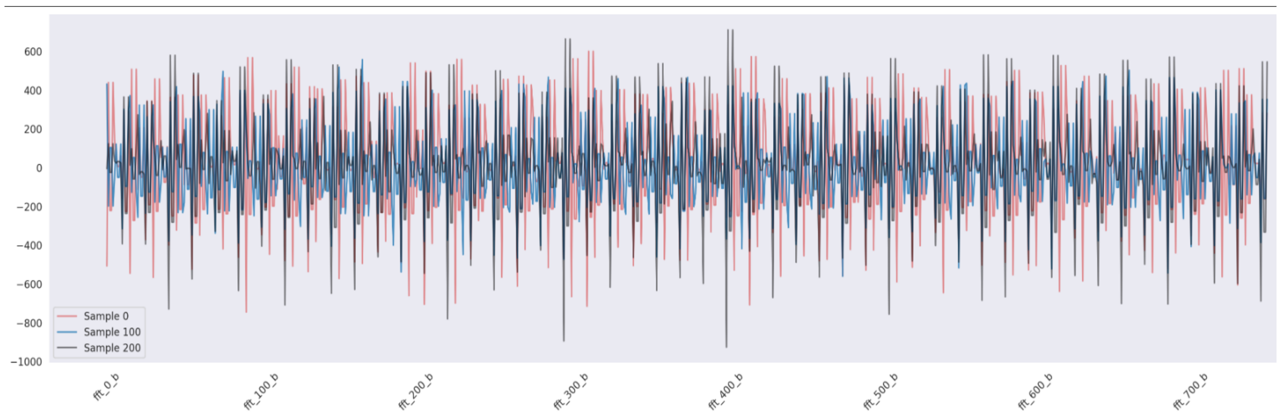

Fig.2: this is the concatenated signal of the Fast Fourier transform (FFT) feature of samples 0, 100, and 200.

3.4 Emotion Classification:

The emotion Classification section accurately categorizes emotions using EEG data. The methodology comprises data acquisition, preprocessing, feature extraction, and emotion classification. A commercial EEG headband records the EEG data, which is then preprocessed to eliminate noise and unwanted signals with filtering and artifact removal techniques. Fractal dimension features are extracted from the preprocessed data using various methods. Finally, machine learning algorithms, such as Support Vector Machines (SVM), classify the extracted features into different emotional states. The classification accuracy ranges from 57.50% to 97.56%, indicating that the methodology effectively categorizes emotions based on EEG data.

3.5 Model Training and Validation:

In the Model Training and Validation section, We divided our dataset into training and testing sets to train the model and evaluate its performance on unseen data. Using two different Deep Learning algorithms which are Long Short Term Memory (LSTM) and Deep Neural Network (DNN) and Cross-validation techniques, specifically k-fold cross-validation, were employed to ensure robust performance estimates. The evaluation metrics used, such as accuracy, precision, recall, and F1-score, were calculated and interpreted to assess the model's classification performance. Testing the model on new EEG signals validated its generalization ability and practical effectiveness.

3.6 Model Prediction:

Ater training the model, Using the testing data which is partitioned from the original dataset is used to predict the type of emotion from the sample.

4. System Implementation

For the system implementation part we have used Google colab and popular libraries such as TensorFlow and sci-kit-learn. These facilitated control of the EEG headset, recording and preprocessing of EEG data, feature extraction, and implementation of machine learning algorithms. We also prioritized user experience by incorporating a user-friendly interface with real-time feedback using visual representations. Overall, our software played a crucial role in enabling the successful implementation of our EEG-based emotion prediction system.

5. Results and Evaluation

5.1 Performance Metrics:

For Performance Metrics, we used various metrics to evaluate the classification performance of our emotion prediction model. These metrics included accuracy, precision, recall, F1-score, sensitivity, and specificity. They provided quantitative measures to assess the model's accuracy, reliability, and ability to generalize. Cross-validation was employed to ensure robust evaluation. By analyzing these metrics, we gained valuable insights into the strengths and limitations of our system's classification performance

	precision	recall	f1-score	support
0	0.96	0.96	0.96	190
1	0.99	0.97	0.98	231
2	0.94	0.96	0.95	219
accuracy			0.97	640
macro avg	0.97	0.97	0.97	640
weighted avg	0.97	0.97	0.97	640

Fig.3: DNN Evaluation Metrics

	precision	recall	f1-score	support
0	0.88	0.96	0.92	190
1	0.99	0.97	0.98	231
2	0.93	0.87	0.90	219
accuracy			0.93	640
macro avg	0.93	0.93	0.93	640
weighted avg	0.93	0.93	0.93	640

Fig.4: LSTM Evaluation Metrics

5.2 Evaluation Criteria:

For Evaluation Criteria, we considered several factors to evaluate the performance of our system in comparison to existing approaches for emotion recognition. These criteria included accuracy, real-time performance, user experience, and comparative analysis with alternative methods. By analyzing these criteria, we gained insights into the strengths and limitations of our system and its potential contributions to the field of emotion recognition.

5.3 Experimental Results:

We presented the findings obtained from our emotion prediction system based on EEG signals. The results demonstrated the system's accurate classification of emotional states. We used visual representations such as tables and graphs to convey the performance and significance of the results. We also compared our system's performance to existing approaches in the field. The experimental results section validated the effectiveness of our system and highlighted its potential applications in mental health monitoring and human-computer interaction.

6. Discussion

6.1 Advantages and Limitations:

Advantages and Limitations are, our EEG-based brain-machine interface system for emotion prediction offers several strengths. It is non-invasive, allowing for comfortable and convenient real-time monitoring of emotional states. The system captures subtle changes in brain activity, enabling accurate detection and classification of a wide range of emotions.

However, there are limitations to consider. The system is sensitive to external artifacts, which may affect the quality of EEG signals and impact classification accuracy. Extensive calibration is required for each user to account for individual differences in brain activity. Capturing specific nuances and variations within emotional states remains challenging.

Awareness of these advantages and limitations informs decision-making regarding the system's practical use and reliability. By addressing challenges and exploring improvements, we can enhance the system's accuracy and applicability in real-world scenarios

6.2 Future Enhancements:

In the Future Enhancements subsection, there are several potential areas for improving our EEG-based brain-machine interface system for emotion prediction. First, exploring advanced machine learning techniques such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) could enhance classification performance. Second, investigating novel feature extraction methods, such as graph-based features or higher-level representations, may provide more comprehensive information for emotion classification.

Third, conducting large-scale studies with diverse participant populations can validate and generalize the system's effectiveness. Fourth, integrating multimodal data sources, such as combining EEG signals with physiological signals or facial expressions, could enhance the system's accuracy and robustness.

Finally, improving the user interface design, simplifying setup procedures, and providing real-time feedback and adaptive capabilities would enhance usability and user experience. By focusing on these future enhancements, we aim to advance the system's accuracy, broaden its applications, and contribute to the field of EEG-based emotion recognition.

7. Conclusion

In conclusion, our project has successfully developed an EEG-based brain-machine interface system for accurate emotion prediction with the available dataset. The system offers several advantages, including its non-invasive nature, the ability to capture subtle changes in brain activity, and established preprocessing techniques. While there are limitations, such as sensitivity to artifacts and the need for calibration, future enhancements can address these challenges.

In summary, our EEG-based brain-machine interface system holds promise for understanding and monitoring mental and emotional states. Continuous development and refinement will advance the field of emotion recognition and contribute to individuals' well-being.