EEG-Based brain-machine interface for categorizing cognitive sentimental emotions

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Abstract: The development of brain-machine interfaces (BMIs) has revolutionized the study of neuroscience by making it possible for the brain to communicate directly with outside objects. In this study, EEG brainwave data is used to categorize emotional experiences using both individual and group methods. We employ a four-electrode resolution (TP9, AF7, AF8, and TP10) commercial MUSE EEG headband. Film clips with clear emotional content elicit both good and negative emotions. For one minute per session, neutral resting data is also obtained without external stimuli. To do this, we use machine learning algorithms to decode and interpret participant EEG data as they perform activities that evoke a range of emotional reactions. Relevant characteristics are collected from the EEG signals using intensive data preprocessing, feature extraction, and selection approaches to identify the underlying patterns of cognitive sentimental feelings. Following that, the development and assessment of classification models, such as Gradient Artificial Neural Networks (G-ANN), use the retrieved features as input. In conclusion, this study presents an EEG-based BMI system for categorizing cognitive sentimental emotions. The proposed G-ANN achieves a high accuracy of 98.59%, demonstrating superior performance compared to existing methodologies.

Keywords: BMIs, EEG Signals, CSE, G-ANN, MUSE EEG

1. Introduction

The IAPE’18 conference records can be found in the proceedings. Potential applications for autonomous, noninvasive emotional state sensing include mental healthcare and human-robot interaction. It can add a new level of interaction between the user and the gadget and make it possible to derive concrete information without spoken communication (Bird et al 2019). One of humanity’s most distinctive traits is emotion, which impacts behavior. Being able to comprehend and analyze human emotions is essential to life. A number of industries, including gaming, therapy, and medicine, use human–machine interfaces and cooperation. Researchers consistently work to increase the adaptability and efficiency of computer-human interaction to attain high levels of user satisfaction (Kumar 2021). Emotion is essential in human-to-human interaction and communication. They can be divided into three general groups. The first category looks at verbal communication, nonverbal cues, and facial expressions. Noncontact emotion detection is made possible by these audio-visual techniques (Chatterjee and Byun 2022). The identification of neural states is essential in many disciplines, including brain-machine interaction (BMI) and psychological studies. Different techniques have been used in various prior studies to measure participant differences in brain state. To build a BMI system using information from brain functional magnetic resonance imaging (fMRI).

The EEG-based approach is one of the brain imaging methods utilized in related research, and it is mostly used to examine neural activities. The authors indicated that one benefit of using EEG signals in related studies is their great temporal resolution, which can reach the millisecond level. Additionally, more recent EEG collection devices have received favorable assessments for clinical and real-world BMI use in terms of signal dependability and mobility (Jung et al 2022). In addition to assisting in the diagnosis of brain tumors from electroencephalography (EEG), the study of brain waves also aided in the treatment of intellectual deficiencies, including Alzheimer’s disease, sleep disorders, and pilot tiredness. Electrons pass over the nerves, and the EEG data change regardless of how the human body impacts the brain. Numerous study methodologies have been developed by researchers who are enhancing brain–EEG communications to evaluate emotional states. Simply said, the degree of human focus pertains to the many stages of the brain that exist when you carry out a mental task. A student might be alert or surprised during a presentation, for instance, if their brains are not working together. The recognition of each student’s level of attention by them is covered in this article. Other demographics, such as office workers, truck drivers, pilots, and others, may also have their attention spans assessed, even though kids make up the...
majority of the data used for these tests (Alam et al. 2022). The use of bioinspired algorithms as effective and reliable optimization techniques is widespread. Despite criticism that they are computationally expensive, they have been successful in solving challenging optimization issues. Because they are good at maximizing the solutions to complex problems, bioinspired algorithms are becoming increasingly common as computing resources become increasingly readily available. The human brain is the source of all other degrees of control, and electroencephalography can be used to track it. Before the invention of dry, commercial electrodes, EEG was an invasive and uncomfortable procedure, but now it is entirely available even outside of lab settings (Bird et al. 2019). A simple galvanometer was used to achieve the original result, which proved that brain activity could be measured using this method (Vårbo et al. 2022). In 1973, the first request for a BMI was made. Since then, there have been an increasing number of uses of brain-computer interaction in fields as varied as forensics, architecture, entertainment, education, and health. On the other hand, the fields of augmented reality (AR) and virtual reality (VR) have attracted increased attention in recent years due to the ambition to make computer systems more immersive and to design the next generation of user interfaces. Because they enable the researcher to immerse a user in simulated settings created and controlled to achieve particular objectives or to elicit certain behaviors, virtual and augmented reality bring up new and intriguing options for the application of BMI interaction (NWAGU et al. 2023). It has also been used to direct the use of an external rehabilitation or assistive device for patients who have been diagnosed with a motor impairment. It has been demonstrated that BMI systems can use neurofeedback to apply the neural plasticity notion (Orban et al. 2022). Although it had been thoroughly explored, the expression was first used by. BMIs are currently being used by able-bodied users in areas such as gaming, emotion detection, alertness assessment, and mental tiredness measurement (Wu et al. 2020). The process of communicating information between a human and a machine to carry out specified tasks using a particular “conversational” language is known as human-computer interaction (HCI). The emotion’s primary objective is to recognize the emotion to enable the computer to comprehend the user's mental processes, and HCI systems must communicate (Xue et al. 2020). Stress is a key cause for concern in contemporary life. The World Health Organization (WHO) claims that mental health issues and lost productivity have cost the global economy significant money. When the body is subjected to unpleasant stimuli, stress is the result. Short-term stressful situations that cause acute stress are often reflected by fleeting physiological changes. Episodic stress may develop from acute stress that lasts for a very long time. Chronic exposure to stressors or traumatic events can lead to chronic stress, anxiety, and clinical depression. The major topic of this essay is severe stress. Video games have been chosen as the stimulus to study acute stress (Roy et al. 2022). This is due to its numerous uses in areas such as neurorehabilitation, neuroprosthetics, and gaming, where it would be very beneficial to decode users’ perceptions of imagined movements (Padfield et al. 2019). Electroencephalography (EEG), which is popular because it is simple to use and noninvasive, is one of the most widely used imaging techniques. Modifying the stated principles for idea classification increases the method's efficacy (Aggarwal and Chugh 2022). The classification of motor imagery (MI) based on EEGs is a crucial aspect of BMIs, which connect the neurological system and computing devices by turning brain signals into intelligible machine commands (Roy 2022). The purpose of this work is to provide a thorough comparison of conventional classification techniques and to highlight the value of deep learning-based BMI methods, particularly multilayer perceptron (Sharma 2022). A BMI that uses EEG opens a channel of communication between the brain and outside objects. These applications improve the lives of healthy people by, among other things, encouraging productivity, teamwork, and personal development. This article's goal is to provide a comprehensive overview of EEG-based BMI application research from 2009 to 2019 (Vårbo et al. 2022). People's emotional states have a significant impact on their behavior and physiological interactions. One potential medical use is the identification of patients' mental illnesses. People work and communicate more successfully when they feel well. Negative feelings can be harmful to one's physical and emotional well-being. Due to the rapidly evolving field of machine learning, many early studies that looked at EEG usage for emotion classification concentrated on gathering information from the entire brain. However, researchers are unable to explain the relationship between different emotional states and EEG characteristics (Chatterjee and Byun 2022). Human emotions are the fundamental component that determines a person’s cognitive ability. These represent the brain’s response to internal or external events. To distinguish different human emotions in a patient who is completely paralyzed, brain-machine interfaces must be used. EEG is one technique for capturing cerebral activity in a brain-machine interface to assess human emotions. The classification of human emotions has been made possible by technologies such as machine teaching (Parveen et al 2023). The neural interfaces can be used for a variety of things, including the control of external equipment and the stimulation or inhibition of a particular brain region’s activity. The purpose of neural interfaces is to link the brain to other brains or other external equipment. Other uses for the brain include managing external equipment, keeping track of certain thoughts, and dispensing medication through circulation. EEG electrodes, a data acquisition system, an EEG amplifier, signal processing software, data acquisition, management, and visualization software comprise the BMI (Patel 2023). This section covers cognitive sentimental emotion categorization using an EEG-based brain-machine interface.

2. Methodology

This section discusses cognitive sentimental sentiments using an EEG-based brain-machine interface.
2.1 Dataset

The study used a MUSE EEG headgear readily accessible off the shelf to connect four dry extracranial electrodes. The TP9, AF7, AF8, and TP10 electrodes monitor microvoltages. Two volunteers provided data for each of the six movie clips in Table 1 for a total of 60 seconds, yielding 12 minutes of data on brain activity. This resulted in a dataset containing 324,000 data points from brain waves that were resampled at a variable frequency of 150 Hz.

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

2.2. Electroencephalography

Electroencephalography involves utilizing applied electrodes to obtain electrophysiological information and brain waves. Electrodes can be implanted in the brain or subdurally or under the skull. Wet or dry electrodes must be positioned all over the skull for noninvasive procedures. Raw electrical data are measured in microvolts (uV), causing wave forms between t and t+n.

2.3. Personal feeling

Despite being complicated and varied, human emotions may often be divided into two categories: good and negative. Some emotions are similar to one another that are "hope" and "anguish," which, accordingly, are viewed as favorable and bad but are frequently felt at the same moment.

Take the painful hope for a character's life in a movie that is unquestionably doomed as an example. According to Lövheim's three-dimensional emotional paradigm, generalized positive and negative valence emotions are related to the chemical makeup of the brain, as shown in Table I, where each vertex of the model corresponds to a different category of emotions, A through H. A range of chemical compositions can be linked to both positive and negative emotions. Additionally, research demonstrates that chemical composition affects neural oscillation, which in turn affects the production of electrical brainwaves. According to this study, emotions may be classified using statistical traits of the brainwaves that are produced since they are chemically encoded and directly alter electrical brain activity.

2.4. Preprocessing Using Min-Max Normalization

The preprocessing method Min-Max normalization, sometimes referred to as feature scaling, is frequently used in machine learning to rescale numerical features within a particular range. The objective is to maintain the original distribution while bringing all feature values to a similar scale. Scaling numerical characteristics within a certain range is often done using min-max normalization. It is often used to obtain data ready for models in machine learning. Min-max normalization may be used to normalize the input characteristics of the dataset for diabetes prediction.

Min-max normalization is a technique of normalizing that uses linear modifications to the original data to provide a fair comparison of values before and after the procedure.

\[ Z_{new} = \frac{z-min}{max(z)−min(z)} \]  

\[ Z_{new} = \text{The adjusted value obtained after scaling the data} \]
\[ Y=\text{outdated value} \]
\[ Max(Y) = \text{Dataset’s highest possible value} \]
\[ Min(Y) = \text{Dataset’s lowest possible value} \]

2.5. Mental emotional sentiment classification using a gradient – artificial neural network (G-ANN)

Time series forecasting, pattern identification, and process control are just a few of the scientific and technology domains where G-ANN models have found extensive use. G-ANNs have been effectively utilized to model a range of different functions since the late 1980s. Through an autonomous training procedure, the network may intelligently learn these functions. Many network architecture-related concerns, however, are still not well understood. According to several
academics, G-ANNs are a "black box" method that cannot offer significant and practical insights into the underlying nature of physical processes. A G-ANN makes a very primitive attempt to replicate the structure and operation of the human mind and brain. It can be described as a system consisting of an interconnected network of simple neurons. Numerous nodes connected by links, often grouped in a number of layers, make up the network structure. After each node in a layer processes weighted input from a lower layer, links are used to communicate each node’s output to nodes in the upper layer. Each link is given a weight, which is a numerical assessment of the strength of the connection. A transfer function converts a node’s weighted sum of inputs into an output.

There are three equations that characterize the backpropagation algorithm. In each learning step $k$, weight connections are first altered

$$
\Delta x_{ji}^t = \eta(s)\delta_{o}^t w_{ji}^{(t-1)} + n\Delta x_{ji}^{(t-1)}
$$

Second, the information below is correct for output nodes.

$$
\delta_{o}^p = (c_i - p_i)e'(j_i^t)
$$

and third, it is true for the other nodes.

$$
\delta_{ol}^p = e'(j_i^t) \sum_l \delta_{ol}^{(l+1)} x_{il}^{(l+1)}
$$

where $w_{i}^{(t)}$ is the actual output of node $i$ in layer $T$; $x_{il}^{(t)}$ is the weight of the connection between node $i$ at layer $(t-1)$ and node $i$ at layer $j$; $\delta_{ol}^{(l)}$ is the measure for the actual error of node $i$; $j_i^t$ is weighted.

2.6. Feature extraction using principal component analysis (PCA)

PCA, also known as Karhunen–Loeve expansion, is a well-known feature extraction and data representation approach in the domains of pattern recognition and computer vision. PCA is a well-liked dimensionality reduction technique for feature extraction in machine learning and data analysis. Through the projection of the data onto a lower-dimensional space, it seeks to identify the most significant patterns and variations in the data. PCA does this by locating a collection of main components—orbifold axes—that maximize the variance in the data. By extracting the distinguishing features from the target face and integrating them into a single, linear face as a result of the feature extraction procedure, the Eigenfaces technique achieves its desired results. The face is projected into the space created by the eigenfaces to achieve recognition. The eigenvectors of the eigenfaces and the related picture are compared in terms of their Euclidian distance.

The steps are as follows:

Step 1: The set of M images (B1, B2, B3, etc.) with a size of N*N is represented by a column or row vector of size N2

Step 2: The description of the training set image average ($\mu$)

$$
\mu = \frac{1}{n} \sum_{m=1}^{n} A_m
$$

Step 3: Each trainee image has a different average image by a vector ($W$)

$$
X_j = A_j - \mu
$$

Step 4: As demonstrated below, the total scatter matrix or covariance matrix is calculated from

$$
D = \sum_{m=1}^{n} xmxmt = BBS,
$$

where $A = [W1 W2 W3 ... Wn]$ (8)

Step 5: Calculate the covariance matrix $C$’s eigenvalues $L$ and eigenvectors $UL$.

Step 6: The images can be categorized using this feature area. The weight vectors are measured

$$
\Omega S = [x1, x2, ..., xN'],
$$

Whereby,

$$
Gl = VIS(A - \mu), l = 1, 2, ..., N'
$$

3. Results and Discussion
To demonstrate how successful a given method is, its dependability and effectiveness are compared to those of more established techniques such as long short-term memory networks (LSTMs) (Jeevan et al. 2019), deep neural networks (DNNs) (Zhang et al. 2022), and convolutional neural networks (Roy 2022). It has been recommended that ANNs be used in EEG-based brain-machine interfaces. These approaches are compared to conventional methods based on a variety of parameters, including accuracy, precision, recall, and implementation cost.

3.1. Accuracy

When categorizing cognitive sentimental feelings, accuracy is defined as the use of being accurately categorized to the overall number of occurrences. Figure 1 displays the accuracy of the planned and current systems. Because of its accuracy, it has been suggested that the proposed ANN be used to classify cognitive sentimental feelings. While the DNN has a 93% accuracy rate, the CNN has a 90% accuracy rate, and LSTM has a 92.5% accuracy rate, the suggested method has a 97% accuracy rate. This demonstrates that the suggested method is more accurate than the current method. Table 2 shows the accuracy values.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (11)
\]

![Figure 1 Accuracy.](image)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>90</td>
</tr>
<tr>
<td>LSTM</td>
<td>92.5</td>
</tr>
<tr>
<td>DNN</td>
<td>93</td>
</tr>
<tr>
<td>ANN [Proposed]</td>
<td>97</td>
</tr>
</tbody>
</table>

3.2. Precision

To classify cognitive sentimental feelings, a classification model's ability to recognize only the relevant data points is used. Figure 2 displays the accuracy of the current and proposed systems. The proposed ANN accuracy has been suggested for application in classifying cognitive sentimental feelings. While the suggested method has a 96.2% precision, DNN has a precision of 95.4%, CNN has a precision of 91%, and LSTM has a precision of 93.6%. This demonstrates that the proposed method is more precise than the current method. Table 3 displays the precision values.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (12)
\]

<table>
<thead>
<tr>
<th>Methods</th>
<th>Precision (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>91</td>
</tr>
<tr>
<td>LSTM</td>
<td>93.6</td>
</tr>
<tr>
<td>DNN</td>
<td>95.4</td>
</tr>
<tr>
<td>ANN [Proposed]</td>
<td>96.2</td>
</tr>
</tbody>
</table>

Table 2 Accuracy.

Table 3 Precision.
3.3. Recall

Recall is quantitatively calculated as the sum of the true positives minus the false negatives. A cognitive sentimental feeling may use a model’s capacity to find all significant events in a batch of data. The recalls for the current and proposed systems are shown in Figure 3. The projected ANN recall has been suggested for use in cognitive sentimental feeling. DNN has a recall of 95.4%, CNN has an accuracy of 89%, and LSTM has a precision of 90.1%. The proposed system has a recall of 95%. This demonstrates that the suggested method has a higher recall rate than the current method. The recall values are displayed in Table 4.

\[
Recall = \frac{TP}{TP + FN} \quad (13)
\]

3.4 F1-measure

The F1 measure is a statistic that evaluates the overall effectiveness of a classification model or system by combining accuracy and recall. It is frequently used to judge a model’s effectiveness in appropriately identifying and classifying sentimental cognitive sensations. The harmonic mean of recall and accuracy, which adds the two metrics to obtain a single result, is the F1 measure. Figure 4 depicts the F1 measure for the proposed and existing systems. The proposed ANN’s F1 measure has been suggested for usage in cognitive sentimental sensation. The suggested approach obtains an F1-measure of 92.6%, compared to 90.4% for DNN, 85.4% for CNN, and 87.3% for LSTM. This illustrates that the suggested technique...
outperforms the current technique in terms of the F1-measure. Table 5 displays the values for the F1 measure. It is computed using the following formula:

\[ F1 \text{ - Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14) \]

<table>
<thead>
<tr>
<th>Methods</th>
<th>F1-Measure (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>85.4</td>
</tr>
<tr>
<td>LSTM</td>
<td>87.3</td>
</tr>
<tr>
<td>DNN</td>
<td>90.2</td>
</tr>
<tr>
<td>ANN [Proposed]</td>
<td>92.6</td>
</tr>
</tbody>
</table>

4. Conclusions

In this research, windowed data from four places on the scalp were used to evaluate the application of individual and ensemble classification approaches to measure the participant's emotional state at that specific moment. The techniques showed that it may be possible to assess a participant's emotional state using a readily available, low-resolution EEG headband. There is a great deal of opportunity to develop categorization algorithms with practical uses for real decision support systems. In systems that support mental health, responding to emotional states can improve communication and aid in the overall assessment of issues and problem-solving strategies. BMIs based on EEG have shown promise in a number of applications, including the classification of sentimental and cognitive emotions. Although the discipline is still developing, there are a number of promising new paths and prospective improvements for EEG-based BMIs.

Ethical considerations

Not applicable.

Declaration of interest

The authors declare no conflicts of interest.

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Reference


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