

EEG-Based Brain Computer Interface for Emotion Recognition

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Abstract—Emotion recognition using electroencephalography (EEG) signal could be a current focus in brain-computer interface research, that is convenient and a reliable technique. EEG-based emotion detection studies are employed in a very spread of fields, including defence, aerospace, and medicine, among others. The purpose of this study is to discover the relationship between EEG signals and human emotions. EEG signals are commonly used to categorise emotions into three groups: positive, negative, and neutral. We first extracted features from the EEG signals in order to classify emotions and used a deep learning classifier: recurrent neural network (RNN) and gated recurrent unit (GRU). Second, a Muse EEG headband with four electrodes (TP9, AF7, AF8, TP10) is used to record brain activity. Positive and negative emotional states are elicited with lucid valence film clips, and neutral resting data with no stimuli is also recorded for one minute per session. EEG data was collected for 3 minutes per state from two people (one male and one female) (positive, neutral, and negative) [5]. This study helps to spot human emotions supported by EEG signals within the brain-computer interface and helps to know the emotion of the mind.

Index Terms—Emotion recognition, EEG, deep learning, RNN, GRU, brainwave, EEG emotion Detection, brain-computer interface (BCI), MUSE EEG-Headband.

I. INTRODUCTION

Emotion recognition is the process of identifying human emotion. Emotions are important in human life, and the necessity and importance of emotion recognition has grown with the increasing role of the brain-computer interface. Text, speech, facial expressions, and body gestures can all be used to detect emotions. However, these methodologies do not produce an efficient or appropriate result. When compared to audiovisual-based methods, bio-signal responses tend to provide more detailed and complex information for determining emotional states. Electroencephalography (EEG) could be used to collect data from sensors. BCI's purpose is to determine how the human brain communicates with external computers or other intelligent technological equipment [1].

A. Electroencephalography

Electroencephalography (EEG) is a cost-effective and reliable technique for measuring the electrical activity of the brain. It is completely painless and can be done without shaving the hair. It can be used to diagnose several conditions, including epilepsy, brain tumours, sleep disorders, and more. EEG-based interfaces are comfortable to use and do not require surgery. The EEG frequency band, which is decomposed into five different frequency bands, is the most commonly used classification [3]. As a result, the five different frequency bands are briefly described below, along with the mental states associated with them.

Delta waves (δ) are observed during deep sleep or coma and have a frequency range of 0–4 Hz. These waves have a greater amplitude and can be measured at less than 100 microvolts.

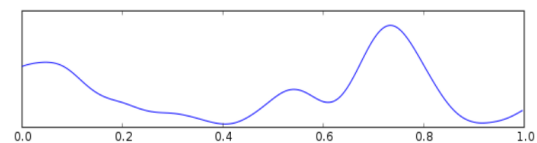


Fig. 1. Delta-waves

Theta waves (θ) have a frequency between 4 - 8 Hz. When you're thinking creatively or when you're focused, you will notice theta rhythms. These waves can also be seen during short-term memory tasks.

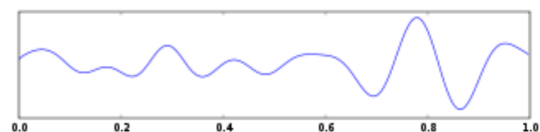


Fig. 2. Theta-waves

Alpha waves(α) have a frequency range of 8–13 Hz. During a state of relaxation and calm, these waves originate in the occipital lobe of the brain. It has also been found that the Alpha rhythm's activity is a reflection of how human vision works [3].

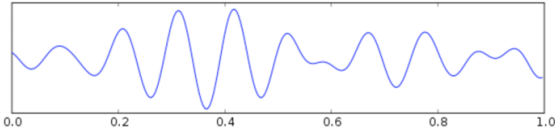


Fig. 3. Alpha-waves

Beta waves(β) These waves, which come from the centre region of the brain, are seen during anxious thought and active concentration.

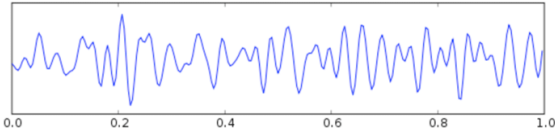


Fig. 4. Beta-waves

Gamma waves(γ) are found at frequencies ranging from 30 to 100 hertz. Multitasking and a conscious waking state are mental states associated with these waves.

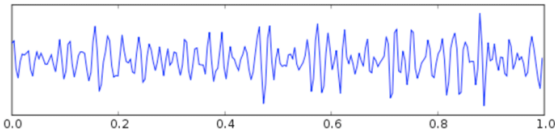


Fig. 5. Gamma-waves

B. Our Contribution

- Exploration of EEG-Brain waves (five distinct frequency bands, as well as the emotional states aligned with them).
- Exploration of Deep Learning models (RNN and GRU) for emotion classification.
- Our work aims to accurately predict a subject's emotional states while watching various movie scenes using recurrent neural network, gated recurrent unit. For this purpose, three emotional states have been specified, such as positive (happiness), negative (anger), and neutral (calm).
- We used an EEG brainwave dataset from kaggle that has been processed with our original strategy of getting good results by analysing EEG signals and classifying human emotions using recurrent neural network and gated recurrent unit classifier.

- We applied model validation using confusion matrix and modification on existing algorithms.

C. Problem Definition

EEG-based emotion recognition has been extensively studied, with different results with different algorithms. In general, there are different methods for recognising the sort of emotion being conveyed, but the output ultimately depends on the algorithm's correctness, and there is another situation to consider. If the algorithm predicts the probabilities of all emotions equally, We need to improve our accuracy in order to correctly classify emotions. This can be done through brain signals by analysing EEG signals and using a recurrent neural network and a gated recurrent unit.

D. Research aims

Finding the link between EEG signals and human emotions is the main goal of the current study. Positive, negative, or neutral emotions are classified using EEG signals.

E. Objectives

The objective of this study is to use signal preprocessing, feature extraction, and classification to provide the emotional state and to detect emotions, which opens up possibilities outside of the medical profession.

F. Motivations

Our main motivation is to use EEG (non-invasive technology) signals to determine human emotions, which is a reliable and cost-effective method. Many models for recognising and classifying emotions with good classification accuracy have been reported in the literature. EEG-based emotion recognition has been widely employed in the military, human-computer interaction, diagnosis, and other fields.

II. LITERATURE REVIEW

Many studies on emotion recognition are applied, and a spread of datasets is generated. Due to its reliability in emotion recognition, researchers are focused on generating EEG-based data for emotion recognition. The work in this paper is specializing in Emotion Recognition during Watching Movies Using Electroencephalography signals in machine learning with specific implementations of the SVM approach EEG signals were used to differentiate between two types of emotions: positive and negative. Using all the features and a support vector machine, a mean test accuracy of 87.53% was obtained. [4].

This paper focuses on single and ensemble methods for classifying emotional experiences in machine learning using EEG brainwave data, using specific implementations of the Random Forest Approach. The approaches outlined in this research comprised measuring the electrical activity of the brain using four extracranial electrodes using the MUSE EEG headband. To classify emotions, several machine learning algorithms were used. A deep neural network was the best single classifier with an accuracy of 94.89%. [5].

The research presented in this paper focuses on disorders

of consciousness, vegetative states, and minimally conscious states caused by brain injury or cerebral haemorrhage. The clinical diagnosis of DOC patients is frequently made in this work using behavioural evaluations, such as the Coma Recovery Scale-Revised. Based on how patients react to outside stimuli, these behavioural scales. [6].

The goal of this paper is to analyse and predict a user's emotions by recognising his or her face using a Feed Forward Neural Network and Nave Bayes [7]. Face recognition is a type of software that recognises a certain individual, and it will be very beneficial in security applications to protect our data. Face unlock is currently the standard for unlocking phones [13].

The goal of this paper is to increase EEG-based emotion classification accuracy while also seeing how emotional states develop over time. The improvement of dry electrode methods, machine learning algorithms, and numerous practical uses of brain-computer interfaces for healthy individuals have all boosted interest in emotion classification from EEG data. [14]. Identifying the brain regions and frequency bands most closely associated with emotions is one of the primary goals of emotion recognition. Numerous studies have been conducted on it. Unpleasant emotion activation was shown to be particularly strong in the right posterior areas of the alpha band by Sarlo et al [15]. According to this study, both internal and external stimuli can significantly change brain waves. Electrodes placed on the scalp were used to transduce and sense brain waves [16]. Noninvasive and invasive electroencephalogram techniques are used to record these brain waves. [17]. Many studies on emotion recognition have been done in recent decades. Anderson and McOwan recognised emotion through facial expressions [18]. Ang and colleagues used prosody to recognise emotions [19]. These signals, however, all had the same flaw. They are ineffective at detecting emotion, especially when people are trying to hide their feelings.

III. PROPOSED WORK

EEG signal classification can be very useful in determining a person's feelings towards a situation. In this context, we propose a method for identifying a person's emotions in a situation. We propose to classify the type of emotion being expressed by using recurrent neural networks and gated recurrent unit. When compared to many other algorithms, GRU provides good performance and accuracy. GRU has the ability to record both long term and short-term memory unit.

A. Methodology

To address the research objectives, an appropriate and effective methodology must be established to ensure that this work yields an accurate and reliable result. Signal acquisition is used to collect EEG signals, which are then cleaned using signal preprocessing techniques to remove noise from the data. Feature extraction is used to extract data from EEG signals, and deep learning algorithms are used to classify emotions. Figure 6 depicts the conventional flow of our method. In this

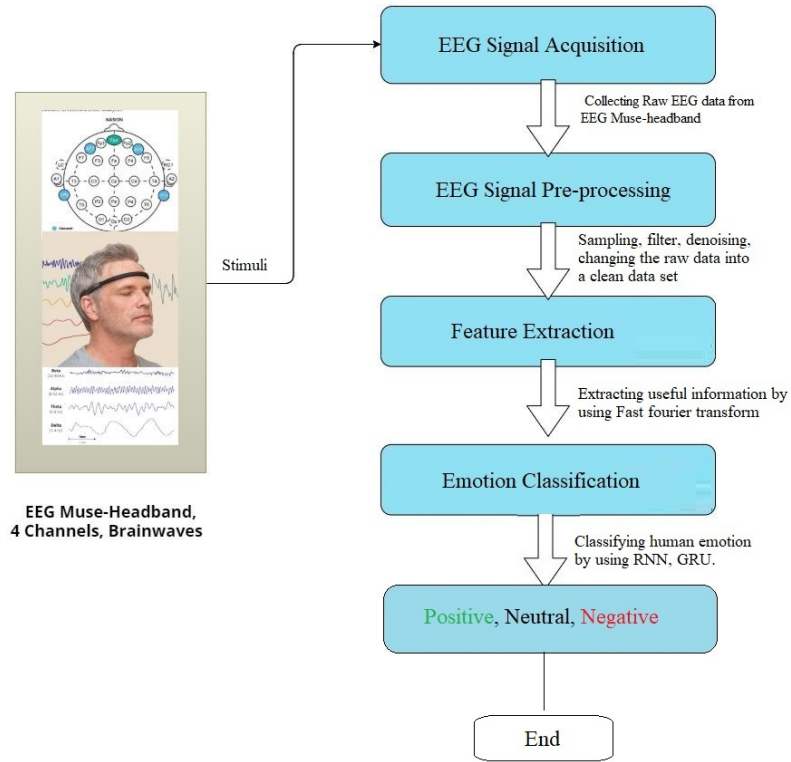


Fig. 6. Block Diagram of EEG-Emotion Recognition

paper, we used techniques that are computationally simple and give accurate results.

1) *Signal acquisition*: The process of measuring the neurocognitive condition of the brain is known as signal acquisition. During an EEG test, electrodes (metal discs) with a sticky substance are implanted on the scalp. These electrodes detect electrical activity in the brain and transmit it to an EEG machine, which records it as wavy lines on paper or a computer. [9].

2) *Signal Pre-processing*: The removal of undesired noises and artefacts is the first stage in using EEG to predict user emotions, followed by categorising EEG signals based on rhythmic activity. Due to their poor signal-to-noise ratio, EEG signals are easily disrupted by noise (SNR). Motion can produce artefacts, including head and eye movements as well as heartbeats, which have a wider wave range than brain waves. During the preprocessing stage, unwanted artefacts such electromagnetic and frequency interferences, EOG, ECG, and EMG interferences, are removed. There have been used Band-pass filter for eliminating EOG and EMG noise [10].

3) *Feature extraction*: The process of removing a particular characteristic from an EEG signal that is pertinent to the goal of the study is referred to as feature extraction. It is crucial for EEG-based emotion recognition to function properly. Its goal is to find the most reliable feature that correlates to the emotions of interest in order to produce accurate classification

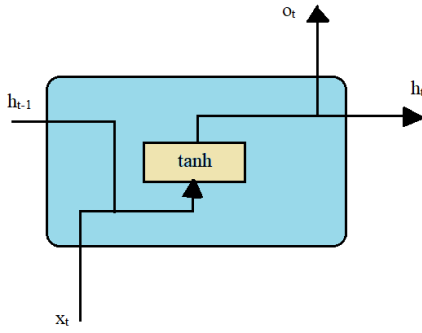


Fig. 7. Recurrent Neural Networks.

results. [10].

4) *Classification*: Based on the data provided by the extracted features, the emotion classification step detects various emotional states. Because deep learning algorithms are extremely efficient for multidimensional EEG features, they are used for this step. We can train a classifier to recognise which of our features belong to which emotional state by using a recurrent neural network and a gated recurrent unit.

B. Recurrent Neural Networks (RNN).

We applied a deep learning model called a recurrent neural network, which is designed to capture temporal correlations between input data. Figure 7 shows a specific RNN node's activity in the time domain. This method explains the recurrent process for a particular node in the interval $[1, t + 1]$. Two variables (h_t for the input and h_{t-1} for the previous hidden state at time t) are input into the node, and two variables (O_t for the output and h_t for the new hidden state at time t) are output at time t . Tanh function squishes values to always be between -1 and 1. The nodes' memory can be thought of as the hidden state, which aids the RNN in remembering previous input [11].

C. Gated Recurrent Units (GRU).

In this paper, we applied a bidirectional GRU network to encode the EEG sequence. The GRU model, which is similar to an LSTM, is a newer generation of recurrent neural network. GRU has one output (h_t) and two inputs (x_t and h_{t-1}), as depicted in figure 8. where h_t is the output at time t itself, h_{t-1} is the output at time t before time t , and x_t is the input value at time t . The mapping is as follows:

$$X_t, h_{t-1} \rightarrow h_t$$

Let's look at how GRU works. A GRU cell, which is similar to an LSTM or an RNN cell, is seen here. It requires an input

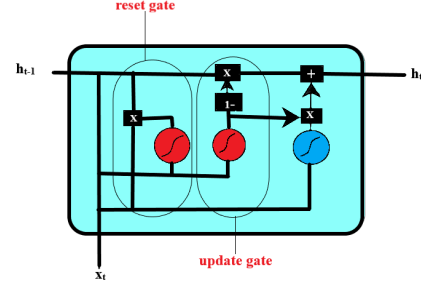


Fig. 8. Gated Recurrent Unit.

X_t together with the hidden state h_{t-1} from the timestamp prior to t at each timestamp t . The subsequent timestamp receives the candidate state H_t . The GRUs eliminated the cell state and used the hidden state to transfer data. However it only has two gates: one for reset and one for update [11].

Update Gate It decides what data to discard and what new data to include. The equation for the update gate is as follows:

$$z = \sigma(W(X_t, h_{t-1}))$$

Reset Gate It determines how much information from the past should be erased. It is responsible for the short-term memory of the network, i.e., the hidden state h_t , logistic sigmoid function σ . The reset gate's equation is as follows.

$$r = \sigma(W(X_t, h_{t-1}))$$

Reset gate r and update gate z . The former determines how the information will be combined with past memories. The latter makes the decision on how much of the previous memory to maintain. The data flow is as follows:

$$H_t = \tanh(W(X_t, r * h_{t-1}))$$

where H_t represents the candidate activation, X_t represents current input, r represents set of reset gates, z represents set of update gates, W is weight.

$$h_t = (1 - z) * h_{t-1} + z * H_t$$

There is an intermediate variable h_t , which is similar to the hidden state of the LSTM. h_t , on the other hand, only works at this time and cannot be passed on to the next. [11].

IV. RESULTS

Our proposed work aims to accurately predict a subject's emotional states while watching various movie scenes. We applied a 30/70 split for training and testing datasets, with the training group consisting of 70% of the data and 30% for the testing groups. We used the Adam optimizer to build the model and sparse categorical crossentropy, which is excellent

Classifier	Train test split	
	70-30	80-20
GRU	96.71%	95.78%
RNN	53.59%	49.53%

Fig. 9. Test Accuracy

for multi-class-function problem. After training the model and recording its results in history, In order to update the internal model parameters, we passed it through x train and y train with a validation split of 20%, a batch size of 32 samples, and 50 epochs, which is the number of times the complete training dataset would be processed by the model. Test accuracy shown in figure 9, On a 30/70 split, our model achieved 96.71% testing accuracy on GRU and 53.59% on RNN. On a 20/80 split, our model achieved 95.78% testing accuracy on GRU and 49.53% on RNN. Look at the classification report and confusion matrix as well. To summarise the confusion matrix, it shows how many times each class was predicted and how many of them were correct. As shown in figure 10, negative was predicted a total of 192 times and, out of that, it was correctly predicted 186 times and falsely predicted positive 6 times.

A. Model validation using confusion matrix

For the three classes of emotion detection EEG signals, the precision, recall, F-score, and accuracy are calculated using the subsequent calculated confusion matrix (Fig. 10 shows the confusion matrix of the gated recurrent unit, and Fig. 11 shows the confusion matrix of the recurrent neural network). Each class is compared to all other classes to determine the performance factors associated with it. The following equations are used to calculate the results: Figures 12 and 13 show the classification reports of the recurrent neural network and gated recurrent unit, respectively.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

$$F - score = 2 * TP / (2 * TP * FP * FN)$$

$$ErrorRate = 1 - Accuracy$$

The classification report displays the performance factors for each of the three emotions: positive, neutral, and negative. It shows how accurately and proportionately the actual positives and negatives of correctly detected emotions are expressed.

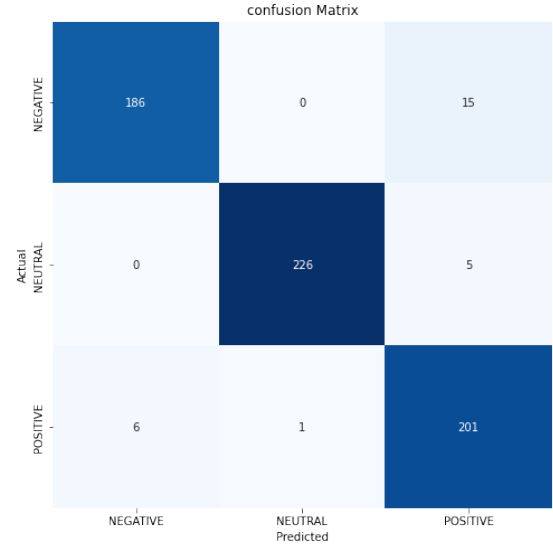


Fig. 10. Confusion matrix of GRU

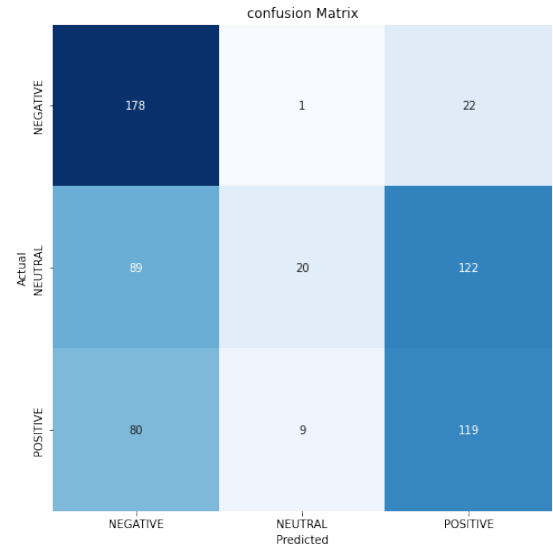


Fig. 11. Confusion matrix of RNN

B. Discussion

Fig. 6 shows the proposed system's structure for this study. In order to classify emotions, we employed deep learning models (RNN and GRU). Four dry extracranial electrodes were employed in the study, and they were attached to a MUSE EEG headband, which is a readily available product. For each of the six video segments, two individuals (1 male, 1 female, aged 20–22) collected 60 seconds of data, comprising 12 minutes of brain activity data [5]. A total of 36 minutes of EEG data was collected from the individuals, including six minutes of neutral brainwave data. Activities were solely stimuli that elicited emotional responses from the set of emotions, and they were

Classification Report:

	precision	recall	f1-score	support
NEGATIVE	0.97	0.93	0.95	201
NEUTRAL	1.00	0.98	0.99	231
POSITIVE	0.91	0.97	0.94	208
accuracy			0.96	640
macro avg	0.96	0.96	0.96	640
weighted avg	0.96	0.96	0.96	640

Fig. 12. Classification report on GRU

Classification Report:

	precision	recall	f1-score	support
NEGATIVE	0.77	0.90	0.83	201
NEUTRAL	0.55	0.08	0.14	231
POSITIVE	0.39	0.69	0.50	208
accuracy			0.54	640
macro avg	0.57	0.56	0.49	640
weighted avg	0.56	0.54	0.47	640

Fig. 13. Classification report on RNN

evaluated based on their valence labels of positive and negative rather than the emotions themselves. To avoid contamination, neutral data was collected prior to any emotional data for a third class, which could be the subject's resting emotional state. To reduce the interference of sleeping spirits, three minutes of data were recorded each day.

V. CONCLUSION & FUTURE SCOPE

In this study, we used RNN and GRU models to classify Electroencephalogram (EEG) brain signals and predict human emotions. In most cases, we do not consider emotion recognition when identifying a criminal. Emotion recognition has been extensively researched using various classification algorithms. Various emotion analysis algorithms exist, but they may or may not be accurate. In this aspect, our proposed model would be more accurate in predicting emotions like in criminal detection models, and many more such applications can be applied. A number of factors must be considered in the research methodology for EEG-based emotion recognition. The final procedure for EEG-based emotion recognition has been observed to begin with proper participant recruitment and stimulus selection, followed by data acquisition, data preprocessing, feature extraction, and emotion classification. Emotion detection systems can also be used to break the gap between robots and humans, because now robots can get more natural emotional feedback from whatever they do. More study on EEG and its relationship to human emotions will be done in the future. Future research, including EEG signals and an understanding of the various stages of how the brain works in different situations depending on the surroundings, can also be viewed as cognitive response.

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