EMOTION DETECTION USING EEG BASED BRAIN-COMPUTER INTERFACE

Abstract

Emotions are integral and one of the most important parts of human communication. To get the most out of any conversation, understanding of contextual meaning as well as the feelings and emotions are very necessary. Emotion detection and classification is a vital field in behavioural studies and designing of context-based systems. For a better Human-computer interface, there is a need for the development of computer algorithms and systems that can understand human emotions. Although there are many ways by which one can determine the emotional state of a person through the person's voice, the facial expressions, the composition of words in the person's text, etc. But all these ways can be easily manipulated and faked. But detection of emotions through EEG has attracted many behavioral study researchers and scientists as EEGs can't be faked. The aim of this study is to detect and differentiate emotions using a dataset obtained from Electroencephalography (EEG) based MUSE headband system. In this paper, we have collected EEG Brainwave dataset in which various time-domain, frequency-domain, time-frequency domain features FFT, Shannon entropy, log-covariance, etc features were already extracted and the dataset was ready to be fed in the model. Various types of classifier models can be used for training and testing by using this data which may give different results. In this paper, we used the Gated Recurrent Unit (GRU) as a classifier model which gives 97.656% accuracy for the given dataset. This technology could be very helpful in AI-based therapy systems or brain-computer interfaces where there is a need for emotion classification.

Keywords

Electroencephalography (EEG), Emotion detection, Brain-computer interface, Gated recurrent unit (GRU).

Introduction

Emotions are the integral and one of the most important parts of human communication. One understands the true meaning behind a sentence by understanding the emotional content behind a person's saying. This can be a verbal and non-verbal way of communication. We will not talk about verbal communications here, rather non-verbal kinds are of our interest. Non-verbal ways of communication like facial expressions, gesture, hand and body movements, composition of words in a sentence, etc can tell us the emotional state of the person. But, we can do it so easily, what about human-computer interfaces, can we program a computer to make them understand the emotional state of a human being. Obviously, the answer is yes. But it is not as simple as it seems. Emotion detection and classification is a vital field in behavioural studies and designing of context-based systems.

Researchers have been trying to detect and classify a person's emotional state by many techniques. Na Yang et. al [2016] proposed a speed-based emotion classification system using several one-against-all SVM and thresholding fusion mechanisms, which they further proved that to be effective in increasing emotion classification accuracy over already existing speech-based classifiers. Shahraki et. al [2017] tried mining the emotions on the basis of text that a person writes. They proposed several lexical and learning methods to classify emotions on the basis of texts from people's social media. Also recently much focus on emotion classification turned towards facial recognition. Yang et.al [2018] used the Haar cascade methods to detect various facial parts and neural network techniques to classify emotional state of a student taking virtual learning platforms to understand the interest and knowledge grasping ability of students. All these above mentioned techniques seem to be promising but can easily be manipulated and faked. Nowadays it is very difficult to understand one's emotional well-being as peoples have developed such astonishing abilities to fake their own emotions even if they know that it is bad for their wellbeing. So, a better and more reliable way of emotion classification is needed. Due to recent advancements in technology and ease of detecting physiological signals like EEG, this method of classifying emotions promises to be a better candidate for the required purpose.

Electroencephalography (EEG) is a noninvasive method of recording and monitoring electrical macroscopic activity of the surface layer of the brain with the electrode placed along the scalp. Different emotions lead to release of different hormones in the nervous system. Secretion of these hormones can affect the electrical activity of neurons present in the brain. By measuring the voltage changes that occur due to the change in the electrical activity of the brain through electrodes placed on the scalp or on the surface layer of the brain, we can predict different emotional states of an individual. Although, detection and classification of emotions on the basis of signals acquired from the surface of brain in the form of EEG is susceptible to many noises, like movement artifacts, powerline interference, EM noise but EEG signals can never be manipulated or faked by the person itself, making it a better method for detection and classification.

The signals (voltage changes) are complex, non-linear, non-stationary, and random in nature.The signals are considered stationary only within short intervals, that is why the best practice is to apply short-time windowing technique.

In this paper we have collected EEG Brainwave dataset from https://www.kaggle.com/birdy654/eeg-brainwave-dataset-feeling-emotions. The signal is acquired through 4 electrodes (TP9, AF7, AF8, TP10) in addition to reference point (NZ) present on the muse headband for 3 different emotional states of subject. This dataset was formed for the purpose of emotion classification using MUSE EEG headband into three classes namely positive, negative and neutral. Researchers have tried different feature extraction techniques along with many machine learning algorithms to classify various emotion states but those are not enough for a reliable commercialised system. These earlier works are discussed in the next section of this paper.

Related works

Bhardwaj et. al [2015] emphasised upon the importance of emotion detection for establishing a good human computer interface. They conducted the study on 32 healthy subjects of age between 20 to 25 years for sessions lasting 20 minutes. For signal acquisition they used BIOPAC, MP-150 recording device of 4 channels with sampling rate of 500 Hz. They used the IAPS database containing photos to invoke emotions and employed Independent component analysis (ICA) and Machine learning algorithms like SVM and LDA for classification and were able to get an average overall accuracy of 74.13 % and 66. 50 % respectively for seven classes of emotions. The drawback of this study is that they used pictures which can invoke different emotions in different peoples, and the accuracy was also not that good.

Jingxin et. al [2016] took the DEAP dataset and extracted various time domain features, frequency domain features, time-frequency domain features and used Maximum Relevance Minimum Redundancy (mRMR) feature selection method to make a set of features which can be fed into a machine learning model. Further they used K-Nearest Neighbour (KNN) and Random Forest as their classification method. The results were not upto the mark and were able to attain accuracies in the range of 60 to 70 %. Showing that a proper choice of features along with a suitable classifier is very necessary to achieve a good amount of accuracy.

Salma et. al [2017] introduced her technique of using Long-short Term Memory (LSTM) for learning of features and verified her model on DEAP dataset for classification of emotions in arousal, valence and liking classes and attained an average accuracy of 85.65%, 85.45% and 87.99% respectively.

Jason et. al [2018] studied emotion recognition based on virtual reality stimulus. Invoking of emotions based on music, image and videos have already been studied earlier. In their paper, they proved that a 4-channel, 256 Hz EEG system is enough for classifying emotions by using SVMs and K-nearest Neighbor (KNN) classifiers with two hidden layers and 200 hidden units per layer by achieving a high accuracy of above 95 %. This result came after so many trials and errors and were able to achieve this level of accuracy for just classification of emotions into two classes namely Rest and Excited making this method unreliable for more emotional states. The dataset was collected for two persons and was not big enough.

Hanieh et. al [2018] used the benchmark multimodal dataset known as DEAP dataset, and developed a smart method consisting of discrete signal processing techniques and genetic evolutionary algorithm for optimisation of SVM for classification of emotions into four different states namely happy, sad, excited and hate. They achieved a good accuracy of about 93.86% accuracy but their results shows that the input length of signal should be 7.5 secs and for 3 channels of EEG only, which is very small as emotions take time to arouse in a person after external perturbation.

Jordan et. al [2018] focused on selecting a subset of highly discriminative features and comparing state-of-the-art classification methods that can categorise EEG signals into different mental states. The sensor Muse Headband was used for data collection. Three stimuli were devised to cover the three mental states available from the Muse Headband - relaxed, neutral, and concentrating. The relaxed task had the subjects listening to low-tempo music and sound effects designed to aid in meditation whilst being instructed on relaxing their muscles and resting. For a neutral mental, a similar test was carried out, but with no stimulus at all, this test was carried out prior to any others to prevent lasting effects of a relaxed or concentrative mental state. Finally, for concentration, the subjects were instructed to follow the “shell game” in which a ball was hidden under one of three cups, which were then switched, the task was to try and follow which cup hid the ball. The EEG data from the Muse Headband was automatically recorded for sixty seconds. The data was observed to be streaming at a variable frequency within the range of 150 - 270 Hz. At each point in the data stream (150 - 270 Hz), all signals were recorded along with a UNIX timestamp which was further used for down sampling the data to produce a uniform stream frequency. Before the features extraction they have down sampled the data. The five generated sets from the original dataset are shown in Table. Five different algorithms were chosen for feature extraction (listed in rows) and 7 different types of classifier models for the acquired data (columns) were used and then their accuracy is checked. The most effective model was a Random Forest classifier along with the dataset created by the OneR Attribute Selector, which had a high accuracy of 87.16% when classifying the data into one of the three mental states.

Aasim et. al [2019] generated enhanced and a more realistic feel of the multimedia content by using hot and cold air effect, and collected EEG data using 4 channel MUSE headband. They did this experiment on a total of 21 participants and tried classifying emotions into categories namely happy, relaxed, sad and angry. They extracted frequency domain features from five different bands of EEG and classified it using support vector machine algorithms (SVM) and achieved an accuracy of about 76.19 % in comparison to time domain features which earlier produced 63.41 % accuracy. Suggesting that frequency domain features are more reliable for classification. But the results are not that upto the mark.

Chen et. al [2019] used a hierarchical Bidirectional GRU model with attention for classification of human emotions using EEG data. They used the DEAP dataset and proved that their model was indeed better than than the best deep baseline LSTM model by outperforming its accuracy. They showed that in valence and arousal dimensions, their model on 1-s segmented EEG signals outperforms the best Shallow baseline model by 11.7% and 12% respectively and outperforms best deep baseline LSTM model by 4.2 % and 4.6% respectively.

Wai-Cheong et. al [2020] considered the spatial-temporal relationships among brain-regions and across time. They proposed a Regionally-operated Domain Adversarial Network (RODAN) to learn these spatial-temporal relationships and used their model on DEAP and SEED-IV datasets to evaluate the performance of RODAN for subject-dependent, subject-independent and subject-biased experiments. Their model achieved accuracies in the range of 50% to 70% accuracies for valence and arousal class in DEAP dataset in all the three categories and 70% to 95% accuracies in SEED-IV dataset in all the three categories.

Although RODAN performed well in some cases but outperformed A-LSTM and MM-ResLSTM in many cases showing inconsistencies in their classification.

Yuling et. al [2020] proposed a novel method of using the Spiking neural networks (SNNs) for the classification of emotions. They included other algorithms like discrete wavelet transform (DWT), variance and fast fourier transform (FFT) to extract information from EEG signals. They checked the performance of their model on DEAP and SEED datasets both. For DEEP dataset, the main emotional classes were arousal, liking, dominance and valence and it achieved accuracies of 74%, 78% , 80% and 86.27% respectively and for SEED dataset categorized into three classes namely negative, positive and neutral, it achieved an overall accuracy of 96.67%. Their study supports their hypothesis of the advantage of using SNN for emotional analysis which are definitely more effective tools than standard machine learning techniques like naive Bayes, Gaussian Bayes, RVM, etc.

All these studies show that many feature extraction techniques have already been employed and many machine learning algorithms have been used alongside for the classification of emotional states in various different categories. But further research is required for better classification of emotions, which can only be achieved by proper feature selection and suitable classifier. In this study we propose a GRU based machine learning model for classification of emotions into three categories positive, negative and neutral on a dataset recorded using 4 channel MUSE headband in which emotions were invoked by asking subjects to see clips from movies.

Methodology

I. Dataset

The data was collected by Jordan et. al [2018] from two people (1 male, 1 female) for 3 minutes per state of emotion - positive, neutral, negative. They used a Muse EEG headband which measures brain activity via 4 encephalography sensors i.e. TP9, AF7, AF8 and TP10. Six minutes of resting neutral data is also recorded. Different movie clips were shown to the subjects which invoke the positive, neutral and negative emotions in them based on which the dataset is prepared. The video clips which invoked neutral state of subject were shown thus the subject was first recorded for neutral emotion state. This was done to avoid the interference of other emotional states as they last longer even after the recording is completed. So, to summarise, the data was collected for 3 minutes per state for 2 subjects each, and 6 minutes of resting neutral data for each subject. Thus we have a total of 30 minutes data in the dataset. The raw data was further processed in order to detect viable features depending upon statistical techniques, time-frequency based on FFT, max-min features, shannon entropy, log-covariance, power spectral density etc. In the end, the total number of features extracted from the data came out to be 2147. After which feature selection algorithms such as OneR, Information gain, Correlation, Evolutionary Algorithm and Symmetrical Uncertainty were further used in order to remove unwanted features and to form a dataset of 2132 data points with fairly balanced classes of 708 for positive and negative classes and 716 for neutral class.

II. Classification algorithm

A recurrent neural network (RNN) is a type of artificial neural network, where the connections between the nodes form a directed graph along a temporal sequence. This helps us in using ANN for datas which exhibits dynamic temporal behaviours. RNNs have “memory” which remembers the information which are calculated till now. The problems which earlier aroused in solving problems by using RNNs were its gradient vanishing and exploding problems. This was recently solved by introduction of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and other techniques. Introduced in 2014, GRU aims to solve the gradient vanishing problem which generally comes in standard recurrent neural networks. GRU is considered as a variation of LSTM as it is similar to it but just has less parameters and lacks output gate. To solve the vanishing gradient problem of a standard RNN, GRU uses, so-called, update gate and reset gate. Basically, these are two vectors which decide what information should be passed to the output. The special thing about them is that they can be trained to keep information from long ago, without washing it through time or removing information which is irrelevant to the prediction. For studying A GRU we will use these notations, x_t is current unit input, h_{t-1} is previous unit output, h_t is current unit output, W is weights corresponding to current input, U is weights corresponding to previous unit's output.

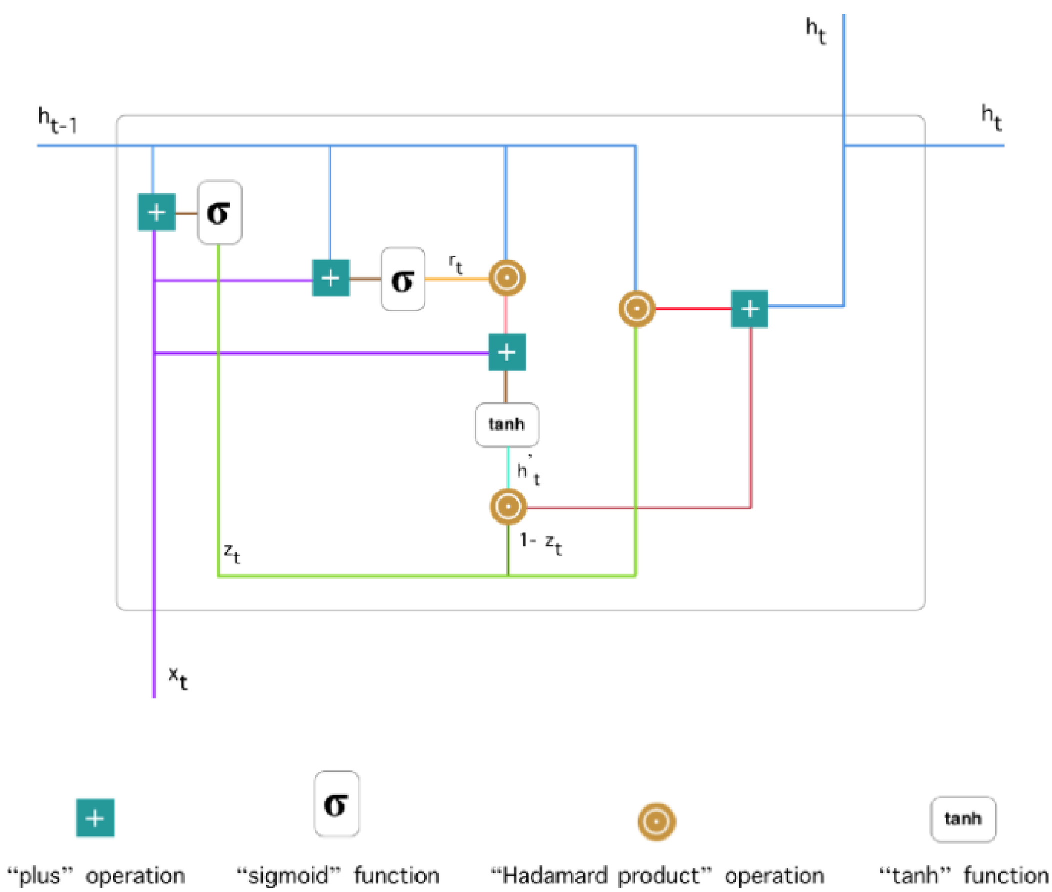

Fig 1. Gated recurrent unit

1. Update gate : The update gate actually determines the amount by which the past information is to be sent down to the future. And is calculated by ;

$$z_t = \boldsymbol{\sigma}(W^{(z)}x_t + U^{(z)}h_{t-1})$$

This actually provides GRU it's ability to tackle the vanishing gradient problem by allowing it to decide to take past information into consideration.

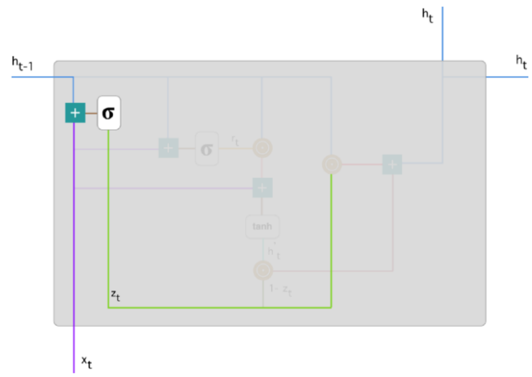

Fig 2. Update gate

2. Reset gate : The update gate is responsible for carrying past information but by how much it doesn't tell, so reset gate is there for this task for deciding how much to forget the past information.

$$r_t = \boldsymbol{\sigma}(W^{(r)}x_t + U^{(r)}h_{t-1})$$

The formula is the same but the difference is in it's weights and gate's usage.

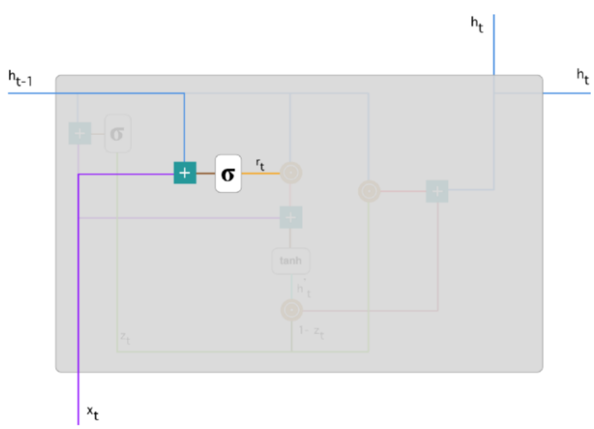

Fig 3. Reset gate

3. Current memory : Now, first of all, a new memory content uses the reset gate to store the relevant information from the past.

$$h_t' = \tanh(Wx_t + r_t \odot Uh_{t-1})$$

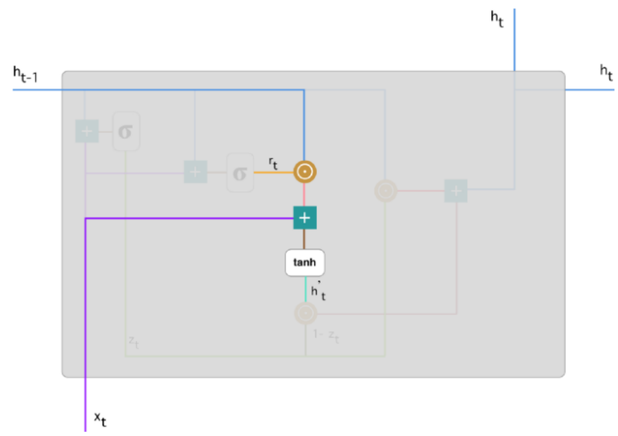

Fig 4. Current memory

4. Final memory at the current time step : Now, we need to calculate the vector which will store the information for the current time step which will pass it down to the network. For that update gate is needed.

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h_t'$$

All these steps help GRUs to store and filter the relevant information using their update and reset gates.

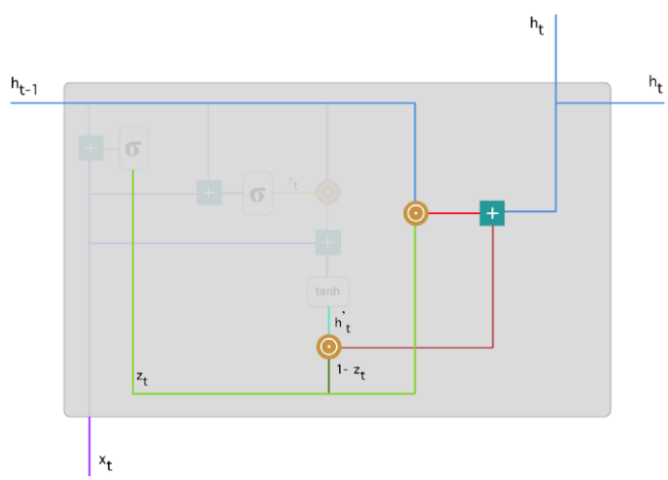

Fig 5. Final single memory unit output

Performance Evaluation

For evaluation of the algorithm various standard measures were calculated like,

I. Classification accuracy : It is the ratio of number of correct predictions to total number of inputs.

Accuracy = Number of correct predictions / Total number of predictions made

II. Confusion Matrix : It is the matrix which is often used to evaluate an algorithms performance. The four important terms in a confusion matrix are-

- True Positives (T.P) : The cases in which we predicted YES and the actual output was also YES.
- True Negatives (T.N) : The cases in which we predicted NO and the actual output was NO.
- False Positives (F.N) : The cases in which we predicted YES and the actual output was NO.
- False Negatives (F.N) : The cases in which we predicted NO and the actual output was YES.

Terms like sensitivity, specificity can be calculated using confusion matrix as follows-

- Sensitivity (True positive rate) = T.P / (T.P + F.N)
- Specificity (True negative rate) = T.N / (T.N + F.P)

III. F1 Score : F1 score is the harmonic mean of precision and recall. The value of F1 score ranges in [0, 1]. It is a better estimate than accuracy as it tells us how precise our classifier is as well as how robust it is.

- Precision = T.P / (T.P + F.P)
- Recall = T.P / (T.P + F.N)

Results and discussion

We have taken the dataset and created a GRU model having 512 units. With an output layer with 3 outputs for each class (emotions) and activation function as softmax. The dataset is divided into two parts, 70 percent of the data is used for training and 30 percent of it for testing which is fed into the model and is trained for 50 epochs in the cloud using Google's cloud platform google colab.
The classification report can be seen in Table I. It shows an accuracy of **97.656**%.

Table I. Classification report of our trained model

	Precision	Recall	F1 Score	Support
NEGATIVE	0.97	0.98	0.98	201
NEUTRAL	1.00	0.98	0.99	231
POSITIVE	0.96	0.97	0.96	208
Accuracy			0.98	640
Macro avg.	0.98	0.98	0.98	640
Weighted Avg.	0.98	0.98	0.98	640

Earlier on the same dataset Jordan et. al [2018] himself used various feature selection techniques and machine learning algorithms to classify the dataset into three classes namely relaxed, neutral and concentrated and came up with the results as shown in table II.

Table II. Accuracies for different models on selected features dataset.

Dataset	Naive Bayes	Bayes Net	J48	Random Tree	Random Forest	MLP	SVM
OneR	56.21	73.67	80	76.21	**87.16**	74.27	61.18
Information gain	54.2	71.64	76.85	65.02	78.02	72.22	64.1
Correlation	56.3	72.69	77.05	75.85	84.17	80.82	75.24
Symmetrical uncertainty	51.49	71.41	76.29	74.35	82.96	72.25	60.1

Evolutionary Algorithm	55.04	70.31	80.65	72.62	85.29	80.85	67.65

It can be seen that the dataset created with OneR attribute selector along with Random Forest classifier gave the highest accuracy of 87.16% which is almost 9% less than that of which we achieved in our study.

Similar work was done by Jordan et. al [2018] in which again for the same set of feature selection techniques they used different single model and Ensemble model for the classification of emotions into three categories positive, negative and neutral, whose accuracies can be seen in table III.

Table III. Classification of single and ensemble models

Dataset	Single mode Accuracy							Ensemble model accuracy		
	OneR	RT	SMO	NB	BN	LR	MLP	RF	Vote	AB(RF)
OneR	85.18	91.18	89.49	66.56	91.18	91.84	92.07	95.26	92.68	95.59
BayesNet	85.27	93.05	89.49	60.69	91.23	91.93	93.81	97.14	93.39	97.23
InfoGain	85.27	94.18	89.82	60.98	91.46	92.35	94.89	**97.89**	94.04	97.84
Symmetrical Uncertainty	85.27	94.15	89.54	69.66	92.03	91.93	94.18	97.56	94.32	97.65

From Table III we can see that for the dataset formed by using InfoGain along with ensemble model Random Forest gives the highest accuracy of 97.89%. Although this is slightly higher than our study, using GRU with just 256 units produces an accuracy of 96.406% and with 512 units it gives an accuracy of 97.656%. Which shows the ability of GRUs to handle datas showing temporal behaviors that we can exploit in order to attain better classification results.

Autonomous non-invasive detection of emotional states is potentially useful in multiple domains such as human robot interaction, mental healthcare, education, and neuroscience. It can provide an extra dimension of interaction between user and device, as well as enabling tangible information to be derived that does not depend on verbal communication. With reducing number of available therapists for patients, chatbots can support this purpose of therapy by interacting with the patient itself, but the ethical and legal dilemmas which we may come across in commercialising these products are needed to be solved first, as excessive dependency of peoples on these kinds of technologies can be damaging. There exists some applications which are already trying to detect emotional states on the basis of composition of text, but no clinical trials have been done yet and the prediction of emotional states on the basis of compositions of text doesn't give accurate results. This tech may help in providing a better emotion classifying system for the above given purpose.

Conclusion

This paper focused on studying mental state classification based on EEG signals. An already existing ready to feed dataset was used to train a GRU model for the classification of mental states into basically three classes : *positive, negative, neutral*. The model attains an overall accuracy of 97.656% which more than almost all state-of-the art techniques and shows the ability of GRUs to process dataset having temporal behaviour. The use of muse headband and its corresponding use commercially along with these artificial intelligence algorithms can be revolutionizing. Further research is always needed in order to provide the best of the facilities in order to produce a better system for human computer interfaces.

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Appendix

Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import tensorflow as tf
from sklearn.metrics import confusion_matrix, classification_report

data = pd.read_csv('/content/EEG dataset/emotions.csv')
data
pd.set_option('max_columns', None)
data
sample = data.loc[0, 'fft_0_b':'fft_749_b']

plt.figure(figsize=(16, 10))
plt.plot(range(len(sample)), sample)
plt.title("Features fft_0_b through fft_749_b")
plt.show()

data['label'].value_counts()
label_mapping = {'NEGATIVE': 0, 'NEUTRAL': 1, 'POSITIVE': 2}

def preprocess_inputs(df):
    df = df.copy()
    df['label'] = df['label'].replace(label_mapping)
     y = df['label'].copy()

    X = df.drop('label', axis=1).copy()
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=123)
    return X_train, X_test, y_train, y_test
X_train, X_test, y_train, y_test = preprocess_inputs(data)
X_train

inputs = tf.keras.Input(shape=(X_train.shape[1],))
expand_dims = tf.expand_dims(inputs, axis=2)
gru = tf.keras.layers.GRU(256, return_sequences=True)(expand_dims)
flatten = tf.keras.layers.Flatten()(gru)
outputs = tf.keras.layers.Dense(3, activation='softmax')(flatten)
```

```
model = tf.keras.Model(inputs=inputs, outputs=outputs)
print(model.summary())

model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

history = model.fit(
    X_train,
    y_train,
    validation_split=0.2,
    batch_size=32,
    epochs=50,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        )
    ]
)
model_acc = model.evaluate(X_test, y_test, verbose=0)[1]
print("Test Accuracy: {:.3f}%".format(model_acc * 100))

y_pred = np.array(list(map(lambda x: np.argmax(x), model.predict(X_test))))

cm = confusion_matrix(y_test, y_pred)
clr = classification_report(y_test, y_pred, target_names=label_mapping.keys())

plt.figure(figsize=(8, 8))
sns.heatmap(cm, annot=True, vmin=0, fmt='g', cbar=False, cmap='Blues')
plt.xticks(np.arange(3) + 0.5, label_mapping.keys())
plt.yticks(np.arange(3) + 0.5, label_mapping.keys())
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

```
print("Classification Report:\n----------------------\n", clr)
```