EEG Based Stress Classification in Response to Stress Stimulus

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Abstract. Stress, either physical or mental, is experienced by almost every person at some point in his lifetime. Stress is one of the leading causes of various diseases and burdens society globally. Stress badly affects an individual's well-being. Thus, stress-related study is an emerging field, and in the past decade, a lot of attention has been given to the detection and classification of stress. The estimation of stress in the individual helps in stress management before it invades the human mind and body. In this paper, we proposed a system for the detection and classification of stress. We compared the various machine learning algorithms for stress classification using EEG signal recordings. Interaxon Muse device having four dry electrodes has been used for data collection. We have collected the EEG data from 20 subjects. The stress was induced in these volunteers by showing stressful videos to them, and the EEG signal was then acquired. The frequency-domain features such as absolute band powers were extracted from EEG signals. The data were then classified into stress and non-stressed using different machine learning methods - Random Forest, Support Vector Machine, Logistic Regression, Naive Bayes, K-Nearest Neighbors, and Gradient Boosting. We performed 10-fold cross-validation, and the average classification accuracy of 95.65% was obtained using the gradient boosting method.

Keywords: Stress classification · Machine learning · MUSE headband · EEG signal

1 Introduction

Stress is one of the most common problems in the western world and is increasing in the middle-class population in India due to the adoption of the western lifestyle. In today's world, work and occupation-related stress are increasing day by day. Moreover, the job that demands to multitask is another major cause of stress [1]. According to the American Institute of Stress, around 73–77% population experience stress that affects

A. Dev et al. (Eds.): AIST 2021, CCIS 1546, pp. 354–362, 2022.
https://doi.org/10.1007/978-3-030-95711-7_30

not only the physical health but also the mental wellbeing. Further, around 48% of people are suffering from sleep disorder due to stress [2]. Recent survey on LinkedIn's showed that 40% of working Indian professionals experience increased stress or anxiety. The survey also showed that 36% of them feel that stress is adversely impacting their work-life balance [3].

According to WHO, by the year 2030, mental illnesses result in various diseases globally. Globally, approximately 15.5% population are affected by mental illnesses and these statistics are rising exponentially. Stress is also a type of mental illness that can badly affect an individual's health. Traditionally, stress was analyzed only by medical personnel without the use of any technology. Medical staff trained in mental health used to perform psychotherapies which involved face to face interaction with the people facing mental health concerns. Advances in computing technology have created opportunities for close collaboration between computer engineers and medical practitioners studying mental health. With the plethora of sensing devices now being available, emerging technologies like Big Data Analytics (BDA), Human–Computer Interaction (HCI), Machine Learning (ML), Artificial Intelligence (AI) and Internet of Things (IOT) have started to emerge as technologies with capabilities to develop applications that help people with their stress-related mental health problems [4–6]. These technologies have become an umbrella to offer new opportunities for screening and predicting stress-related mental health problems. Coupled with the power of data science, these can transform the way technology can be used to identify and treat people who have stress-related mental illnesses. A persistence of long term or short-term stress effect the individual neurology and thus results in depression [7–10]. Moreover, stress-related disorders such as cardiovascular disease, anxiety and depression are also rising in today's busy world [11]. Thus, to prevent the onset of depression it is important that stress symptoms can be detected timely.

In order to detect stress and initiate stress management treatment it is vital to have reliable tools to measure physiological stress in response to stimulus [12]. Stress can be quantified using different features and biomarkers extracted from electroencephalography (EEG) and electrocardiography (ECG) signals [13]. EEG is one of the most common, widely, and non-invasive modality to record signal in order to study brain function [14–18]. Each frequency band of EEG signals (delta, theta, alpha, beta, and gamma) can be used to extract the distinguishing feature to classify different brain states [17, 19–21].

2 Related Work

For stress management, it is vital to detect the stress level timely, which reduces the risk of adverse health consequences. The accuracy of the designed methods relies on various factors such as sensors that can measure physiological signals, quality of signal and the machine learning model. Different authors made multiple attempts to classify stress. Different datasets, stress induction methods, EEG headbands with varying channels, machine learning models etc. were used to classify stress into various categories.

In one of the studies, the authors related stress with the circumplex model of affect. This model characterizes several emotions in the domain of arousal and valence [22]. The authors used the DEAP dataset, containing 32-channel EEG data, for the detection of stress. They extracted time-based, spectral features from complex non-linear EEG signals. They found that stressed state is associated with reduced asymmetry as compared to non-stressed state. Using coherence analysis, they also found that during the stressed state the activity in the right side of the brain is more than the left.

In another study, the authors induced stress into the subject using Stroop and memory test [1]. They used 14 channel EEG device to acquire the data. Band power features were extracted from the EEG signals. These features were used to classify stress type from relaxed condition using Support Vector Machines (SVM). The authors obtained an accuracy of 77.53% in this three-level classification of stress. The subjects provided the ground truth in 3-item questionnaire presented after each task.

In another paper [17], the authors performed 2 and 3 class stress classification using EEG signals. They used a MUSE headband containing four electrodes for the acquisition of the EEG signal. Frequency domain features were extracted from the Fast Fourier Transformed (FFT) EEG signal. The stress was induced using audio tracks and State Trait Anxiety Inventory (STAI) was used to assess subject's self-reported stress. They performed classification using various machine learning methods and achieved the best classification accuracy of 98.7% and 95.6%, for 2 and 3 classes respectively, was achieved using Logistic Regression.

In another study, the authors used Stroop color-word Test (SCWT) to induce the stress and used a combination of power-based features, fractal dimension (FD) and statistical features for the inter-subject classification [23]. The features were extracted from 14 electrode EEG headbands. The stress level was classified using k nearest neighbors (k-NN) and support vector machine. Finally, the fivefold cross-validation was performed to validate the model. It was found that SVM outperformed k-NN when a combination of statistical and FD features was used. Three levels stress classification achieved an average accuracy of 75.22% whereas, two levels stress classification resulted in an accuracy of 85.17% using SVM.

The system proposed by authors for stress classification extracted various features such as correlation, rational asymmetry, power spectral density, differential asymmetry, and power spectrum from different EEG frequency bands [24]. They compared the SVM (with polynomial kernel function), MLP (4 hidden layers) and Naïve Bayes for stress classification. Their system achieved the best accuracy of 92.8% (2 class) and 64.28% (3 class) using MLP.

In another paper, system was proposed to classify different mental states - relaxing, neutral and concentrating [25]. They tested a various features selection algorithms and classifier. They compared the performance of the proposed system in terms of accuracy and number of features used. They perform 10-fold cross validation to validate the accuracy of the designed model. They summarized optimal 44 features, from a set of 2100 features, required for the stress classification. Their designed system resulted in overall accuracy of 87% with Random Forest Classifier.

In [26], the frequency domain features were extracted from EEG recordings. They found support vector machine as the best classifier, among all the tested classifiers, to classify human stress when used with alpha asymmetry as one of the features. They found that alpha asymmetry can be regarded as one of the potential biomarkers for stress classification, when labels are assigned using expert evaluation.

The authors in [27] utilized frequency-based features to classify four types of negative emotions using 4 channel EEG signals. They used movie clips as emotion elicitation material. They tried multiple machine learning algorithms and found that Long Short-Term Memory (LSTM) can achieve the best accuracy of 92.84% by using 10-fold cross validation.

Various authors proposed different systems to classify stress. However, we found no studies to see the impact of COVID news and videos on human stress levels. We examine the effect of videos related to COVID on the human mental state using EEG signals on healthy participants. Four groups of features (five PSD features for each of the four electrode positions) are extracted from EEG signals acquired using MUSE headband. These features were then used to classify data into stress and non-stress using six different classifiers - Logistic Regression, Random Forest, Naive Bayes, Support Vector Machine, K-Nearest Neighbors and Gradient Boosting methods. The major contributions of the paper are:

1. A 4-channel EEG dataset containing the brain activity of 20 subjects while watching stressful covid video.
2. To perform stress classification from various classifiers using four groups of frequency domain features.

The paper is structured as follows: Sect. 3 explains the detailed methodology. Experimental results obtained for stress classification are presented in Sect. 4. The limitations of the current work and the possible ways to address these in the future are written in Sect. 5.

3 Methodology

Various steps involved in the proposed system for stress classification using EEG signals consists of inducing stress, EEG data acquisition, pre-processing, feature extraction, and classification. The subsequent section describes each step for stress classification using EEG signals.

3.1 EEG Data Acquisition

Device Description: The EEG signal of subjects was acquired using a four channel MUSE EEG headband in response to stimulus. The MUSE headband is an off-the shelf non-clinical device for capturing the brain signals (see Fig. 1a). This device contains 4 sensors: TP9, AF7, AF8 and TP10. These sensors are in turn dry electrodes that have been placed according to the 10–20 system of electrode placement (Fig. 1b). The device produces raw as well as pre-processed FFT signals. These signals can be transferred over Bluetooth from the device to an android application called MUSE monitor. This application can store the signals in csv format and transfer to the laptop for further processing.

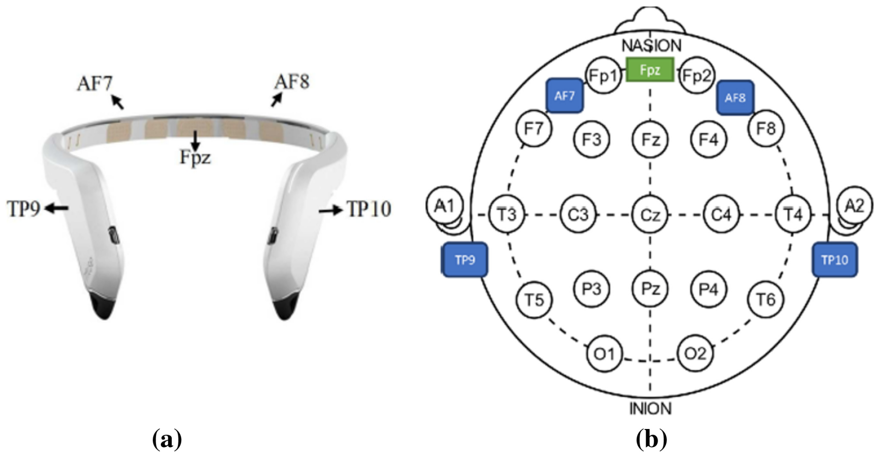

Fig. 1. (a) MUSE headband to record EEG signal (b) Electrode positioning on head scalp

Stimuli: To induce the emotion of stress, we chose two kind of video content: a) Stressful video content and b) Relaxing video content. The stressful videos were those containing covid related news showing the number of increasing covid cases and deaths and the severity of the disease. The relaxing videos had comedy scenes that would relax the subject. Each video was of a duration of 3 min. A gap of 2 min was given between each video clip to avoid the interference of stressed feeling on non-stressed feeling and vice versa. This stimulus is chosen to target two classes of stress: stressed and non-stressed.

Subjects: A total of 20 healthy subjects, in the age group of 18–30 years, (both males and females) voluntarily participated in this study. The data from 2 subjects were dropped because two sensors got disconnected in the middle of the experiment. Therefore, we performed analysis on the EEG data of 18 subjects. The procedure and protocol were explained thoroughly, and consent form was taken from each of the participants. The experiment was conducted according to the principle of Helsinki. After watching each clip, a self-assessment form was filled by the subjects to rate their experience about the video shown on a five-point scale (0-Non stressful at all, 5-lot stressful). A rating of greater than 3 was regarded as stressful. The labels provided by them was considered as ground truth. Since stress also depends on the perception of an individual, these self-reported labels were compared with the labels that we had set for the videos. If the labels did not match, we dropped the data of the subject from our analysis. But the self-reported labels of all the subjects matched with the pre-rated labels. This served as validation for ground truth.

3.2 Data Pre-Processing and Feature Extraction

Recorded EEG data often contains noise and artefacts. Thus, signal pre-processing plays an important role to remove noise to improve signal to noise (SNR) ratio. The MUSE headband gives the pre-processed Fast Fourier Transform signals. The built-in pre-processing system of MUSE headband was used to remove the noise from the

EEG signals. It applies a notch frequency of 50 Hz. Butterworth's fourth order filter with different cut-off frequencies are used inside MUSE to remove undesirable frequency signals to extract the five frequency bands of interest \cite{teo2018eeg}. The pre-processed data in the frequency domain are categorized in the following frequency ranges: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–32 Hz) and gamma (32–100 Hz). Each of these signals corresponds to the four electrode positions. Thus, the pre-processed dataset contains 20 features (five features from each of the four sensor positions). Figure 2 shows the raw data visualized using Mind Monitor android application. Each of the features derived through FFT are discrete frequency values on a log scale.

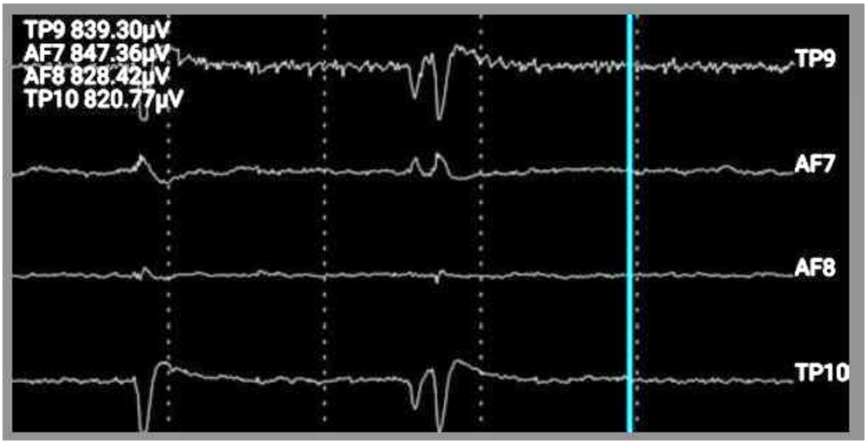

Fig. 2. Raw EEG values show each sensor raw data in microvolts (μv), the range of which is 0-~ 1682

3.3 Classifiers

To classify the EEG recording into stress and non-stress categories, different classification algorithms were used and compared. We used Random Forest, Support Vector Machine, Logistic Regression, Naive Bayes, K-Nearest Neighbors and Gradient Boosting methods for stress classification. The performance of the classification algorithms was assessed using a 10-fold cross validation method. During the validation process using 10-fold cross validation method, first the data was divided into 10 equal parts and out of which one part was used to test the data and remaining data was used to train the model.

This process was repeated, and each iteration yield different performance parameters. Thus, minimum, maximum, and standard deviation was evaluated and presented in Table 1.

Table 1. Table summarizing the results obtained for stress classification using different classifiers

Algorithm		Accuracy	Precision	AUC
Logistic regression	Min	77.43	85.76	83.4
	Max	83.4	96.82	91.56
	Avg.	82.26	87.33	85.75
SVM	Min	78.88	87.2	91.5
	Max	88.52	95.17	95.6
	Avg.	85.46	92.26	93.89
Random Forest	Min	92.85	93.78	92.67
	Max	96.86	97.67	97.29
	Avg.	94.68	95.55	96.77
Naive Bayes	Min	76.23	86.26	89.26
	Max	82.45	91.89	92.57
	Avg.	81.99	84.78	87.64
K-NN	Min	82.22	86.59	87.20
	Max	88.43	89.21	90.5
	Avg.	85.91	88.51	89.28
Gradient Boosting	Min	94.43	94.6	93.65
	Max	97.78	98.29	98.89
	Avg.	95.65	96.54	96.72

4 Result

In this work, the task of stress classification while watching COVID news has been accomplished. Table 1 shows the results obtained from stress classification using various algorithms. The performance metrics - Accuracy, Precision and Area under the ROC curve (AUC) have been used to compare the results. This table also shows the statistical measure such as: minimum (Min.), maximum (Max.) and average (Avg.) of performance metrics. For example, the metrics - Min. and Max - denote the minimum and maximum accuracy obtained at a particular fold in 10-fold cross-validation; Avg. denotes the average accuracy obtained from all folds. Results show that the Gradient Boosting algorithm outperformed all other algorithms with an average accuracy of 95.65% as shown in Table 1. Moreover, the precision obtained with Gradient boosting is high, and it shows the robustness of the proposed system. High precision shows the percentage of correctly classified instances among the ones classified as stress groups. Stress classification system proposed by different authors used 32 channel EEG acquisition device [22, 28] and uses different features or feature selection methods [17, 23]. We have proposed a simple system that uses direct features provided by a 4-channel EEG system for stress classification.

5 Conclusion

In this work, we have presented EEG signals-based stress classification using various machine learning models. In our study, the Gradient Boosting classifier obtains the highest accuracy. Furthermore, various studies used the 4 channels Interaxon Muse for stress classification [17, 18, 24–26] which is the same as used in this study. We achieved either comparable or better accuracy compared to their studies. Moreover, our system outperforms as compared to the approach proposed in [1, 23] for stress detection. But at the same time, it is essential to note that direct comparison is not possible because of the difference in the type of stimulus used, the number of participants, the feature selection techniques and classifiers used in all the studies.

Various studies induce stress in the participants using multitasking activities (such as Stroop and a memory test) [1, 29]. In contrast, we used COVID videos to induce stress in the participants during the 2nd wave of the pandemic. Furthermore, to reduce the bias of having an already stressed subject in our study, we selected the participants who did not have any causality in their family or immediate family. From the result obtained, we can conclude that the impact of our stress stimulus (covid news and videos) was so much that we could differentiate between stressed and non-stressed states with high accuracy.

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