Two-Level Classification of Chronic Stress in EEG Recordings Two-Level Classification of Chronic Stress Using Machine Learning on Resting-State EEG Recordings

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Completed Research

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Abstract

While there are several works that diagnose acute stress using electroencephalographic recordings and machine learning, there are hardly any works that deal with chronic stress. Currently, chronic stress is mainly determined using questionnaires, which are, however, subjective in nature. While chronic stress has negative influences on health, it also greatly influences decision-making processes in humans. In this paper we propose a novel machine learning approach based on the fine-graded spectral analysis of resting-state EEG recordings, to diagnose chronic stress. By using this new machine learning approach, we achieve a very good balanced accuracy of 81.33%, outperforming the current benchmark by 10%. Our algorithm allows an objective assessment of chronic stress, is accurate, robust, fast and cost-efficient and substantially contributes to decision-making research, as well as Information Systems research in healthcare.

Keywords

Electroencephalography, Chronic Stress, Machine Learning, Decision Making

Introduction

Chronic stress is highly prevalent in today's society with 25%/28% of Americans reporting stress having a strong influence on their physical/mental health (American Psychological Association 2015). Through stress the productivity of an individual person can be drastically decreased and in some extreme cases stress can also endanger life and health (Iampetch et al. 2012). A study on the effects of stressful workplaces showed that as stress levels rise, job satisfaction falls, which indicates that job satisfaction is negatively affected by stress (McGowan 2001; Ragu-Nathan et al. 2008). Chronic stress has many negative effects and is associated with various diseases like cardiovascular disease, diabetes, cancer and asthma (Cohen et al. 2007; Boll et al. 2004). Besides, chronic stress can also negatively influence the decision-making of individuals (Ceccato et al. 2018; Radenbach et al. 2015; Tryon et al. 2013). Stress also leads to burnout (Wright and Bonett 1997), which is a syndrome that is a huge financial burden on society, with an estimated annual cost of $4.6 billion only for the effects of physician burnout (Han et al. 2019). For this reason, a lot of research has been conducted on the physical and psychological aspects of health, as well as cognitive performance (Lupien et al. 2007; Schneiderman et al. 2005). In psychology it is assumed that stress results from an imbalance between the demands which one encounters and the self-perceived ability to cope with these demands (Lazarus and Folkman 1984). It is possible to divide stress into chronic and acute stress. While acute stress sees the body prepare to defend itself, which lasts till the situation is over, chronic stressors are long-lasting and the sufferer does not know whether or when they end, or feels like they may never end (Schetter and Dolbier 2011). Although many psychological questionnaires for subjective stress scenarios exist, in some scenarios objective measures such as biomarkers could be more helpful, especially since results of questionnaires can be biased through multiple factors like misunderstanding of the questions or social desirability effects (Podsakoff et al. 2003; McDonald 2008). Electroencephalogram

(EEG) signals directly reflect the brain's electrical activity, and because of that it could be used as an objective measure for the diagnosis of stress (Dias-Ferreira et al. 2009; Friedman et al. 2017). EEG is the second most dominant tool in NeuroIS research, widely used in medicine (Riedl et al. 2020). Enormous amounts of aperiodic, time series data from multi-channel EEG are examined by experts for disorders and effects in the brain (Siuly and Li 2015). Due to the combination of increasing computational power and the higher availability of huge data sets, neurophysiological evaluation of mental concepts has undergone a dramatic upswing (Riedl et al. 2020). For acute stress multiple approaches have been proposed (Subhani et al. 2017; Hosseini and Khalilzadeh 2010). However, there is still no robust, fast and easy to use method for the evaluation of chronic stress using physiological data.

We thus propose a novel machine learning approach for robust detection of chronic stress from resting-state EEG data. As a result, we surpass the current benchmark 71.41% by almost 10 % for classifying chronic stress using resting-state EEG recordings. We achieve these results by using a novel machine learning approach based on the fine-grained EEG spectrum proposed by Buettner et al. (2019b). With this algorithm we offer a way to measure stress objectively instead of relying on the subjective view of the participant, which could influence the results in the different questionnaires. Furthermore, our classifier is accurate, robust and cost-efficient, and contributes towards decision-making research by providing an objective measurement of chronic stress (Romanow et al. 2012). The paper is organized as follows: First we provide an overview over of some related work before setting out our research methodology, this covers both our machine learning method as well as the data we used for this research. After that we present the results of our classifier including its performance indicators. We then discuss those results, before concluding with limitations and proposing some ideas for future work.

Related Work

There have also been efforts to determine stress using machine learning algorithms in EEG data. Hosseini and Khalilzadeh (2010) for example, proposed an emotional stress recognition system using multi-modal bio-signals for classification of two emotional states with an accuracy of 82.7% using the Elman classifier. Subhani et al. (2017) were able to predict two levels of stress with an accuracy of 94.6%, and four levels at 83.43% (Subhani et al. 2017). Both of these machine learning approaches used data sets in which the healthy participants were brought into a stressful situation. Opposite to our method, these two cases are based on EEG data for acute stress situations, instead of resting state EEG data. For a classification of chronic stress, the current benchmark by Saeed et al. (2015) ranges from 64.28% to 71.42% using different machine learning approaches and a single channel EEG on the FP1 position (Saeed et al. 2015).

Table 1. Related Work on EEG classification of chronic and acute stress.

Year	Reference	Type of Stress	Classifier	Accuracy
2010	Hosseini and Khalilzadeh (2010)	Acute stress	Elman classifier	82.7%
2015	Hou et al. (2015)	Acute stress	Support Vector Machine	85.71 % (two levels)
				75.22% (three levels)
				67.06% (four levels)
2017	Subhani et al. (2017)	Acute stress	Naïve Bayes	94.6% (two levels)
				83.43% (four levels)
2018	Jebelli et al. (2018)	Acute Stress	Support Vector Machine	71.1%
2019	Jebelli et al. (2019)	Acute Stress	Deep Neural Network	86.62%
2015	Saeed et al. (2015)	Chronic stress	Naïve Bayes	64.28%
			Support Vector Machine	71.42%
			Multilayer Perceptron	67.85%

Methodology

Novel machine learning approach

Our novel machine learning algorithm is based on the fine-grained EEG spectra proposed by Buettner et al. (2019b), where the five standard EEG bands are replaced by a fine-grained 99-band EEG spectrum. This method has already been used successfully in diagnosing various diseases, like epilepsy (Buettner et al. 2019a), alcoholism (Rieg et al. 2019), schizophrenia (Buettner et al. 2020) and internet addiction (Gross et al. 2020). The hypothesis behind this approach is that finer grained frequency bands should give a higher information content to get the best possible classification result, the information density must also be as high as possible (Buettner et al. 2019b). We extracted these sub-bands with a step-width of 0.5 Hz in the range of 0.5 to 50 Hz. In order to separate the described frequency sub-bands, the EEG data has to be transformed into a frequency signal (Delorme and Makeig 2004), using a Fast Fourier Transformation. Then the spectral power for the respective frequency ranges is added up, the power spectral density describes the power distribution into frequency components composing that signal (Park et al. 2011).

As for classification, we used the Random Forest algorithm by Breiman (2001), because it showed very good results in the identification of several other diseases by using EEG recordings (Rieg et al. 2019; Buettner et al. 2019b). The Random Forest is a decision tree-based algorithm and consists of an ensemble of individual decision trees. The output of this classifier is based on the classification of the individual trees. Such ensemble methods follow the concept that a decision which is concluded by the aggregation of several experts, is often better than the decision from only one single system (Breiman 2001). Additionally, we performed an evaluate and selection of the most predictive features using the feature importance of the Random Forest algorithm in order to further improve the classification results.

Dataset

We used the mind-brain-body dataset by Babayan et al. (2019) from the Department of Neurology of the Max Planck Institute in Leipzig, Germany. It consists of 62-channel resting-state EEG recordings of 227 healthy participants. The electrodes were attached according to the 10-10 system and referenced the FCz. The complete EEG session consisted of 16 blocks, each lasting 60 seconds, of which 8 were recorded with eyes open (EO) and 8 with eyes closed (EC) (Babayan et al. 2019). Additionally, a psychological assessment was carried out, including the German version of the PSQ by Fliege et al. (2005). Before the data could be used for the training of the machine learning model it was downsampled from 2,500 Hz to 250 Hz. Afterwards a band-pass filter from 0.5 Hz to 50 Hz was applied, followed by independent component analysis (ICA) for the removal of EEG artifacts (Bell and Sejnowski 1995).

The “Perceived Stress Questionnaire” was developed by Levenstein et al. (1993) with the help of experienced clinicians and patients with stress symptoms. It makes it possible to asses subjective experiences of stress reactions and perceived stressful situations, whereby a stronger emphasis is placed on cognitive perception than on emotional states or specific life events. There are two versions, a general form covering “the last two years” and a recent form covering “the last two weeks” (Levenstein et al. 1993). The data for this work was gathered using a short variant of the general form. It consists of 20 items and the scale contains four subscales of “Worries”, “Tension”, “Joy”, and “Demands” (Babayan et al. 2019).

Validation procedure

We used the Random Forest Classifier of the caret package for our classification. The dataset was divided as follows: A total of 202 participants from the dataset had finished the fully 16-minutes EEG cycles as well as complete PSQ results. Due to low occurrence of participants with severe perceived stress, we used the 25 subjects with the highest and the 25 with the lowest score. By using this approach, we ensured the differences in the brain activities between the subjects were as high as possible regarding the PSQ score. We divided the probands into two different groups: lesser stressed and more stressed individuals. The final dataset that we used for this paper, consists of a total of 50 subjects (25 lesser stressed individuals and 25 individuals with a higher stress level). After a hyperparameter tuning the number of trees were set to n = 100 and the variable importance were used to determine the most important frequency bands and channels.

In order to detect potential overfitting of our machine learning model, we followed the standard machine learning guidelines using the k-fold cross validation in combination with a repeated hold-out-cross validation. The repeated hold-out-cross-validation used a standard 75% train and 25% test split (LeCun et al. 2015). The training data was only used for the training, and the test data was only used for validation after the training. This validation approach randomly divides the data in k equal parts. The training is then executed on the k-1 data, and the validation is performed on the excluded data, which is used as a test set. This is repeated exactly k times so that every part is used for validation once. We decided to set k to 10 in this work and repeat this procedure 50 times. The results reported are based on the hold-out-cross validation.

Results

Identified Feature Subset

The first evaluation of the variable importance analysis of the frequency bands revealed that the frequency sub-bands at 2.5-3 Hz (delta), 24.0-24.5 Hz (beta), 24.5-25.0 Hz (beta) and 26.0-26.5 Hz (beta)were highly relevant for the classification (Figure 1). Therefore, these four sub-bands were then used to train a Random Forest classifier that distinguishes between more and less stressed participants. Looking at the classical frequency bands, three of the four sub-bands are in the beta range and one in the delta range.

After the most predictive EEG sub-bands were selected, the variable importance of the EEG channels was also assessed. As the evaluation of the feature importance showed, the F7 and AF7 electrodes have a high level of influence on the classification, both of which are on the left frontal side of the scalp.

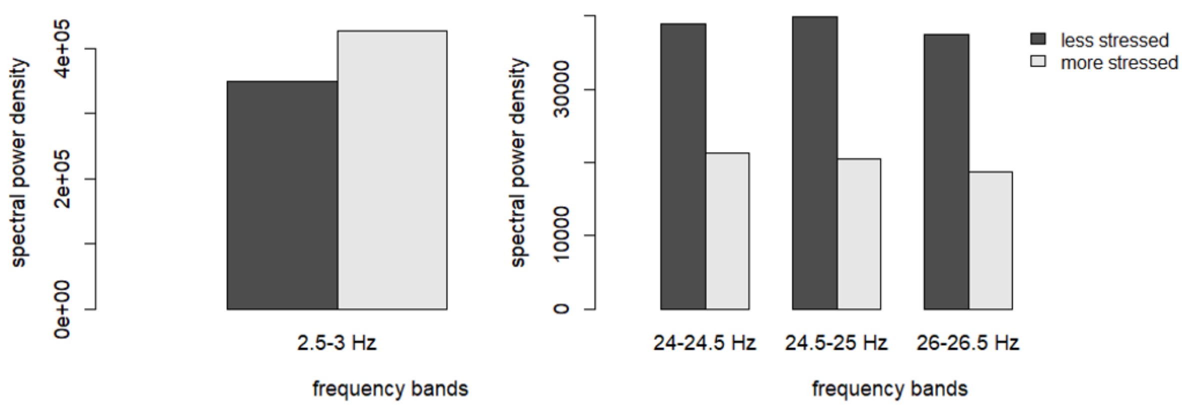

Figure 1. Comparison of the spectral power between more and less stressed

Results of the Classification

The Random Forest based classifier which was trained on the four EEG sub bands (2.5-3 Hz, 24.0-24.5 Hz, 24.5-25.0 Hz and 26.0-26.5 Hz) of the two electrodes (F7 and AF7) achieved a balanced accuracy of 81.33% (Table 2), while the other performance indicators underpin these good results (Table 2).

The model was able to assign 41.17% of the more stressed participants to the right class, over 50x repeated 10-fold cross validation. This resulted in a true positive rate of 82.33%. It also assigned 40.17% of the lesser stressed participants correctly, with only 8.83% and 9.83% examples falsely classified. Table 3 shows the summarized confusion matrix of the 50x repeated cross-validation.

Table 2. Performance of our classifier. Values based on unseen test data.

Performance Indicator	Value	Standard Deviation
Balanced Accuracy	81.33%	0.09
Sensitivity (true positive rate)	82.33%	0.17
Specificity (true negative rate)	80.33%	0.14
Positive predictive value	81.89%	0.11
Negative predictive value	84.52%	0.13
Prevalence	50%	-

Discussion

As shown in Table 2 our chronic stress detection algorithm performs very well and achieves a good classification performance. With its accuracy of 81.33 percent using unseen data, our algorithm significantly outperforms the current approaches for classifying chronic stress using resting-state EEG recording. Since our classification problem is balanced the prevalence score is at 50%, the baseline performance using a majority rule dummy classifier would also be 50%. With our novel machine leanring approach we achieved a total lift in balanced accuracy of 31.33% over the random baseline. We also surpass the current benchmark of 71.41% by Saeed et al. (2015) by almost 10 %.

Table 3. Confusion matrix of our classifier. Values based on unseen test data.

		Reference	
		More stressed	Less stressed
Predicted	More stressed	**41.17% (4.94)**	9.83% (1.18)
	Less stressed	8.83% (1.06)	**40.17% (4.82)**

An analysis of the spectral power between more and less stressed persons in the four identified EEG sub-bands revealed strong differences (Table 4). While more stressed people have higher spectral power in the Mid-Delta sub-band 2.5-3 Hz (427,122.99 vs. 349,536.23, Cohen's d: -0.2609; p-value: n.s.), they have a much lower spectral power in the High-Beta sub-bands 24.0-24.5 Hz (21,279.86 vs. 38,985.87, Cohen's d: 0.8356; p-value: <0.01), 24.5-25.0 Hz (20,442.63 vs. 39,935.12, Cohen's d: 0.8634; p-value: <0.01), and 26.0-26.5 Hz (18,719.62 vs. 37,523.95, Cohen's d: 0.8933; p-value: >0.01) as you can see in Figure 1.

Table 4. Spectral power and statistical characteristics of the 4 bands, healthy vs. stressed.

Characteristic	2.5-3.0 Hz	24.0-24.5 Hz	24.5-25.0 Hz	26.0-26.5 Hz
Mean healthy	349,536.23	38,985.87	39,935.12	37,523.95
Mean stressed	427,122.99	21,279.86	20,442.63	18,719.62
SD healthy	260,806.10	24,012.48	26,886.70	26,032.53
SD stressed	329,864.50	17,927.83	17,217.94	14,441.22
Cohen's d	-0.2609	0.8356	0.8634	0.8933
p-value	n.s.	<0.01	<0.01	<0.01

Although our findings of decreased spectral power in the High-Beta in highly stressed participants are in line with the results of a negative correlation between the PSS score and the spectral power in alpha and beta bands (Hamid et al. 2010), our findings did not confirm that perceived stress was associated with decreased spectral power in the delta band and an increased EEG beta power (Hall et al. 2007). Also, our evaluation partially confirms that chronic stress leads to increased spectral power in the prefrontal cortex (Peng et al. 2013; Goodman et al. 2013), which can be found in the Mid-Delta sub-band. In addition, the non-significant p-value of the subband 2.5-3.0 Hz indicates that the Random Forest classifier is also capable of performing a classification using non-linear features, which for example has already been used for the classification of heart rate variability signals (Jovic and Bogunovic 2011).

Conclusion

We built an effective chronic stress detection algorithm that achieved a good performance based only on resting-state EEG recordings. The algorithm achieved an accuracy of 81.33 percent which significantly outperforms the current benchmark of 64.28 to 71.42 percent (Saeed et al. 2015). In contrast to previous work, the classical frequency bands are not specified with the highest accuracy but go much deeper into the specific frequency ranges. Looking at the previous literature on the detection of perceived chronic stress often there is no agreement on which of the classical frequency bands is most relevant for the diagnosis of chronic stress. This new algorithm is accurate, robust, and more cost-efficient than the traditional PSQ assessment using questionnaires and can substantially contribute towards the evaluation of chronic stress in decision-making research using non-invasive and objective neuro-physiological measurements

With our findings we can confirm that more stressed people have an increased spectral power in the left prefrontal cortex (Hamid et al. 2010; Goodman et al. 2013). Our work also supports Hamid et al. (2010) statement that a higher stress level is associated with a lower power in the beta band. In addition to confirming these research results, we found a higher spectral power in the mid-delta sub-band 2.5-3.0 Hz, which has not yet been published yet. This fact may stimulate future empirical research on analyzing the Mid-Delta band 2.5-3.0 Hz and the High-Beta band 24.0-26.5 Hz. Our novel algorithm for chronic stress detection based on resting state EEG recordings is also highly relevant for Information Systems research in healthcare, since stress is omnipresent in society and can lead to various diseases (Cohen et al. 2007; Boll et al. 2004; Romanow et al. 2012). Technostress – stress, induced by the usage of information and communication technologies, can act as an additional stress factor in today's growing technological age and is one of the most relevant topics todays IS research (Riedl et al. 2020). With this algorithm we show a way to measure stress objectively instead of relying on the subjective view of the participant, which could influence the results across the different questionnaires. Furthermore, our algorithm can be implemented in the evaluation of technostress when developing new IS artifacts.

Limitations

While the internal validity of our classifier is very high due to the rigorous k-fold-cross-validation, the external validity of the results is one of the main limitations. External validity could be improved by training using additional datasets or by introducing the algorithm as a medical application in a clinical environment in order to get more data of patients, which could be analyzed to validate the results of this research. Another aspect that should be tested is the influence of other mental illnesses on the results of classification, because other illnesses could affect the same frequency bands and therefore could eventually bias the data.

Future work

In order to further improve our machine learning based stress detection algorithm, we want to re-evaluate our classifier on a larger variety of datasets to increase external validity. Furthermore we want to re-evaluate or stress prediction model using a biomarker based stress indicator like cortisol in order to circumvent biases induced by usage of questionnaires (Riedl et al. 2012). Since (techno-)stress is induced by many IT-artifacts, our algorithm can be applied in many IS research directions (Riedl 2012). Furthermore, we want to apply our identified resting-state EEG sub-bands to different machine learning models, like convolutional neural networks (LeCun et al. 2015), XGBoost (Chen and Guestrin 2016), and Support Vector Machine, in order to differentiate more stressed people from less stressed.

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