Assessment of how easy people get stressed by using EEG signal

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CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

Electroencephalography, stress,EEG features

ACM Reference Format:
Nattapat Dilokthammapan, Ploypan Phrukampai, Wasakorn Yousub, Nuttasit Pasukdee, Thanakit Phanthawit, Widya Eka Sandri, and Jakrapop Akaranee. 2018. Assessment of how easy people get stressed by using EEG signal. In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Stress becomes an inevitable part of human life. Stress activates the hypothalamus-pituitary-adrenocortical axis and the sympathetic nervous system leading to the release of stress hormone (cortisol) in the adrenal cortex. When an individual finds itself in a situation that it perceives as stress, various physiological reactions happen. Some physiological reactions include increased heart rate, sweating, digestive upset, muscle activation, higher blood pressure, faster breathing, fatigue as well as the lower skin temperature of the hands and feet [25]. In a student life, the intense pressure of achieving high grades, dealing with assignments and exams, maintaining a social life, dealing with financial obligations while away from family or home become challenges that college students must deal with every day which can lead to the presence of stress. Due to stress, human daily activities will be influenced because of the body systems not working properly such as the nervous system, cardiovascular system, endocrine system and reproductive system that contributes to physical and physiological health problems such as anxiety, depression, stroke, and even addiction. Therefore, an accurate stress detection method at its early stage is crucial to prevent students from getting into severe state and experiencing those health problems which can lead to the decline of student academic performance.

The concept of stress has attracted interests ever since its first use in physiological and biomedical research. A lot of research has been undertaken in the assessment of stress over the last years. There are many ways to assess stress, one of them is by using questionnaires. There are some questionnaires available such as the Perceived Stress Scale (PSS)[26], hospital anxiety, and depression scale [27], Depression Anxiety Stress Scale (DASS) [28], Social readjustment rating scale [29]. Though these studies were successful in capturing signs of stress over a long period, the result could be biased since they rely on the reconstruction of feelings in the past and sometimes participants can hide their real conditions due to some personal circumstances. Recently, the use of biosignals such as brain signals from electroencephalogram (EEG) has become another way to detect or measure some physiological disorders such as mental stress.

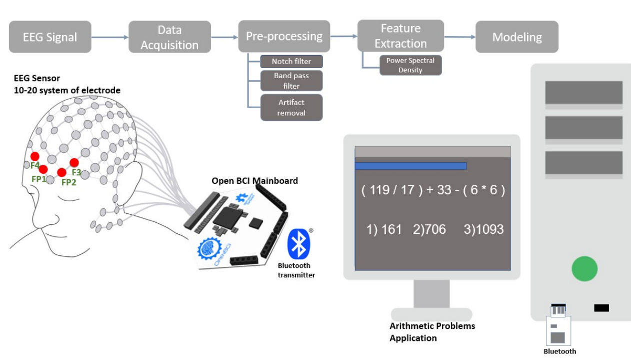

Figure 1: Pipeline of EEG analysis

This study aims to investigate the feasibility of exploiting Electroencephalography (EEG) signals to identify some students who are easily stressed, or less easily stressed according to their stress level from the EEG signal. This proposed assessment method may form an important first step towards the early detection of mental stress disorders.

Therefore, in this study, we want to develop a system that can detect stress among students and evaluate the stress levels to find out the possibility of them getting stressed by capturing brain signals from the EEG device while doing the three different difficulty levels of the arithmetic problem-solving (+ - × ÷) experiment under the pressure of a specified amount of time and negative feedback from the experimenter when participants give the wrong answers. After each equation, each participant will be required to answer whether they feel stress or not. The proposed experiment process is shown in Figure 1. For the classification method, we use the Support-Vector-Machine (SVM) algorithms as the classification method to classify the model into 2 groups, which are easily-stress people and less easily-stress people. Then we calculate the percentage of accuracy based on the proposed classification method.

We propose to measure EEG signals from participants using 4 electrodes (FP1, FP2, F3, and F4) of the frontal lobe (Figure 2) . EEG alpha band signals from 8 Hz to 12 Hz, which were separated to 8-12 Hz for Alpha band, 8-10 Hz for Alpha band1, and 10-12 Hz for Alpha band2, were highly correlated with mental stress states [3].

We built a model to classify the participants' mental stress state based on their stress level by using static four-electrodes EEG with expected accuracy more than 50 percent. The model can be used as a measurement tool to cross-validate with a psychological questionnaire to effectively detect and measure the stress level of participants who have the probability to develop the stress into a depressive disorder.

The main contributions of this study are as follows:

- With our technique, the system can detect the people who tend to get stressed easily.
- Our system can provide an assessment of stress symptoms for people who tend to develop their stress symptoms into depression before going to the doctor.

2 RELATED WORK

Stress analysis has been discussed largely among researchers in order to find alternative diagnostic methods that can be used instead of the current state of the art which is the model form Al-Shargie et al. [2] which has an accuracy of 97.61% but they used 7 electrodes for modeling. Recently, some studies used EEG signals conducted with various signal processing and machine learning methods to detect stress. Several studies have demonstrated the relationship between stress and EEG signals and show that EEG can be used as an input variable in stress analysis. The mental states in humans are typically categorized into four classes based on their underlying time-line. First, attention which lasts for a fraction of second. Second, full-blown emotions which usually last more than the attention and persist for some seconds to minutes. The next type is known as mood which is usually assigned to a set of emotions which last for minutes to hours. The last set which typically is realized as a mental disorder can show its signs during a long period such as a year to part of the life [1].

2.1 Brain signals location

Measurements are often taken from the prefrontal cortex (PFC) [10–13], which is the brain region responsible for regulating thoughts, actions and emotions. The PFC has been identified as the most sensitive to the detrimental effects of stress exposure [19, 20] and displayed behavioral and somatic responses to stress [14–17]. Fares Mohammed Al-Shargie [2], all electrodes (seven active electrodes namely as FP1, FP2, F7, F3, Fz, F4, and F8) were placed on the PFC surface scalp based on the international 10-20 system of electrode placement, and the results from lateral index demonstrated the dominance of right PFC at all the three levels of mental stress with most significant at level one of mental stress.

In one study, they were able to measure the stress level by implementing an Artificial Neural Network using EEG signals captured from four electrodes (FP1, FP2, F3, F4) of the frontal lobe from twenty-five subjects [30]. Another study was able to identify stress among students by using a single electrode (FP1) portable EEG based device called NeuroSky Mindwave Mobile [31].

Fares Al-Shargie [3], measured the brain activities simultaneously at the prefrontal cortex (PFC) using EEG (BrainMaster 24E system; 7-electrodes) and fNIRS (OT-R40, Hitachi Medical Corp, Japan; 23 channels) techniques, and the statistical analysis of JSCCA fusion confirmed the localization of mental stress to the right ventrolateral PFC. Ali Darziet al. [1], recorded the EEG data using bilaterally attached electrodes (F3, F4, C3, C4, P3, P4, T7, T8). The 10-20 system of electrode placement was implied using the BIMEC from Brain-marker BV. The BIMEC has 1 reference channel plus 8 EEG channels with a sampling rate of 250 Hz. Jun Guo, [21] used 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) placed on the scalp following the international 10-20 system.

2.2 Emotional Stimuli

The EEG offers several advantages such as non-invasive data acquisition, ease to use, low-cost set-up and its high temporal resolution at the millisecond scale [6]. Some previous studies have used EEG to study mental stress. The brain region under study depends on the type of stimuli or tasks given (visual, working memory or audio). Hill and Castro found that there is high beta rhythm activity in the sensory-motor area during a stressful healing task [7].

Deepan et al. [4] conducted experiments to classify cognitive stress, at an interpersonal level, induced by a proposed Stroop Colour-Word game using Electroencephalogram (EEG), Galvanic Skin Response (GSR), and Photoplethysmogram (PPG). They collected EEG signals from 22 subjects while they were playing the Stroop test. Different levels of stress were induced by playing game tasks with a specified amount of time. A gamified version of the Stroop test was considered a universal stressor for the subjects. In the first level of the session, participants play the easy level of stress game within 180 seconds. In the second level of stress of the next session, participants play the hard level of stress game with the same amount of time.

Jun and Smitha, [5], arithmetic problems were used to induce different levels of mental stress. They found that arithmetic problems can induce stress more than the Stroop test. Fares Mohammed Al-Shargie [2], EEG signals were recorded for 15 minutes while participants solved four arithmetic problems at three levels of difficulty. The half of the participants began with the control task (no time-limited) while another half began with the stress task (under 40 seconds time-limited and negative feedback). All participants got 30s of rest to avoid the occurrence of habituation and to give sufficient time to determine brain areas activated during the MA task.

Ali Darziet al. [1] The impedance of the Ag/AgCl electrodes was kept below 10 kilo ohms . They considered the cerebral lateralization during emotional perception. The EEG data were collected for a 6-min period of time that comprised of 1 min eyes-closed condition, 1 min eyes-open condition, and 1 min for each emotional stimulus. The subject was exposed to 4 sets of different emotional stimuli.

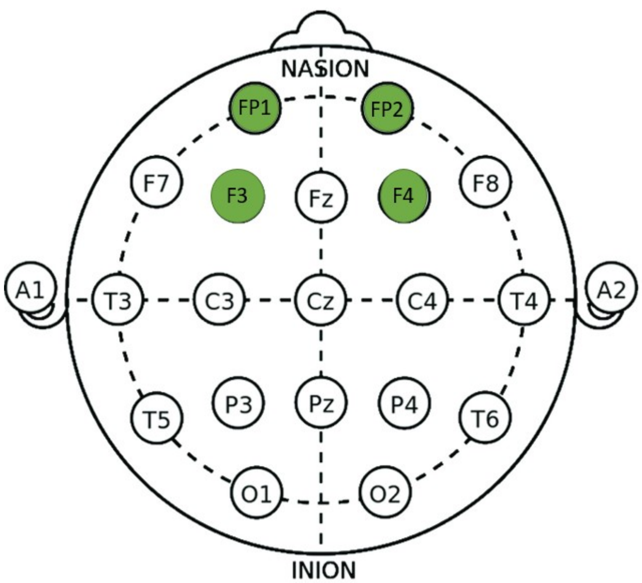

Figure 2: Electrode placement for International 10-20 system.

2.3 EEG Data pre-processing

Proper signal analysis and classification are essential and important to remove the noise from the signal and from other sources. Independent component analysis (ICA) is widely used in EEG research in the clinical domain to remove electrical power lines, eye blink, muscle activity, and heart muscle activity in the EEG signals [23].

Manish et al. [22] used a length-6 filter bank(FB) to decompose the EEG signals taken from the left and right hemispheres of the brain into 7 wavelet subbands(WSBs). They applied the logarithm of L2 norm (LL2N) on each WSB to extract 7 features each for both the hemispheres and they also applied the Student's t-test to calculate the significance of each feature before inputting it to classification modeling. In one study, they used 'Power Spectral Density', 'Wavelet coefficient', 'Fourier Transform', 'Kalman Filter', 'Hjorth Complexity' and 'Hjorth Mobility' as feature extraction techniques to extract six features from the recorded EEG data [30].

Guo and Smitha, [21], computed the signal power by converting the discrete time signal to frequency domain using Discrete Fourier Transform (DFT). In addition, fast fourier transform (FFT) is used to convert and process the time domain EEG signal. The average power in the frequency range specified, theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz) were calculated by the power spectral density (PSD).

2.4 Classification Techniques

Advanced neurocomputing and machine learning techniques have been used for the EEG-based diagnosis of various neurological disorders that are able to detect stress. Al-Shargie et al. [2] show the result of using EEG signals of 7 electrodes (FP1, FP2, F3, F4, F7, F8, and Fz) to classify three levels of stress classification (low, moderate, high stress) with an accuracy of 97.61% 95.37% and 91.40% respectively. Dongkoo et al. [24] used the k-nearest neighbor classifier with the genetic algorithm as a feature selection technique to classify the data from the DEAP dataset which data labeled as the stress state and calm state according to the values of arousal and valence by calculating the degree of separation between the two classes in order to find the feature combination that distinguishes between the classes. The experiment result shows that the genetic algorithm-based method with k-nearest neighbor classifier achieves 71.76% classification accuracy.

Support Vector Machine (SVM) is a supervised machine learning technique widely used for classification, regression and density estimation [18]. Fares Mohammed Al-Shargie [2] used a technique that transformed the data into a higher-dimension space using kernel function and classified them with a hyper-plane. SVM was selected for its ability to model linear as well as more complex decision boundaries. Fares Al-Shargie [3], The performance evaluation of the proposed method in detecting stress was then performed using a support vector machine (SVM) with a radial basis function. The classification accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AROC), positive prediction value (PPV) and negative prediction value (NPV) were calculated for individual modality and after fusion then two-sample t-test was used to check the significance of the proposed method [3]. In some studies, a linear SVM has been used to avoid the setting of parameters in SVM with kernels such as sigma in radial basis function (RBF). The classifiers parameters were tuned so that leads to the highest accuracy rate [1]

Artificial Neural Network is one of the techniques which is used to solve classification based problems. Mukherjee and Roy [30] designed a multilayer feed-forward neural network for predicting the mental stress condition of the subject using the extracted six features values of EEG data from six feature extraction techniques i.e. 'Power Spectral Density', 'Wavelet coefficient', 'Fourier Transform','Kalman Filter', 'Hjorth Complexity' and 'Hjorth Mobility'. The multilayer perceptron has three layers i.e. input layer, hidden layers, and output layer. Then they used the neural network to predict the stress level and indicated the stress level of the subjects through the Stress Indicating Circuit made of one Arduino UNO, three light-emitting diodes and one alarm. The circuit indicates the stress level of the subjects by using three LEDs (Green, Red and Yellow) and one piezo buzzer as indicators. When the subject is in 'Relaxed', 'Less Stressed' state, at that time all three LEDs of the stress detection circuit are in off state. If the subject is in 'Moderately Stressed' condition then only the Yellow LED of the stress detection circuit is in on state, the other two LEDs (Green, RED) are off. When the subject is 'High Stressed', only Green LED is in on state. Alarm rings if the stress level of the subject is 'alarmingly stressed'. They computed efficiency of the designed multilayer neural network by using the test dataset and obtained 91% efficiency of the trained neural network.

3 EXPERIMENTAL DESIGN

In this study, a sample of 8 participants are collected according to our experiment design. Their EEG signals will be recorded during the experiment of solving arithmetic problems (+ - × ÷) in different five difficulty levels within a specified amount of time. It is significant to note that the mental arithmetic tasks could induce a level of stress in participants [2].

We used the mental arithmetic tasks with five levels of difficulty as our stimuli in this study. Each level of an arithmetic task corresponds to one level of stress. The task at level one difficulty consists of a maximum two-digit of integer numbers with 5 operands using only + operator. At task with level two of difficulty we used + and - operators with 5 operands and maximum two-digit integers. For the task at level three difficulty, the calculation will be using +, -, and * operators with 5 operands and maximum two-digit integer numbers. At the task level four difficulty, there will be 5 operands using a combination of +, -, *, and / operators with a maximum three-digit integer numbers. For the highest difficulty level, the task involves the calculation with maximum three-digit integer numbers using 5 operands using +, -, *, and / operator. The details of the arithmetic level design are in Table I.

Difficulty level	Operators	Num of Operand	Max digits
1	" + "	5	2
2	" + - "	5	2
3	" + - * "	5	2
4	" + - * / "	5	3
5	" + - * / "	6	3

Table I. The arithmetic level design

The arithmetic tasks contain 10 questions for each block from a total of 3 blocks for each participant. During answering the questions, the feedback of "Correct" or "Incorrect" will be informed by the experimenter for each question after participants completed answering each question. After they completed all 10 questions in each block, each participant will be required to answer the questionnaire by telling "stress" if they feel stressed and "not stress " if they feel otherwise at the end of each block.

In our experiment we implemented a within-subjects experiment design in which all eight participants are exposed to every treatment or condition where they were assigned to do 10 mental arithmetic tasks in each block from a total 3 blocks with a time-limit of 40 seconds. We allow participants to have a rest time for 10 seconds before continuing to the next question. At the end of each block participants will have 5 seconds for answering the questionnaire. After completing one block, participants will be allowed to have a break for 30 seconds before continuing to the next block. Therefore, the total time of the experiment for each participant is 26.25 minutes as shown at the illustration in Figure 3.

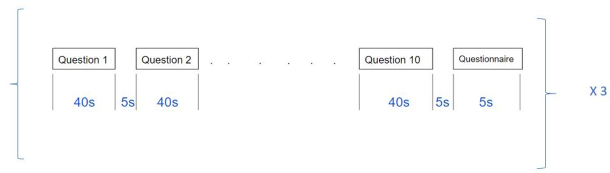

Figure 3: Time Experiment

Total time for each participant = (40s each task × 10 tasks × 3 blocks) + (10s each answer question and rest × 10 tests × 3 blocks) + (5s each questionnaire × 3 questionnaires) + (30s each break × 2 breaks) = 1575 second = 26.25 minutes

4 METHOD

4.1 Participant

In total participants 9 students were recruited for the experiment with age range from 23 to 37 years old (M = 28.67, SD = 4.44). All the participants were identified healthy and non-smoking. Before the experiment day, participants were informed not to have any drink that contains alcohol or caffeine, and they were suggested to have enough rest before the experiment day. In addition, on the experiment day, a form of consent will be signed by each participant.

Data from 9 participants gathered from the experiment; however, due to some mistakes in the experiment, the EEG ear-clips from one of the participants were not attached during the experiment. As a result, only eight data of the participants can be used for further analysis.

4.2 Task and Procedures

In the beginning, all participants will be asked to fill the standard pre-questionnaire of stress assessment which is questionnaire-based self-reporting from the International Stress Management Association UK[2] that commonly used as a subjective method [9] to measure an individual's level of mental stress [8]. Then those participants will be separated into two groups which are people who get stress easily and less easily. After filling the pre-questionnaire, there will be a short instruction about the experiment from the experimenter. An EEG headset and ear-clips were attached to participants with the help of one of our experimenters. The participants were asked to do arithmetic tasks, and participants' EEG signals were recorded during the experiment while solving arithmetic problems (+ - × ÷) in different difficulty levels within a specified amount of time. In this study, we used time pressure and negative feedback on participants' performance as our stressors. For the time pressure, each participant has 40s to answer with a 10s break before continuing to the next question. In addition, participants have to answer the question at the end of each question at the beginning of resting time. The answer will be written on the answer paper sheet. We conducted an experiment with three blocks consisting of ten arithmetic equations in each block. For the negative feedback, participants will get "correct" or "incorrect" as a feedback while solving the tasks, then at the end of the test participants will get performance indicators from the experimenter in which participants can see their performance in terms of accuracy that can induce their stress. At the end of each block, there will be a post-questionnaire that needs to be filled by the participants to identify their mental state whether they are stressed or not after solving the equations. However, participants were allowed to practice during the training block before starting the real experiment. The experiment took approximately 30 minutes.

4.3 EEG measurement

In this study we used Neurotechnologist's Starter Kit as our EEG device, equipped with 2 active electrodes FP1, FP2, F3, and F4 shown in figure 4. All electrodes were placed on the cap based on the international 10-20 system. The sampling frequency of 250Hz was used.

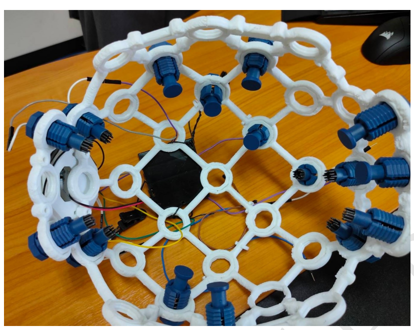

Figure 4: Neurotechnologist's Starter Kit contains 2 electrodes FP1, FP2

4.4 Data analysis

4.4.1 Preprocessing: We applied a 50 Hz notch filter on the data obtained at each channel in order to eliminate power line interference (power supply frequency is 50 Hz). Since the signal analysis involves frequency components up to the alpha band which is typically most apparent at 8-12 Hz. The component corresponding to eye blink artifacts was removed using ICA.

4.4.2 Feature Analysis: We acquired the cleaned EEG signal from the preprocessing step. The data was processed offline using Jupyter notebook. As figure 5, The channels were decomposed into a number of independent components. The signals were further processed through power spectral density (PSD) using Welch's method as it is suitable for power content versus frequency. A PSD is typically used to characterize broadband random signals. The amplitude of the PSD is normalized by the spectral resolution employed to digitize the signal. As figure 10, the PSD decomposed EEG signals into set of frequency band, which are Delta (0.5-4 Hz), Theta (4-7 Hz),

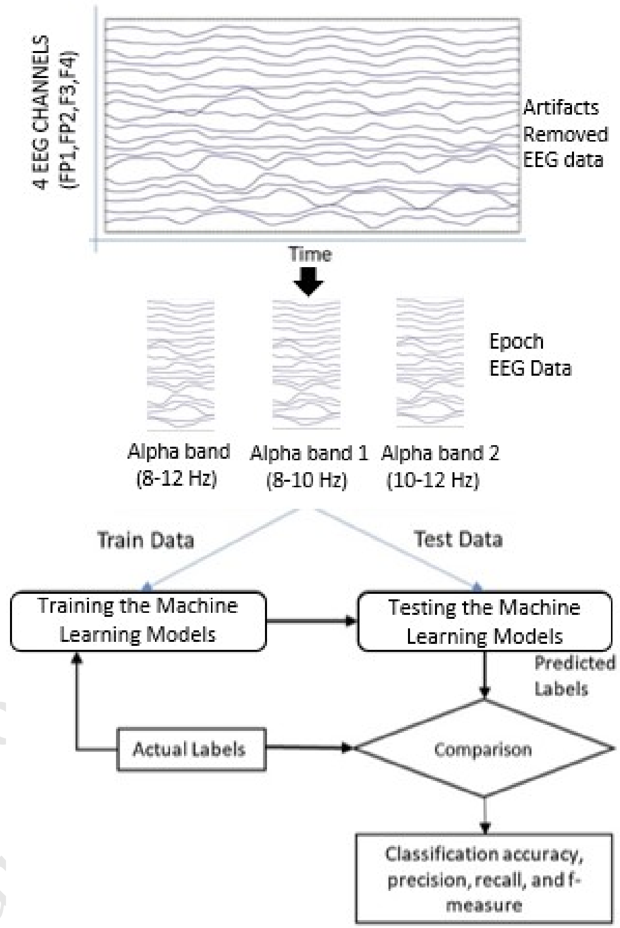

Figure 5: Proposed machine learning model for automatic diagnosis of stress

Alpha1(8-10 Hz), Alpha2 (10-12Hz), Beta (12-20 Hz), Low gamma (20-30 Hz), and Midgamma (30-50 Hz).

The data was collected from 4 electrodes but only two of them (FP1, FP2) were used for the frequency band since the other two (F3, F4) were not consistent and the data was lost at some point; therefore, that the data cannot be used. Since we found that EEG alpha band signals were highly correlated with mental stress states [3], we decided to focus on that power band. In this study we used Alpha1 (8-10 Hz) and Alpha2 (10-12 Hz). Therefore we limit the analysis to EEG alpha rhythm power in this study.

After the data was collected, we acquired Alpha1-FP1, Alpha1-FP2, Alpha2-FP1, Alpha2-FP2, Alpha-FP1 and Alpha-FP2 data from participants. We computed the average of FP1 and FP2 of Alpha, Alpha1 and Alpha2 and then we averaged those three in order to analyze and find out whether factors have a significant effect on the difference between easily-stressed and less-easily-stressed people or not. By looking at the data, we selected some data attributes which may be possible for data and used the JASP (Jeffreys's Amazing Statistics) program to analyze the result.

Participants	Label	B1_1st level	B1_2nd level	B1_3rd level	B1_4th level	B1_5th level	B2_1st level	B2_2nd level	B2_3rd level	B2_4th level	B2_5th level	B3_1st level	B3_2nd level	B3_3rd level	B3_4th level	B3_5th level
p001	easily_stress	0.149568733	0.040399916	0.233990217	0.033132022	0.177407527	0.012885795	0.011302152	0.175967815	0.176760012	0.060507868	-0.26329143	-0.05302509	0.20682297	0.002934951	-0.00650924
p002	non_easily_stress	0.555145054	-0.04657313	-0.10441314	-0.10481303	-0.10275836	-0.07613896	0.912473471	0.228085525	1.802463341	-0.15789487	0.591369421	-0.28810404	-0.34677221	0.022497023	-0.22861943
p004	easily_stress	0.031895378	-0.15342749	-0.20335009	-0.18238904	-0.08873499	0.032937714	-0.14949309	-0.16391934	-0.06834855	-0.0807551	-0.01367095	-0.03504599	-0.01742545	0.115627659	0.026326319
p005	easily_stress	-1.27082942	0.016153217	0.718671385	0.19954159	-0.12526217	-0.1242629	-0.11181834	-0.10222992	1.09770984	-0.0077168	-0.11083926	-0.05145504	-0.06839232	-0.06274003	-0.00572536
p006	non_easily_stress	-0.0153099	0.176582681	0.055395443	0.072531665	0.141582193	-0.03057374	-0.06271961	-0.00819739	-0.06126856	-0.00737514	-0.09452044	-0.03655585	0.035794018	-0.19763719	-0.11224661
p007	non_easily_stress	-0.00878064	0.000192021	0.277560944	0.033984408	-0.06605689	-0.10524118	-0.14573697	-0.12031901	-0.12845726	-0.12075905	0.016332187	-0.01400248	0.045400576	-0.05311896	-0.04398192
p008	non_easily_stress	-0.08951119	-0.13820553	-0.14309306	-0.13153458	-0.14389122	-0.1506234	-0.16231996	-0.14613642	-0.12902106	-0.12635354	-0.13098868	-0.13255819	-0.11305143	-0.1326589	-0.14449937
p009	easily_stress	0.05167159	0.074393897	-0.03332978	-0.04703981	0.053463812	0.106731034	0.097646696	-0.17310493	0.066663399	-0.05930687	-0.03569718	-0.06952299	-0.12788271	-0.13976133	0.183022962

Figure 6: EEG data of each participants

Descriptive Statistics ▾

Descriptive Statistics

	V1_1st level		V1_2nd level		V1_3rd level		V1_4th level		V1_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	3.309e−11	1.429e−11	1.212e−11	1.179e−11	1.988e−11	1.289e−11	1.544e−11	1.085e−11	1.732e−11	1.218e−11
Std. Deviation	3.209e−11	8.415e−12	5.989e−12	1.079e−11	1.356e−11	1.143e−11	7.555e−12	8.869e−12	1.107e−11	1.209e−11
Shapiro-Wilk	0.799	0.989	0.864	0.881	0.768	0.855	0.789	0.801	0.687	0.838
P-value of Shapiro-Wilk	0.100	0.950	0.276	0.345	0.056	0.244	0.084	0.103	0.008	0.190
Minimum	8.570e−12	4.860e−12	3.480e−12	3.120e−12	7.060e−12	2.100e−12	8.000e−12	2.490e−12	1.090e−11	3.340e−12
Maximum	8.030e−11	2.430e−11	1.710e−11	2.670e−11	3.160e−11	2.480e−11	2.200e−11	1.910e−11	3.390e−11	2.940e−11

Figure 7: Alpha1 FP1 Descriptive Statistics - Block1

	V2_1st level		V2_2nd level		V2_3rd level		V2_4th level		V2_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	1.413e−11	7.185e−12	1.106e−11	1.342e−11	1.517e−11	1.212e−11	2.700e−11	2.003e−11	1.432e−11	7.500e−12
Std. Deviation	6.839e−12	5.506e−12	6.345e−12	1.141e−11	1.349e−11	8.795e−12	1.862e−11	2.214e−11	7.253e−12	7.258e−12
Shapiro-Wilk	0.833	0.878	0.923	0.878	0.800	0.921	0.933	0.754	0.990	0.857
P-value of Shapiro-Wilk	0.176	0.330	0.553	0.332	0.102	0.544	0.609	0.042	0.958	0.251
Minimum	8.610e−12	2.370e−12	5.240e−12	3.480e−12	5.590e−12	4.280e−12	1.000e−11	5.620e−12	6.190e−12	1.550e−12
Maximum	2.410e−11	1.370e−11	1.990e−11	2.700e−11	3.500e−11	2.420e−11	5.210e−11	5.290e−11	2.300e−11	1.800e−11

Figure 8: Alpha1 FP1 Descriptive Statistics - Block2

	V3_1st level		V3_2nd level		V3_3rd level		V3_4th level		V3_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	1.251e−11	1.263e−11	1.399e−11	8.045e−12	1.654e−11	8.182e−12	1.410e−11	5.963e−12	2.433e−11	4.855e−12
Std. Deviation	3.963e−12	8.168e−12	7.778e−12	4.242e−12	1.005e−11	5.167e−12	4.248e−12	1.901e−12	1.747e−11	2.822e−12
Shapiro-Wilk	0.994	0.925	0.917	0.965	0.909	0.960	0.804	0.975	0.810	0.909
P-value of Shapiro-Wilk	0.978	0.565	0.523	0.809	0.478	0.780	0.109	0.870	0.121	0.477
Minimum	7.630e−12	4.000e−12	6.070e−12	3.720e−12	7.480e−12	2.790e−12	1.040e−11	3.970e−12	1.110e−11	2.420e−12
Maximum	1.720e−11	2.370e−11	2.470e−11	1.330e−11	3.070e−11	1.430e−11	1.840e−11	8.470e−12	5.000e−11	8.600e−12

Figure 9: Alpha1 FP1 Descriptive Statistics - Block3

The figure 6 is the example of data used in the analysis. Column one, Participants, are the participant's IDs, Column two, Label, are the state of stress from participants (easily-stress or less-easily-stress) collected from the Pre-questionnaire, and Column three to seventeen are the alpha signals at each difficulty level in each block start from first block at first difficulty level until third block at fifth difficulty level.

Unfortunately, the result from JASP analysis cannot indicate any significant effect on the participant's stress state (easily-stress or less-easily-stress). As a result, we decided to analyze Alpha1 and Alpha2 separately in each brain location (FP1 and FP2).

From the second data analysis that Alpha1-FP1, Alpha1-FP2, Alpha2-FP1, and Alpha2-FP2 were being analyzed, we found that the data of Alpha1-FP2 and Alpha2-FP2 did not have a significant effect on difference between easily-stressed and less-easily-stressed state. On the other hand, Alpha1-FP1 and Alpha2-FP1 showed a significant effect on the difference between those two states as shown in the data analysis part by JASP.

- Alpha1 FP1
  From the figure 7, 8, and 9, illustrates the descriptive statistic of data, which divided into each block and difficulty level, e.g. V1_1st1 level is Block1_1st_difficulty_level. In order to test the normality of the data used, we perform descriptive statistics using Shapiro-Wilk test. Based on the descriptive statistics, the Shapiro-Wilk test showed that most data collected from each level in Block 1, Block 2, and Block 3 from

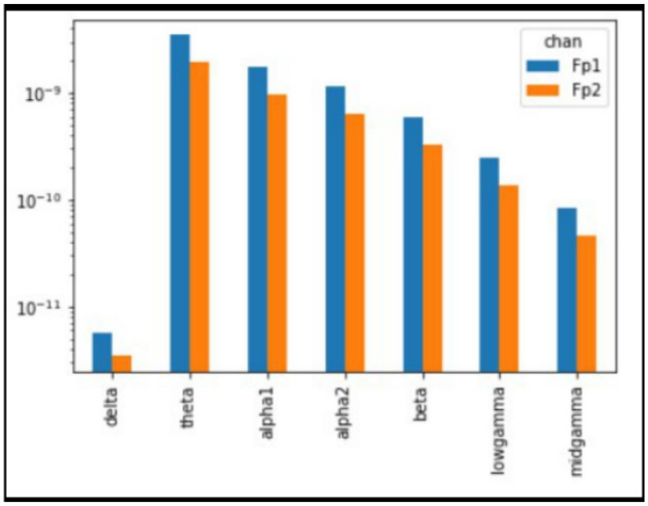

Figure 10: Power spectral density of the EEG signal

Alpha1 are normally distributed (p > .05), and only two of them are not normal (V1_5th level and V2_4th level) with p < .05. Therefore, we can conclude that the data is not completely normal.

Assumption Checks

Test of Sphericity

	Mauchly's W	Approx. X^2	df	p	Greenhouse-Geisser ε	Huynh-Feldt ε	Lower Bound ε
Level	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ
Block	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ
Block ∗ Level	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ

ᵃ Singular error SSP matrix: The repeated measure has only two levels, or more levels than observations. When the repeated measure has two levels, the assumption of sphericity is always met.

Test for Equality of Variances (Levene's)

	F	df1	df2	p
V1_1st level	3.866	1.000	6.000	0.097
V2_1st level	0.045	1.000	6.000	0.839
V3_1st level	0.968	1.000	6.000	0.363
V1_2nd level	1.167	1.000	6.000	0.321
V2_2nd level	3.886	1.000	6.000	0.096
V3_2nd level	0.637	1.000	6.000	0.455
V1_3rd level	3.333	1.000	6.000	0.118
V2_3rd level	0.675	1.000	6.000	0.443
V3_3rd level	0.900	1.000	6.000	0.380
V1_4th level	4.542	1.000	6.000	0.077
V2_4th level	0.121	1.000	6.000	0.740
V3_4th level	14.720	1.000	6.000	0.009
V1_5th level	0.005	1.000	6.000	0.945
V2_5th level	0.022	1.000	6.000	0.888
V3_5th level	5.216	1.000	6.000	0.062

Figure 11: Alpha1 FP1 Assumption Checks

From the figure 11, we performed Assumption Checks using Sphericity checks and Test for Equality of Variance (Levene's). From the Sphericity checks, all the tests have epsilon (ϵ) = 1 means that the conditions of sphericity are exactly met. From the Test for Equality of Variance (Levene's), most of the data passed the equality variance with p > .05, except V3_4th level with (p < .05). Therefore, there is a difference between the variances in the population.

In this study we performed a within subject design where the subjects have undergone three conditions or factors (Level, Label, and Block). Therefore, we implement two-way mixed measures ANOVA to understand if there is an interaction between these three factors. Based on the figure 12, the mixed measures ANOVA result, we found a main effect on

Repeated Measures ANOVA ▾

Within Subjects Effects ▾

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Level	2.532e −22	4	6.330e −23	0.667	0.621	0.015	0.100
Level ∗ Label	2.824e −22	4	7.060e −23	0.744	0.572	0.017	0.110
Residual	2.278e −21	24	9.490e −23				
Block	3.005e −22	2	1.503e −22	1.057	0.378	0.018	0.150
Block ∗ Label	8.780e −23	2	4.390e −23	0.309	0.740	0.005	0.049
Residual	1.706e −21	12	1.422e −22				
Block ∗ Level	1.440e −21	8	1.799e −22	2.135	0.050	0.088	0.262
Block ∗ Level ∗ Label	6.385e −22	8	7.982e −23	0.947	0.488	0.039	0.136
Residual	4.045e −21	48	8.427e −23				

Note. Type III Sum of Squares

Figure 12: Alpha1 FP1 Mixed Measures ANOVA

Block*Level interaction of Alpha1 ($F(8, 48) = 2.135$, p=.05), but we failed to find significant effect on Level, Level*Label interaction, Block, Block*Label interaction and Block*Level*Label interaction.

Independent Samples T-Test

Independent Samples T-Test

	t	df	p
V1_1st level	1.133	6.000	0.300
V1_2nd level	0.053	6.000	0.960
V1_3rd level	0.788	6.000	0.461
V1_4th level	0.788	6.000	0.460
V1_5th level	0.627	6.000	0.554
V2_1st level	1.581	6.000	0.165
V2_2nd level	−0.361	6.000	0.730
V2_3rd level	0.379	6.000	0.718
V2_4th level	0.482	6.000	0.647
V2_5th level	1.330	6.000	0.232
V3_1st level	−0.026	6.000	0.980
V3_2nd level	1.343	6.000	0.228
V3_3rd level	1.481	6.000	0.189
V3_4th level	3.497	6.000	0.013ᵃ
V3_5th level	2.200	6.000	0.070

Note. Student's t-test.

ᵃ Levene's test is significant (p < .05), suggesting a violation of the equal variance assumption

Figure 13: Independent Sample T-Test on Alpha1 FP1

From figure 13, the Independent Samples T-Test shows that all of the experiments result with a non-significant (p > .05). Since we do not have many participants, the experiment could not provide a difference among them. However, the Independent Samples T-Test illustrates the significant effect on block3 on 4th difficulty level (p < .05).

- Alpha2 FP1
  From the figure 14, figure 15, and figure 16 , the descriptive statistic using Shapiro-Wilk test. We can see at the p-value of Shapiro-Wilk that most of the power spectrum density of Alpha2 are more than .05. Based on the descriptive statistics, the Shapiro-Wilk test confirmed that most data collected from each level in Block 1, Block 2 and Block 3 from Alpha1 are normally distributed (p > .05), but five of them are not normal (V1_1st level, V2_3rd level, V2_4th level, V2_5th level, and V3_1st level) with p < .05. Therefore, we can conclude that the data is not completely normal.
  The figure 17, illustrates the result of assumption check of the Sphericity test, the degree to which sphericity is represented by a statistic called epsilon (ϵ). An epsilon of 1 (

Descriptive Statistics

	V1_1st level		V1_2nd level		V1_3rd level		V1_4th level		V1_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	5.105e−11	1.503e−11	1.301e−11	1.095e−11	2.077e−11	1.162e−11	1.407e−11	8.237e−12	1.528e−11	9.857e−12
Std. Deviation	6.359e−11	9.676e−12	6.160e−12	7.563e−12	1.360e−11	8.929e−12	5.578e−12	5.452e−12	4.043e−12	8.199e−12
Shapiro-Wilk	0.718	0.922	0.963	0.945	0.990	0.846	0.995	0.776	0.950	0.840
P-value of Shapiro-Wilk	0.018	0.550	0.800	0.684	0.957	0.213	0.981	0.066	0.715	0.195
Minimum	1.220e−11	5.110e−12	4.740e−12	3.810e−12	5.880e−12	3.340e−12	7.670e−12	3.150e−12	1.140e−11	3.790e−12
Maximum	1.460e−10	2.570e−11	1.930e−11	2.110e−11	3.800e−11	2.090e−11	2.070e−11	1.310e−11	2.070e−11	2.160e−11

Figure 14: Alpha2 FP1 Descriptive Statistics - Block1

	V2_1st level		V2_2nd level		V2_3rd level		V2_4th level		V2_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	1.643e−11	7.075e−12	1.326e−11	1.489e−11	1.461e−11	1.023e−11	3.403e−11	2.109e−11	1.499e−11	6.337e−12
Std. Deviation	4.866e−12	4.806e−12	5.890e−12	1.513e−11	1.087e−11	5.563e−12	2.956e−11	2.465e−11	4.456e−12	5.784e−12
Shapiro-Wilk	0.927	0.920	0.958	0.826	0.763	0.832	0.753	0.718	0.950	0.759
P-value of Shapiro-Wilk	0.580	0.539	0.767	0.158	0.050	0.173	0.041	0.018	0.714	0.047
Minimum	1.180e−11	2.790e−12	7.130e−12	4.140e−12	7.550e−12	4.160e−12	1.340e−11	6.080e−12	9.670e−12	2.620e−12
Maximum	2.320e−11	1.370e−11	2.120e−11	3.650e−11	3.070e−11	1.500e−11	7.790e−11	5.790e−11	1.950e−11	1.490e−11

Figure 15: Alpha2 FP1 Descriptive Statistics - Block2

	V3_1st level		V3_2nd level		V3_3rd level		V3_4th level		V3_5th level	
	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress	easily_stress	non_easily_stress
Valid	4	4	4	4	4	4	4	4	4	4
Missing	0	0	0	0	0	0	0	0	0	0
Mean	1.393e−11	1.494e−11	1.600e−11	7.770e−12	1.881e−11	7.733e−12	1.838e−11	6.960e−12	2.210e−11	4.887e−12
Std. Deviation	5.018e−12	1.508e−11	7.071e−12	3.398e−12	9.946e−12	3.697e−12	7.406e−12	1.712e−12	8.820e−12	2.213e−12
Shapiro-Wilk	0.955	0.761	0.859	0.943	0.921	0.865	0.957	0.839	0.990	0.774
P-value of Shapiro-Wilk	0.745	0.049	0.255	0.674	0.542	0.277	0.757	0.193	0.959	0.063
Minimum	9.010e−12	4.320e−12	9.810e−12	3.150e−12	9.250e−12	4.760e−12	1.080e−11	4.470e−12	1.090e−11	2.950e−12
Maximum	2.030e−11	3.730e−11	2.400e−11	1.130e−11	3.270e−11	1.240e−11	2.840e−11	8.370e−12	3.210e−11	6.980e−12

Figure 16: Alpha2 FP1 Descriptive Statistics - Block3

Assumption Checks

Test of Sphericity

	Mauchly's W	Approx. X²	df	p	Greenhouse-Geisser ε	Huynh-Feldt ε	Lower Bound ε
Level	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ
Block	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ
Level ∗ Block	1.000ᵃ	NaNᵃ	NaNᵃ	NaNᵃ	1.000ᵃ	1.000ᵃ	1.000ᵃ

ᵃ Singular error SSP matrix: The repeated measure has only two levels, or more levels than observations. When the repeated measure has two levels, the assumption of sphericity is always met.

Figure 17: Assumption Checks on Alpha2 FP1

ϵ = 1) indicates that the condition of sphericity is exactly met. The further epsilon decreases below 1 ($\epsilon < 1$), indicates the greater the violation of sphericity. The lowest value that epsilon (ϵ) can take is called the lower-bound estimate. Therefore, the epsilon is a statistic that describes the degree to which sphericity has been violated. From the table of sphericity test below, all epsilons are equal to one, it means that the conditions of sphericity are exactly met.

From the figure 18, the assumption check of homogeneity test for equality of variances (Levene's test) can not confirm the normality of the data on Block3 on 2nd difficulty level (p-value= 0.04 / p< 0.05). Therefore, there is a difference between the variances in the population.

Based on two-way mixed measures ANOVA result from the figure 19, we can conclude that Level * Block interaction has

Test for Equality of Variances (Levene's)

	F	df1	df2	p
V1_1st level	5.940	1.000	6.000	0.051
V2_1st level	0.001	1.000	6.000	0.972
V3_1st level	3.226	1.000	6.000	0.123
V1_2nd level	0.225	1.000	6.000	0.652
V2_2nd level	2.144	1.000	6.000	0.193
V3_2nd level	7.277	1.000	6.000	0.036
V1_3rd level	0.465	1.000	6.000	0.521
V2_3rd level	1.332	1.000	6.000	0.292
V3_3rd level	1.730	1.000	6.000	0.236
V1_4th level	0.109	1.000	6.000	0.752
V2_4th level	0.129	1.000	6.000	0.732
V3_4th level	2.746	1.000	6.000	0.149
V1_5th level	1.301	1.000	6.000	0.298
V2_5th level	0.158	1.000	6.000	0.705
V3_5th level	2.925	1.000	6.000	0.138

Figure 18: Test for equality of valances (Levene's) of Alpha2 FP1

a marginal result which indicates either significant or it does not affect the power spectrum of Alpha2 (F(8,48) = 1.929, p

Repeated Measures ANOVA

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Level	9.870e−22	4	2.467e−22	1.306	0.296	0.032	0.179
Level ∗ Label	4.455e−22	4	1.114e−22	0.590	0.673	0.014	0.089
Residual	4.534e−21	24	1.889e−22				
Block	2.956e−22	2	1.478e−22	0.430	0.660	0.010	0.067
Block ∗ Label	1.231e−22	2	6.154e−23	0.179	0.838	0.004	0.029
Residual	4.130e−21	12	3.441e−22				
Level ∗ Block	3.291e−21	8	4.114e−22	1.929	0.077	0.106	0.243
Level ∗ Block ∗ Label	1.688e−21	8	2.110e−22	0.990	0.456	0.054	0.142
Residual	1.024e−20	48	2.133e−22				

Note. Type III Sum of Squares

Figure 19: Alpha2 FP1 Mixed Measures ANOVA

= 0.08 / 0.05 < p < 0.1). Therefore, we considered analyzing these data further in the T-Test.

Independent Samples T-Test

Independent Samples T-Test

	t	df	p
V1_1st level	1.120	6.000	0.306
V1_2nd level	0.422	6.000	0.687
V1_3rd level	1.125	6.000	0.304
V1_4th level	1.495	6.000	0.186
V1_5th level	1.185	6.000	0.281
V2_1st level	2.734	6.000	0.034
V2_2nd level	−0.201	6.000	0.847
V2_3rd level	0.718	6.000	0.500
V2_4th level	0.672	6.000	0.527
V2_5th level	2.371	6.000	0.055
V3_1st level	−0.127	6.000	0.903
V3_2nd level	2.099	6.000	0.081 ᵃ
V3_3rd level	2.088	6.000	0.082
V3_4th level	3.004	6.000	0.024
V3_5th level	3.786	6.000	0.009

Note. Student's t-test.
ᵃ Levene's test is significant (p < .05), suggesting a violation of the equal variance assumption

Figure 20: Alpha2 FP1 Independent Samples T-test

From the figure 20, the Independent Samples T-Test shows that all of the experiment's results have a non-significant effect (p > .05). Since we do not have enough participants, the experiment could not provide a difference among them. However, the Independent Samples T-Test illustrates the significant effect on and block 3 on 4th difficulty level (p = 0.02 / p < .05) and block 3 on 2nd difficulty level (p = 0.08 / p < .05); however, block 3 on 2nd difficulty level did not passed the Levene's test that indicates a violation of the equal variance assumption.

JASP analysis using both data from Alpha1-FP1 and Alpha2-FP1 indicate that the 4th-difficulty-level factor has some significant effects on both power spectrum, Alpha1 and Alpha2 in FP1 electrode. Therefore, we decided to choose the 4th-difficulty-level factor as our training data that will be processed using the SVM model.

4.4.3 SVM:. Since the feature extraction indicated that the 4th-difficulty-level can represent the easy-stress state of participants, we used this data as input data to the SVM model with a linear kernel which was binary classification. Two bit codes were used (1, -1) to represent each class, which are Easily-stressed and Less-easily-stressed, respectively. The data of question 4th-difficulty-level was separated into each question by its time duration before it was sent to the model. The columns of data equal to (38s * 2 alpha band * 2 electords) + 1 labeling. Therefore, the shape of the matrix was 8 rows x 153 columns. We used 38s instead of 40s because some data was extracted at around 38s (it may happen due to some delays on the device). As a result, we had to cut each question into 38s in order to maintain the consistency.

The performance metrics of the classifier are classification accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). The classification accuracy is defined as the ability of the classifier to correctly identify positive and negative results. The formula can be seen in the figure 21.

$$Accuracy = \frac{TP + TN}{P + N} \times 100$$

Figure 21: Accuracy formula

The sensitivity measures the classifier ability to correctly identify positive result and calculated using the formula in the figure 22, where false negative (FN) refers to data points incorrectly labelled as stress at the corresponding level.

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

Figure 22: Sensitivity formula

Specificity gives a measure of the classifier ability to identify negative results defined as the formula in the figure 23.

$$Specificity = \frac{TN}{TN + FP} \times 100$$

Figure 23: Specificity formula

At the specificity formula, true negative (TN) are data points correctly labeled as not stressed at the corresponding level and false positive (FP) refers to data points incorrectly labelled as not stressed at the corresponding level. The positive and negative prediction values calculated using the below formula in the figure 24.

$$PPV = \frac{TP}{TP + FP} \times 100$$

$$NPV = \frac{TN}{TN + FN} \times 100$$

Figure 24: PPV and NPV formula

5 RESULT

In our experiment, we used the SVM method for classifying participants' mental state whether it is easily-stress or less-easily-stress. The classification report shows the main classification metrics precision, recall and f1-score on a per-class basis. The metrics are calculated by using true and false positives, true and false negatives. Positive and negative in this case are generic names for the predicted classes. There are four ways to check if the predictions are right or wrong:

- TN / True Negative: when a case was negative and predicted negative
- TP / True Positive: when a case was positive and predicted positive
- FN / False Negative: when a case was positive but predicted negative
- FP / False Positive: when a case was negative but predicted positive

Table 1: Classification report

Class	Precision	Recall	F1-score	Support
-1	0.00	0.00	0.00	1
1	0.50	1.00	0.67	1
AVG/Total	0.25	0.5	0.33	2

From the table 1, class -1 means "less easily stressed" and class 1 means "easily stressed". Precision is the ability of a classifier not to label an instance positive that is actually negative, which in our prediction percentage of class "less easily stressed" is 0% while the class of "easily stressed" is up to 50%. Recall is the ability of a classifier to find all positive instances, which in our percentage of the positive cases we acquired 0% for class "less easily stressed" and 100% for "easily stressed". The F1 score is a weighted harmonic mean of precision and recall such that the best score is 1.0 and the worst is 0.0. The percentage of positive predictions that were correct is 0% for class "less easily stressed" and 67% for class "easily stressed". In conclusion, we got an average precision 25%, average recall 50%, and the total classification accuracy 50%.

The statistical of assessment of how easy people get stressed by SVM is summarized in Table 2. The table provides the performance metrics (accuracy, sensitivity, specificity, positive predictive value(PPV), and negative predictive value(NPV)) of the classifier under the two levels of mental stress (Easily stress, Less easily stress). The results show that there is 50 percent for Accuracy, 100 percent for Specificity, and 50 percent for PPV. However, NPV is N/A due to division by zero exception.

Table 2: Statistical Parameters

Statistical Parameters	Value (%)
Accuracy	50.00%
Sensitivity	100.00%
Specificity	0.00%
PPV	50.00%
NPV	N/A

6 DISCUSSION

In our study, we used EEG signals to detect the stress level of participants while solving arithmetic tasks with five levels of difficulty. In this work our aim is to identify whether someone can get stress easily or less easily. We proposed an assessment method that combined subjective assessment results from questionnaires (pre and post questionnaire) and an objective assessment using EEG based stress detection system. Using the SVM as a classifier with mixed measure ANOVA analysis method we were able to identify participants that tend to get stress easily and less easily using their brain signals. From the subjective assessment using questionnaires, we found that 4 out of 8 participants were feeling stressed after completing the arithmetic tasks. It is also consistent with the result that we collected from the pre-questionnaire that was given before the experiment was conducted. The objective assessment using EEG signals demonstrated that we can detect stress among students and assess their stress level to identify whether they get stress easily or not according to their stress level. We obtained the average accuracy of 50% using the SVM classifier. Admittedly, there are few limitations of our study that need to be addressed in the future studies. Firstly, we only recruited nine subjects to perform the experiment, which is very few compared to previous studies. This few number of subjects may affect the accuracy that we got from the experiment. Future research will investigate the tendency of people to get stressed or not with more number of subjects. Secondly, in this study we used SVM as our classification method and obtained only 50% on the accuracy which is low compared to previous research. Future research will investigate the tendency of people to get stressed or not with more number of subjects. For further improvement we need to obtain a higher percentage of accuracy by improving the classification method and then comparing several classification methods such as Convolutional Neural Network (CNN) to compare the accuracy obtained from each method.

7 CONCLUSION

We have made a system that can measure how easy people get stressed by analyzing the EEG data. The designed system can distinguish human stress considering 5 levels of arithmetic tasks difficulty which corresponds to each level of stress to identify whether people have a tendency to get stress easily or not. The study reported a significant difference between the easily-stressed and less-easily-stressed people with an accuracy of 50% by using the proposed binary classifier SVM. Furthermore, the study revealed the dominance of the left-prefrontal cortex toward mental stress as supported by the result of t-test that showed a significant effect (p-values of 0.05).

The proposed stress assessment may therefore be used as a form for an early detection of mental stress disorders among students.

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