EEG-BASED STRESS RECOGNITION AMONGST UNIVERSITI SAINS MALAYSIA (USM) STUDENTS

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UNIVERSITI SAINS MALAYSIA

2021

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by

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Research project submitted in fulfilment of the requirements for the degree of Master of Cognitive Neurosciences

AUGUST 2021

ACKNOWLEDGEMENT

In the name of God, Most Gracious, Most Merciful, Syukur Alhamdulillah, thanks to ALLAH, the Almighty, for giving me the strength and confidence to complete Research Project Stage III.

My sincere gratitude and appreciation to my supervisor, Professor Dr Putra Sumari, for whom I respect and salute to the utmost degree. Thank you for providing me with this excellent opportunity to conduct research under your privilege's supervision. Thank you, Dr Putra Sumari, for your idea, support, advice, patience, cooperation, and understanding. Your guidance has enormously contributed a lot to my self-improvement. I want to thank my co-supervisor, Dr Mohamed Faiz bin Mohamed Mustafar for his ideas and advice. Thank you also to Dr Mohammed Faraque Reza, Dr Tahamina Begum, Assoc. Professor Dr Najib Majdi Bin Yaacob and Dr Anis Kausar Ghazali for their guidance and support. To the Program Coordinator, Master of Cognitive Neuroscience, Prof Dato' Dr Jafri Malin Abdullah, for believing in me and give me the courage to try this course. Finally, Dr Aini Ismafairus Binti Abd Hamid, for the time, ideas, opinions, as well as your support. Thank you.

Thank you to Audrey Antoine, Siti Hajar Zabri and Shamsul Omar Tajidin for their ultimate motivation and support. To my beloved husband, En. Mohd Zaki bin Abdul Razak for his moral support, thorough patience and understanding, sharing of knowledge, and heatedly assisting me in preparing this research project.

Table of Contents

LIST OF TABLES

Page

LIST OF FIGURES

Page

LIST OF SYMBOLS

δ	Delta
θ	Theta
α	Alpha
β	Beta
γ	Gamma
$\sum$	Sum

LIST OF ABBREVIATIONS

EEG	Electroencephalography
USM	Universiti Sains Malaysia
SRC	Students Representative Council
EDA	Energy
ENT	Entropy
SD	Standard Deviation
HPA	hypothalamus-pituitary-adrenocortical
Hz	Hertz
MLP	Multilayer Perceptron
SVM	Support Vector Machine
KNN	K Nearest Neighbors
NB	Naïve Bayes
LR	Logistic Regression
MSD	Mental Stress Detection
PCA	Principal Component Analysis
SMEQ	Subjective Mental Effort Questionnaires
MIST	Montreal Imaging Stress Task
MA	Mental Arithmetic
WT	Wavelet Transform
FFT	Fast Fourier Transform
LH	Intra-Left Hemisphere
IH	Inter Hemisphere
RH	Intra-Right Hemisphere
QDA	Quadratic Discriminant Analysis
IMF	Intrinsic Mode Function
AR	AutoRegressive
IAF	Individual Alpha Frequency
GSVM	Gaussian Support Vector Machine

PSS	Perceived Stress Scale
STW	Stroop colour-word test

LIST OF APPENDICES

PENGESANAN TEKANAN BERASASKAN EEG DI KALANGAN PELAJAR UNIVERSITI SAINS MALAYSIA (USM)

ABSTRAK

Pengenalan: Ramai pelajar bergelut dengan tekanan yang berkaitan dengan pembelajaran tidak kira di sekolah, kolej mahupun universiti. Penyelidikan telah menunjukkan bahawa pelajar yang mempunyai tekanan yang berlebihan akan menyebabkan kesukaran untuk fokus dalam pembelajaran dan ini memberi kesan yang negatif terhadap hasil akademik serta menjurus kepada masalah kesihatan.

Objektif: Kajian ini bertujuan untuk mengesan tekanan di kalangan pelajar prasiswazah dan pascasiswazah dari pelbagai fakulti Universiti Sains Malaysia (USM), Kampus Utama, Pulau Pinang.

Metodologi: Sistem *Electroencephalograhy* (EEG) digunakan untuk mengenal pasti corak otak pelajar sambil mendedahkan tahap tekanan yang berbeza. EEG dipilih kerana ia menawarkana beberapa kelebihan seperti pemerolehan data bukan invasif, kemudahan penggunaan, penyediaan kos rendah, resolusi temporal yang tinggi dalam milisaat. Selain itu, penyelidik menggunakan *Perceived Stress Scale (PSS10)* – instrument penilaian diri, untuk menilai tahap tekanan pelajar. Dalam kajian ini, penyelidik menggunakan empat ujian *Stroop* untuk mendorong tekanan.

Dapatan: Hasil kajian menunjukkan gelombang alfa dan beta adalah kumpulan frekuensi tinggi yang paling biasa di kalangan pelajar prasiswazah dan pascasiswazah. Penyelidik memutuskan untuk menggunakan kajian ini dari Priyanka (2016); oleh itu, gelombang beta dianggap sebagai tahap pengesanan tekanan. *Entropy* dan Standard *Deviation* adalah pengelas yang tepat untuk mengesan tahap tekanan. Analisis statistik menunjukkan nilai min bagi skor PSS10 sarjana muda (n = 24) = 21.67 dan bagi sarjana (n = 6) = 21.17 dengan nilai p .228. Nilai p lebih besar daripada 0.05 (p> 0.005), oleh itu, tidak ada perbezaan min yang signifikan dari *Perceived Stress Scale* antara pelajar sarjana muda dan sarjana dari pelbagai fakulti Universiti Sains Malaysia (USM), Kampus Utama (Pulau Pinang) semasa menjalani ujian tekanan. Untuk skor *Perceived Stress Scale* antara jantina (lelaki dan wanita) menunjukkan bahawa nilai min untuk lelaki (n = 15) = 21.47 dan perempuan (n = 15) = 21.67 dengan nilai p dari .847, dan nilai p adalah lebih besar daripada 0.05 ($p > 0.05$). Justeru itu, tidak ada perbezaan yang signifikan dalam skor tekanan yang dirasakan antara lelaki dan wanita dari pelbagai fakulti Universiti Sains Malaysia (USM), Kampus Utama (Pulau Pinang) semasa menjalankan tugas yang menimbulkan tekanan. ANOVA pengukuran dua hala untuk jangka masa tidak menunjukkan perbezaan yang signifikan dalam tempoh ujian Stroop (F (3, 87)) = 1.860, p = .142, dan untuk interaksi antara kumpulan tidak menunjukkan perbezaan yang signifikan dalam jangka masa daripada ujian Stroop antara program dalam empat ujian Stroop (F (3,84)) = .061, p = .980.

Kesimpulan: Ia boleh disimpulkan bahawa kajian ini yang mengesan tahap tekanan di kalangan pelajar yang menggunakan sistem EEG boleh mengubah cara pengesanan dan rawatan beberapa masalah kesihatan yang serius berbanding dengan amalan semasa yang lain. Ia memberikan kita penilaian yang berbeza tentang keadaan tekanan yang mungkin tidak mungkin bagi seseorang itu untuk menyatakan. Gabungan teknik pemprosesan isyarat seperti *Wavelet Transform* dan *Coiflet1* dengan tiga formula dari ciri *Energy*, *Entropy* dan *Standard Deviation* yang dibangunkan oleh analisis frekuensi masa isyarat EEG terbukti meningkatkan ketepatan.

Kata Kunci: *Gelombang Otak, Tekanan Pelajar, Elektroencephalography (EEG)*

EEG-BASED STRESS RECOGNITION AMONGST UNIVERSITI SAINS MALAYSIA (USM) STUDENTS

ABSTRACT

Introduction: Many students struggle with stress associated with their studies regardless of school, college, or university. Research has revealed that students who have excessive stress will have difficulty focusing on learning, which has a negative impact on academic outcomes that lead to health problems.

Purpose: This study aimed to detect stress among undergraduate and postgraduate students from various faculties of Universiti Sains Malaysia (USM), Main Campus, Penang.

Methodology: The electroencephalography (EEG) system was used to identify student's brainwave patterns while exposing different stress levels. EEG was chosen because it offers several advantages such as non -invasive data acquisition, ease of use, low-cost preparation, and a high temporal resolution in milliseconds. Besides that, the researcher used the Perceived Stress Scale - the self-assessment instrument, to assess students' stress levels. In this study, the researcher applied four Stroop Tests to induce stress.

Results: The results showed that the alpha and beta waves were the most common higher frequency bands among undergraduate and postgraduate students. The researcher decided to apply the study from Priyanka (2016); therefore, the beta wave was considered the stress detection level. Entropy and Standard Deviation were the accurate classifiers to detect stress levels. Statistical analysis showed the mean values for PSS10 Score undergraduate (*n=24*) = 21.67 and for postgraduate (*n=6*) = 21.17 with the *p*-value of .228. The *p*-value was greater than 0.05 ($p > 0.005$), therefore, there were no significant mean differences of the perceived stress scale between

undergraduate and postgraduate students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress-inducing tasks. For perceived stress scale score between gender (male and female) revealed that the mean values for male (*n=15*) = 21.47 and female (*n=15*) = 21.67 with the *p*-value of .847, and the *p*-value was greater than 0.05 ($p > 0.05$). As a result, there were no significant differences in perceived stress scores between males and females from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress-inducing tasks. The two-way repeated-measures ANOVA for duration revealed no significant difference in the duration of the Stroop tests ($F_{(3, 87)}$) = 1.860, p =.142, and for between-group interaction showed no significant difference in the duration of the Stroop tests between programs within the four Stroop tests ($F_{(3,84)}$) = .061, p = .980.
Conclusions: It can be concluded that this study that detects the stress level among students using an EEG system could alter the way of detection and treatment of some severe health problems over other current practises. It provided us with a more diverse assessment of stress conditions that might not be possible for one to express. The combination of signal processing techniques such as Wavelet Transform and Coiflet1 with three formulas from Energy, Entropy and Standard Deviation features developed by the time-frequency analysis of EEG signals proved to enhance accuracy.

Keywords: *Brain Waves, Students' Stress, Electroencephalography (EEG)*

CHAPTER 1

INTRODUCTION

1.1 Background

In the twenty-first century, mental stress has become a societal phenomenon. It affects the individual's and nation's ability to operate in their daily lives and economies. Stress was a term that everyone uses daily because it was unavoidable from time to time. Stressful situations surround modern life offerings challenges and human beings due to a hectic work schedule and deadlines, relationship difficulties, family issues, and financial problems. According to the National Health and Morbidity Survey (NHMS) conducted in Malaysia in 2017, one in every five adolescents aged 13 to 17 was depressed.

Two in every five were anxious, and one in every ten was stressed (NHMS, 2017). Because everyone was equally vulnerable to stress, detecting and monitoring stress levels for early diagnosis to prevent potential future illnesses was critical. Stress was defined as a state of emotional pressure or strain resulting from disturbing or challenging circumstances (Mheidly, N., et al., 2020). Some of the major effects of stress on the primary biological systems of humans (Yaribeygi, H., et al. 2017). The researchers conducted surveys and monitored stress levels to understand better how each coped with stress differently.

Stress can be classified as both beneficial and harmful. Beneficial stress raises awareness and alerts to danger, resulting in better outcomes. In contrast, harmful stress could cause social and emotional changes when one does not feel at ease connecting to various issues (Pera, A. 2020).

Enthusiast stress arises due to job pressure, compliance with time limits, examinations, and many more reasons. There were numerous causes of initiation of stress. Researchers considered the human brain to be the primary source of stress. Therefore, surveys and individual monitoring were used to investigate the impact of stress on different people. One of the most common methods for determining an individual's stress level was to conduct a self-assessment questionnaire (Crosswell, A. D., and Lockwood, K. G., 2020).

Stress had become part of the lives of students and employees due to the multiple internal and external demands assigned to them and mainly being exposed to social stress issues as changes arise at the individual and community level. It was, therefore, essential to detect stress to obtain appropriate and successful prevention efforts. Stress was a condition that arises when people was presented with events that they interpret as endangering their physical or psychological well-being and are unaware of their ability to cope with those events (Cohen, S., Murphy, M., and Prather, A. A., 2019). Sources of stress were referred to as stressors. Based on most research, stressors include environmental, human, and organisational variables (Bhui et al., 2016).

The question now was whether it was possible to detect stress in its early stages. It was, indeed. Many psychologists or therapists do this. However, it takes active participation on the part of the person seeking treatment. In some cases, whenever a stressed person was incompetent to reveal himself honestly, this situation may not be achievable. It complicates the job of a therapist. This issue was solvable if brain signals are recorded and analysed to detect stress. Neuron signals and brain signals are the same things. Electric potential was generated in various parts of the brain by the electrical activity of neurons (Chrysafides SM, Bordes S, Sharma S., 2021). The difference in these electric potential levels can be measured and used for various applications, such as stress recognition (Abdulkader, S. N., Atia, A., and Mostafa, M. S. M., 2015).

These brain signals are known as Electroencephalogram (EEG) signals. Different types of brain states result in different kinds of neuronal electrical activity in the brain. Therefore, various signal values appear in different mental processes. These sensors could be recorded using various available equipment, including electrodes placed on the scalp with conductive gel between the electrodes and the scalp. Electrodes are attached to the scalp in various locations to collect sensory information from areas of the brain. Stress cannot be discovered using unprocessed EEG signals directly. It needs to be extracted practical features that can be used with various algorithms, and a pre-processing was needed. (Attallah O, 2020; Chetan et al., 2016).

1.2 Problem Statement

A university academic life was the most constant period in the lives of young people. It can occasionally present significant challenges to learn, enjoy, meet new people, and live simultaneously. Inability to address these issues effectively may result in poor mental health and negative implications for those involved. Hence, youths can be tense and concerned about their upcoming years. Severe cases can worsen the symptoms, anxiousness, and even death. Effective analyses of young people's mental health must be conducted regularly to avoid such problems occurring (Bhui et al., 2016).

Stress was defined as any situation that causes a person to experience unpleasant emotions. Individuals do not experience negative thoughts and feelings when stressed because they do not have the same disorder. One significant problem with academic stress was that it affects both studying and wellbeing. According to research presented at a Malaysian public university, the adaptation issues faced by the first learners were educational, wellness, financial collapse, and individual and societal problems. The purpose of this study was to detect or stress recognition via EEG-based.

This research was necessary, created a baseline stress detection dataset and could be included in the current literature.

1. To provide advice or direction for dealing with student stress more successfully.

2. It was hoped that the findings of this study would contribute to future research on public and private universities.

3. The study may also assist Universiti Sains Malaysia (USM) in closely monitor the students in terms of stress.

4. This study aimed to identify stress levels among students at Universiti Sains Malaysia (USM) and other Malaysian universities.

The study would not only contribute to detecting the stress, thus assisting the respective institution on early detection of stress among students. The researcher hopes that this piece of work would be of great importance to a large number of institutes or organizations concerned with the well-being of students pursuing tertiary education in the various universities in this country.

This study acts as a guide for other campus-based institutes like the Students Representative Council (SRC), counsellors, lecturers and teachers who handle students and individuals who might be going through stress.

1.3 Research Objective

1.3.1 General

To detect stress among the students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang).

1.3.2 Specific

Research Objectives

1. To identify the brain activation (gamma, beta, alpha, theta and delta) differences among the undergraduate and postgraduate students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress inducing tasks.

2. To determine the features extraction of Energy (EDA), Entropy (ENT) and Standard Deviation (SD) considered an accurate classifier to detect stress.

3. To compare the mean differences of perceived stress scale score among undergraduate and postgraduate students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress inducing tasks.

4. To compare the mean differences of the perceived stress score among male and female students.

5. To compare the four Stroop Test duration among undergraduate and postgraduate within the four Stroop test.

Hypothesis

H1: There was brain activation differences among the students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress inducing tasks.

H2: Entropy (ENT) and Standard Deviation (SD) considered accurate classifier to detect stress level among the students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang).

H3: There was significant mean difference of Perceived Stress Scale between undergraduate and postgraduate students from various faculties of Universiti Sains Malaysia (USM), Main Campus (Penang) during stress inducing tasks.

H4: There was a significant difference of perceived stress score between male and female.

H5: There was significant difference of the Stroop Test duration between undergraduate and postgraduate within the four Stroop test.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Background of the study

In this study, the researcher aimed to detect stress during a task to the participants to induce stress. A questionnaire was one of the traditional methods for detecting stress. This method was entirely dependent on the responses given by individuals; people will be hesitant to say whether they were stressed or normal. Only medical and physiological experts could determine whether a person was depressed (stressed) Sriramprakash, S. et al., 2017). Another method, Electroencephalogram (EEG), is a non-invasive and electrophysiological technique for recording electrical movement from an individual brain. Because of its exceptional temporal sensitivity, EEG is most useful in assessing dynamic cerebral functioning (Britton, J.W., et al., 2016). The past research helped the researcher better understand how the previous researchers conducted their EEG research and detected stress.

Stress detection was a topic of ongoing research among both psychologists and engineers. People experience stress in their daily lives (Can, Y. S., Arnrich, B., and Ersoy, C., 2019). Stress means different things to different people in different situations. Hans Selye suggested the most basic meaning of stress: “Stress was indeed the body's non-specific reaction to every request” (Godoy, L. D., et al., 2018)." Selye's broad definition applied to the stress response in all three phylogenetic domains of organisms, from bacteria to humans. Other definitions have evolved to address specific situations, such as cognitive (G. Fink, 2017).

Stress could impair the responsiveness of central-peripheral regulatory systems, allowing someone to be less efficient in improving wellness (Forteza, F. et al., 2021). It had been described as a critical contributor to neurological disorders and lost productivity. It influences oneself willingness to work, quality at work, and one's view of life. Chronic stress has been linked to several health problems. (Al-Shargie et al., 2016). Stress was essential in fundamental and medical neuroscience studies (Romeo, R. D., 2017). This neurological occurrence was necessary for survival and was strongly linked to several mental illnesses, including depressive symptoms, anxiety, and post-traumatic mental disorder (Nemeroff, 2016).

Although stress study remains a challenge, a few types of research in living creatures have contributed significantly to its advancement in past years. There were several studies on stress focused on a different section of the human brain. A study on the nervous system concerned with stress was complex, with modulation at multiple central nervous system stages that control learning, cognition, and rational decisions (Bains et al., 2015). The hypothalamus-pituitary-adrenocortical (HPA) vector and the nervous system were triggered in response to stress (Herman, J. P., et al., 2016). When the HPA vector is activated, the suprarenal glands produce glucocorticoids (cortisol), regulating many biological processes such as heart rate, blood, and metabolism of glucose (Godoy et al., 2018).

2.2 Electroencephalography or EEG

EEG was one of the earliest and most well-known methods of determining sensory neurons in the brain with numerous applications in neurological practice. EEG measures the difference in the electrical energy among the set of electrode pairs placed around different areas of the head. EEG was a method of examining and documenting data about the electrical movement of the individual brain. EEG signals were produced by natural and recurrent stimuli of the brain nerve cell. In neuroscience and psychology, it was proposed that EEG signals could explained affected brain conditions and human actions (Ackermann et al., 2016). Despite having low longitudinal solution, this method has a greater temporal resolution (fit for hundreds of Hz). Hence, EEG can deduce brain flows (typically ranging from one to 100 Hz) and electric potentials induced by specific events (He, B., et al., 2018).

EEG was a practical tool for studying the wide-ranging neuronal circuit fleeting trends inside the human brain. Electrodes were positioned on the head's skin to keep strong interaction with the scalp and record electrical activity induced by neural action (Britton et al., 2016). As for its high temporal resolution, EEG provided good observational data of mental status variability. The person's conscious level determined the amplitude and frequency of the EEG waveform (Roohi-azizi et al., 2017). Table 2. 1 showed the characteristics of the five basic brain waves and Figure 2. 1 showed the brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves.

Table 2. 1 Characteristics of the Five Basic Brain Waves

Signal	Frequency	Brain states
Gamma (γ)	>35 Hz	Concentration
Beta (β)	12 – 35 Hz	Anxiety dominant, active, external attention, relaxed
Alpha (α)	8 – 12 Hz	Very relaxed, passive attention
Theta (θ)	4 – 8 Hz	Deeply relaxed, inward focused
Delta (δ)	0.5 – 4 Hz	Sleep

Source: Priyanka et al., (2016)

Brain waves were oscillating electrical voltages in the brain that were only a few millionths of a volt in magnitude. There were five widely recognised brain waves, and the main frequencies of human EEG waves and their characteristics were listed in Table 2.1. Different parts of the brain do not emit the same brain wave frequency at the same time. An EEG signal between electrodes placed on the scalp was made up of many different waves. The large amount of data was taken from even a single EEG recording complicates interpretation. All person's brain wave patterns were distinct (Priyanka et al., (2016).

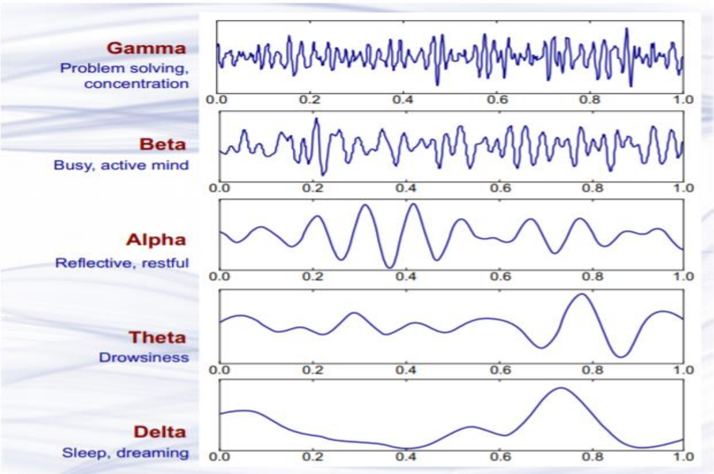


Figure 2. 1 Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves. Source: Priyanka et al., (2016)

EEG correlated with mental stress because of suppressing alpha waves and improving theta waves. Alpha waves were more highly activated in the occipital and frontal regions of the brain (Nunez, P. L. (2016). Alpha waves were dominant when there was no stress, and the brain was not active. In stressful situations, the power of alpha waves decreases, indicated a change in response. Beta waves behaved differently in different parts of the brain at different frequencies, and theta wave power increased during stress, or mental tasks showed the activity of EEG signals during stress (Chandra, S. et al.,2017).

In stress research, the most common active brainwaves were Alpha and theta bands. However, the researcher decided to apply the characteristics of brainwaves from Priyanka, et al., (2016) suggested that the beta band contributed to stress condition.

2.3 Stress and Electroencephalography studies (EEG)

Stress research was a growing field of study of electroencephalography (EEG) signal processing (Katmah, R., et al. 2021). When mental health facilities were unavailable, use EEG as a continuous action for a cost-effective and individually tailored strain procedure. Stress could be monitored and assessed using perception, behaviour, and physiological consequences. Psychological questionnaires were frequently used to gather stress from behavioural changes (Crosswell, A. D., and Lockwood, K. G., 2020). Advancement in science and technology has provided methods for measuring stress using neurophysiological signals, which involved neurological signals (Borghini, G., et al., 2020). Many types of research have been conducted regarding stress and EEG with the different focus of the brain areas and waves. Table 2.2 summarises previous studies related to mental stress classification using EEG signal. These studies contributed outcomes and knowledge concerning to the researcher's understanding of stress and EEG.

Table 2. 2 Previous studies related to mental stress classification using EEG signal

Year	Subjects	Number of channels	Types of stress	Duration	Frequency bands	Features
2021	25	7	Mental arithmetic	15 minutes	Alpha	Power Spectral Density
2020	25	4	Montreal Imaging Stress Test	24 minutes	Theta, Alpha, Beta, Gamma	Frontal asymmetry alpha, beta, and gamma power
2020	33	5	Baseline Stress	39-58 minutes	Delta, Theta, Alpha, Beta	Neural oscillatory
2020	50	1	Computer Task	10 minutes	Alpha, Beta	Statistical Analysis
2020	20	14	Cognitive Task	30 minutes	Alpha	Discrete wavelets transform
2019	24	2	Cognitive Task	11 minutes	Delta, Theta, Alpha, Beta	Power Spectral Density
2019	14	3	Mental arithmetic, Stroop Test	34 minutes	Low (0.04-0.15Hz) High (0.15-0.4Hz)	Normalized band power, power asymmetry
2019	17	14	Mental arithmetic task, relaxing videos, playing games	31 minutes	Delta, Theta, Alpha, Beta	Shannon entropy, mutual information, covariance, precision
2018	10	4	Montreal Imaging Stress Test	30 minutes	Theta, Alpha, Gamma	Average relative gamma
2018	1	14	Mental Arithmetic	31 minutes	Delta, Theta, Alpha, Beta	Self-Entropy, Mutual Information, conditional mutual information
2018	28	1	Baseline stress	3 minutes	Low beta, high beta, low gamma	Neural oscillatory features
2018	23	30	Trier Social Stress Test	13 minutes	Delta, Theta, Alpha, Beta	Transivity, modularity, path

						length, efficiency
2017	25	7	Montreal Imaging Stress Test	10 minutes	Delta, Theta, Alpha, Beta	Canonical Correlation Analysis
2017	28	1	Baseline Stress	3 minutes	Low beta (13-17Hz) High beta (18-39Hz)	Low beta waves, Linear regression
2016	22	7	Montreal Imaging Stress Test	25 minutes	Delta, theta, alpha, beta	Mean power
2016	6	14	Mental Arithmetic	20 minutes	Delta, theta, alpha, beta	Intrinsic mode function, instantaneous frequency (using Hilbert-Huang Transform)
2016	10	14	Mental Arithmetic Task, Stroop Test	18 minutes	Theta, alpha, beta	Power Spectral Density, relative difference of alpha and beta power
2015	9	14	Stroop Colour Words Test	12 minutes	Theta, Alpha, Beta	Power Spectral Density, Fractal Dimension, Six statistical features.

Source: Katmah, R., Al-Shargie, F., Tariq, U., Babiloni, F., Al-Mughairbi, F., & Al-Nashash, H. (2021).

2.3.1 The Multilevel Classification of Stress Using EEG

This study was about the researchers (Al-Shargie et al., 2017) using EEG to classify multilevel psychological stress (Katmah, R. et al., 2021). Their study measured to distinguish between stress and rest states during mental arithmetic tasks and based on the emotional tension, and the researcher categorised it into three-level namely L1 (Level 1), L2 (Level 2) and L3 (Level 3). They conducted the psychological arithmetic tasks with three difficulty levels associated with the degree of anxiety. They applied the method of time constraints and peer criticism were used in the experiment as the stressors. To classify the stress level L1, L2 and L3, the researchers used the multiclass classifier known as Support Vector Machine (SVM). SVM was supervised (programming) to conduct learning models with related learning algorithms (Gudivada, V. N., et al., 2016) that analyse data for the categorisation and regression analysis. In their study, 12 male adults aged 20 to 24 were involved. The inclusion of their study focused only on right-handed and healthy participants. The participants' EEG signals were recorded for quarter-hour as they solved math challenges. The researcher used the BrainMaster 24E system – EEG biofeedback, which had seven active electrodes, namely Fp1, F3, F7, Fz, Fp2, F4, and F8, and one reference, A1 connected to the ears, to evaluate the EEG signals. To investigate the effects of arithmetic tasks on mental stress levels, the researchers computed the alpha and beta frequency values in all electrodes for all participants. When participants were exposed to high levels of stress, the results of their EEG recordings revealed that they were unable to keep up with the tasks given and seem to be less responsive (Saeed et al., 2020). This situation indicated that cortical stimulation expanded with minimal strain and lessened with high-level tension and lack of time. The findings revealed that alpha frequency decreased from level one to level two of mental stress but did not decrease from level three.

On the other hand, beta frequency enhanced with maths response speed, suggesting that participants were required to pay closer attention to complete the task under time limits. However, their attention would reduce as they confronted high-stress levels. The study discovered a dominant alpha frequency in the right prefrontal cortex (Srinivasan, R., and Nunez, P. L., 2016), recommended as an appropriate biomarker or mental stress. Their study only focused on two brainwaves, mainly alpha and beta. They predicted that these two frequencies contributed to the stress level of the participants. Stressors such as constraints, time, and peer criticism were considered excellent methods to induce the stress. Hence, the researchers were not further explained in detail on how the peer criticism was conducted. This research provided an important information on the techniques to induce the stress.

2.3.2 Stress Detection Using Perceived Stress Scale and EEG

The researchers studied the relationship between stress detection and EEG by conducted human stress recognition using two different labelling techniques. Saeed et al. (2020) used self-assessment questionnaires and specialist assessment to classify the increased tension in humans using EEG signals. In the data collection process, the EEG signals were taken when the participants were at rest for three minutes and at the condition of closed eyes. The researcher used the EMOTIV Insight headset in their study with five channels – AF3, AF4, T7, T8 and Pz. After documentation of EEG data, the participants were asked to complete the PSS-10 survey questions and then meet with a psychologist for about 25 minutes.

Based on the PSS scores and interviews, the psychiatry classified each participant into two categories - stress and control. This study involved 33 participants that were split into two groups: stressed and non-stressed. The research findings showed that when an expert evaluation was used as ground truth (Hoel, E., 2021), alpha asymmetry was discovered to be a distinguishing characteristic among the 45 signal features used to classify chronic stress.

The alpha asymmetry was suggested as a promising market for detecting chronic stress in individuals (Quaedflieg et al., 2016). The researcher performed a test and validated the proposed model, including the five classifiers. When they compared to alpha asymmetry, the classification accuracy of gamma and beta oscillations was lower. Alpha asymmetry, beta, and gamma waves from channel AF3 were used, and the five classifiers were known as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Linear Regression (LR), Multilayer Perception (MLP) and Naïve Bayes (NB) were used to classify long-term stress. The stress group was straightforwardly classified than the control group regardless of the five classifiers used. No significant factors were found when the Perceived Stress Scale (PSS) scores were used exclusively for labelling. Based on their results, the Support Vector Machine (SVM) and the Logistic Regression (LR) contributed the highest classification accuracy of 85%. The SVM classifier was used, and the researchers determined that alpha asymmetry could be used as a potential biomarker for long-term stress classification. They suggested that due to the limited size of the data, Multilayer Perceptron (MLP) was the only class of neural network-based classifier that could fit for stress classification.

For the researcher’s study, the perceived stress scale (PSS) was used to identify the participants' stress levels. The higher the scores (value point of 28 scores and above), the participant was considered as in the stress condition. However, this PSS method was used to identify the participants' stress levels, not to diagnose mental stress among the participants.

2.3.3 Establish Mental State Using EEG Signals

The study of Attallah O. (2020) investigated a person's mental state by analysing EEG signals. Her primary goal was to develop a suitable real-time EEG-based mental training neuro-feedback system for detecting and assessing stress levels in real time. In her study were 36 (females – 27 and males – 9) and the age range of 18.6 years old. The inclusion of this study was that the participants were eligible for not having any medical signs of cognitive or mental deficiency, oral or nonverbal learning disabilities, and normal or adjusted-to-normal image awareness and colour vision. Medication, psychoactive drugs, and neurological or illnesses were all considered as exclusion criteria. The electrodes involved in this study were temporal lobe - T3, T4, T5, T6, frontal lobe - Fp1, Fp2, F3, F4, Fz, F7, F8, central area - C3, C4, Cz, occipital lobe - O1, O2, and parietal lobe O1, O2) (P3, P4, Pz). The ear electrodes were used as a reference.

The researcher also conducted specific tasks to induce stress, and it was the mental arithmetic task. During the calm state, the tasks consist of specific mathematical counting events and series of calculations of two numbers. Throughout the stress condition, the tasks consist of counting and a series of subtraction of two numbers. Each series calculation test started by deducting four figures from two. The researcher divided the participants into two groups - the first group was high stress, which included the participants who struggled with the arithmetic tasks and exercised more effort to complete the arithmetic tasks. The low-stress group consisted of participants who completed the arithmetic tasks without any difficulties.

The researcher proposed a new system for detecting stress conditions and classifying the degree of stress. Thus, the two mental stress conditions were measured in the study. The three experiments were involved in the proposed Mental Stress Detection (MSD) system. In experiment one, the two feature sets were used separately to build the MSD system, then merge to form a hybrid feature-set to investigate the effect of combining time and frequency features. In experiment two, the electrodes were placed on different sites on the skull. The two feature sets were used separately to build the MSD system in the first test, then combined to form a hybrid feature-set to investigate the effect of combining time and frequency features. To reduce the number of channels used to build the MSD system and improve the effectiveness of the proposed approach, the location with the most significant influence on the system's accuracy was chosen. Finally, in experiment three, the Principal Component Analysis (PCA) feature reduction method was used to select the optimal number of PCA in sequential forward search and reduce the dimension of feature space (Jollife, I. T., and Cadima, J., 2016).

The five well-known classification models were built using the three feature sets created during the feature extraction phase. Linear discriminate analysis (LDA), k-nearest neighbour (KNN), linear and cubic support vector machine (SVM), and random forest classifiers were all examples of classifiers (Thanh Noi, P., and Kappas, M., 2017). For the KNN, the Euclidian distance metric was used, and the number of neighbours (K) was equal to one. Initially, these classification models were used to distinguish between stress and non-stress states. They were then used to distinguish between two levels of stress (low and high-stress levels). All models were tested using five-fold cross-validation. Based on the findings, frontal brain activation significantly impacts the detecting and evaluating stress levels. The study found that Principal Component Analysis (PCA) could reduce the feature space and improve stress detection rates. Only one or two frontal electrodes could detect stress and non-stress. The three frontal electrodes, on the other hand, could assess stress levels. The results showed that the proposed method could identify and classify stress levels based on a hybrid feature set.

2.3.4 Stress Recognition with Different Stress-Relief Approaches Using EEG

In the study of Zhang, Y., et al. (2020), their research was about the possibility of recognising different stress levels using electroencephalography or EEG and assessed the effectiveness of a variety of stress-relief methods. A total of 25 with 14 males and 11 females aged 16 to 19 years were involved. The researcher collected the data while the participants were at rest, and they used three different levels of stress induced through mental arithmetic tasks. The EEG signals were recorded from four active electrodes namely FP1, FP2, TP9 and TP10 that was placed on the forehead and behind the ears using the MUSE headband. The experimental process divided into two stages – stage one involved of three rounds of mental arithmetic tasks based on Montreal Imaging Stress Task (MIST) as induced task (Al-Shargie, F., Tang, T. B., and Kiguchi, M., 2017) and in stage two, there were five activities, and one of the five stress-relief tasks was presented in each round.

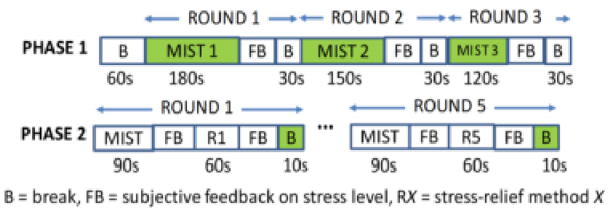


Figure 2. 2 The experiment timeline

Figure 2.2 showed that the experiment timeline where in Phase 1, the participants carried out three MIST tasks with the durations last from 180s to 150s to 120s, to induce three different stress levels. In phase 1, the participants required to solve the same number of the mental arithmetic questions in each task as the time limit decreases. In Phase 2, there were five rounds, and one of the five stress-relief tasks is presented in each round. The EEG data in the highlighted green sections was used to train the classification models to differentiate the four sessions: rest state, and three levels of stress through MIST 1, MIST 2 and MIST 3.

In this study, the researcher used Linear Discriminant Analysis (LDA) as the classifier to classify the stress level. The stress levels were classified based on the average of accuracies of the 10-fold cross validation (Iqbal, T., et al., 2021). The participants also required to fill in the Perceived Stress Scale (PSS) form with the stated scores of 1=very calm and 9=very stress during the MIST tasks. It slightly differed from the original PSS introduced by Sheldon Cohen where the score from 0 = never and 4 = very often. Nonetheless, the aimed of the PSS was to detect the level of stress among the participants during the MIST tasks so that the researcher can categorized them. From the EEG data analysis, they identified that the time segment and the frequency bands that generated rather greater classification accuracies of 86% and 71% for the 2-class and 3-class of LDA classifier and the power of beta and the prefrontal relation to the power of gamma was found to be considered as stress level.

2.3.5 Mental Stress Quantification Using EEG

In this study, the researchers (Al-Shargie et al., 2016) used an arithmetic task to design stress stimuli to elucidate three stress levels. The researchers hope to distinguish between stress levels and rest states using EEG signals collected while performing mental arithmetic tasks. To simulate the brain, they used three levels of difficulty in mental arithmetic tasks. The participants in this study were twelve healthy male right-handed adults ranging in age from 20 to 24 years. The Brain Master 24E system, which had seven active electrodes Fp1, F3, F7, Fz, Fp2, F4, and F8 and one reference A1 attached to the earlobes, was used to record EEG signals from the frontal cortex. The international 10-20 electrode placement system was used to place all electrodes on the surface scalp. The sampling frequency of the EEG was set to 256 Hz. By applying a small amount of gel directly to the scalp, the impedance of the EEG was reduced. They developed the control technique in this experiment by sending a marker through EEG Brain-Master channels 23-24. A marker with the value '1' indicates the start of the task, and a marker with the value '0' indicates the end of each block's task. The entire track, which lasted nearly an hour, was composed of four blocks.

The mental stress experiment was designed using the Montreal Imaging Stress Task (MIST). The protocol for the experiment consisted of four steps. 1) The participants were given a quick overview of the experiment. 2) The participants were trained for five minutes at each level of difficulty in the mental arithmetic (MA) task to estimate the time required to answer each question. 3) (control phase), the participants' EEG signals were recorded for a total of 15 minutes while they solved arithmetic problems of varying difficulty with no time limit per question. Following the EEG recording, the participants completed a task loading questionnaire using the NASA-TLX rating scale. Furthermore, to stress the participants, the average time recorded during the training phase was reduced by 10%. (Stress phase). In this study, the proposed wavelet transform (WT) for feature extraction can deal with both stationary and non-stationary signals. WT may provide useful features that were highly correlated with levels of mental stress because EEG signals were non-stationary (Rhif, M. et al., 2019).

This research aimed to distinguish among stress and relaxation states using EEG signals accumulated as performing a three-level mental arithmetic task. In this experiment, stress levels were determined by time constraints and negative feedback. This study developed mental stress stimulus caused variations in cortical brain activity as measured by EEG signals (Khosrowabadi, R. (2018). To investigate the effects of mental stress levels induced by arithmetic tasks, the researchers calculated the alpha and beta rhythm power values in all electrodes for all subjects.

When subjects were exposed to high levels of stress, the results of their EEG recordings revealed that they were unable to rest and seemed less responsive, which means that cortical stimulation rose with minimal stress and reduced with high stress and time limit. Their findings revealed that alpha rhythm energy decreased from level one to level two of mental stress but did not decrease from level three. However, beta rhythm power increased with mental arithmetic response speed, implying that subjects needed to pay more attention to finish the task under time constraints, but their attention would decrease when they were stressed (Al-Shargie et al., 2017; Newson, J. J., and Thiagarajan, T. C., 2019).

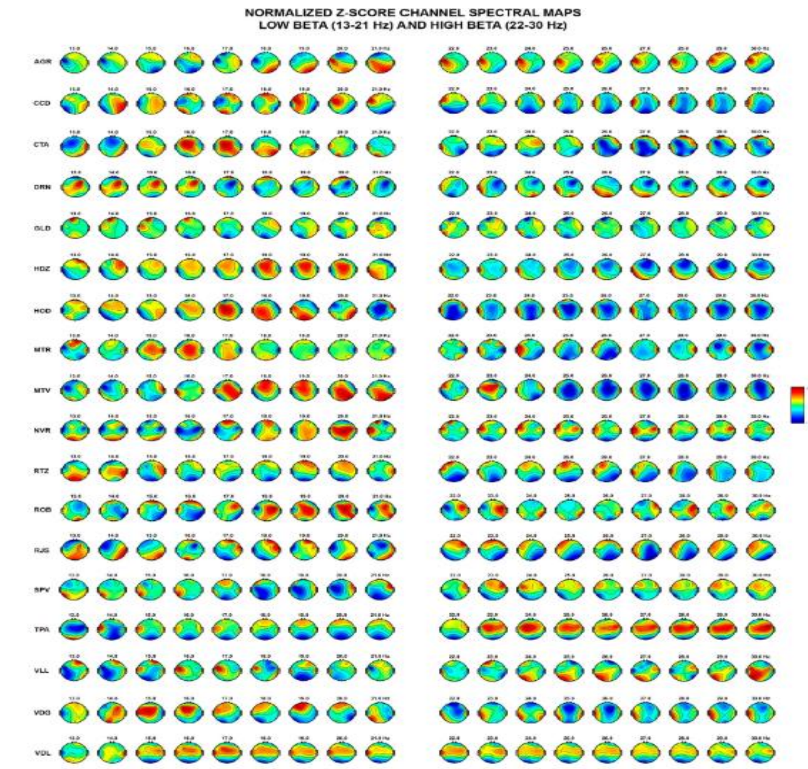
2.3.6 Assessing Stress and Anxiety based on EEG Beta Frequency Band

In this study, Hernán et al. (2019) investigated on the beta wave of low and high during the three minutes of resting, basal closed eyes situation. The total of twenty-six healthy adults aged 25 to 45 were participated in this study. EEGLAB toolbox on MATLAB2008a was used to filter the beta frequency and pre-processed by the visual inspection and artefactual component cleaning with automatic detection and assisted rejection. They obtained the two minutes of clean EEG data in the basal closed eyes condition for each participant. The researcher used Fast Fourier Transform (FFT) to filter the bands which was based on the three EEG time series of two minutes each. The bands that involved were beta (13-30 Hz), beta low (13-21 Hz), and beta high (22-30 Hz) and these bands were assessed to identify the level of highly correlated with the EEG electrodes (Alptürk, E. K. and Kutlu, Y., 2020). Then, it will be sorted it into the three interconnection systems of Intra-Left Hemisphere (LH), Inter Hemisphere (IH), and Intra-Right Hemisphere (RH) for two levels of basal conditions with the closed eyes state for three minutes.

The EEG data were collected at a 128 Hz sampling rate involved 14 channels - AF3-AF4, F7-F8, F3-F4, FC5-FC6, T7-T8, P7-P8, O1-O2 and referenced to mastoid bones using EMOTIVE EPOC Research Edition. For the time-domain amplitude analysis power spectral records were required, and the electrodes were averagely re-referenced. The reason of re-referenced was to express the voltage at the EEG scalp channels about a new reference (EEGLab.Org., 2021; Olejarczyk, E., Bogucki, P., and Sobieszek, A., 2017; Choi, S. I., and Hwang, H. J.,2019).

Based on Figure 2.3, the individual EEG signal during relaxation, basal eye closed situation, for low (12-21Hz) and high beta (22-30Hz) displayed as cortical relative power spectral maps. Over striking from observed distribution, a Yerkes-

Dobson profile (relationship between performance and arousal (Yebra, M., et al., 2019)) of arousal versus stimulation, none of the extremes (red or blue) was advisable.



Normalized z-score power spectral maps for low beta (13-21 Hz) left, and high beta (22-30 Hz) right, during basal EC condition for a representative sub-sample of eighteen subjects.

Figure 2. 3 Normalized Z-Score Channel Spectral Maps Low and High Beta

The figures (Figure 2.3) were rather activated in the middle have a small number of extreme power spectrum maps for less variable extremes of energy distribution. Concerned with low (left) and high (right) beta, the researcher’s proposed to reduce the power in the fast beta oscillation range of 22-30Hz. When the eyes were closed at rest, their brain's workload was expressed as the inverse percentage of synchronised channels. It described the effect of unexpected, self-generated, self-sustaining, and power-use endogenous attractors on desynchronizing the global beta EEG signal and driving it away from the natural relaxing synchronicity promoting attractor. The scientists investigated the change from basal eyes closed conditions to the subsequent