MENTAL WORKLOAD CLASSIFICATION ON TWO FRONTAL EEG CHANNELS USING ARTIFICIAL NEURAL NETWORK WITH PEAK FREQUENCY BASED INTRINSIC MODE FUNCTION SELECTION

MOHD NURUL AL HAFIZ BIN SHA'ABANI

A thesis submitted in
fulfilment of the requirement for the award of the
Doctor of Philosophy in Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

OCTOBER 2022

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious and the Most Merciful. Alhamdulillah, I have finally completed this thesis successfully. First and foremost, I would like to express my appreciation to my supervisor Assoc. Prof. Ir. Ts. Dr. Norfaiza binti Fuad for her compassion, wisdom, guidance and enthusiasm throughout this PhD study. Her willingness to help and continuously giving motivation has greatly encouraged me to complete this thesis. Not to forget those who were great and once supervised me, Dr. Babul Salam KSM Kader Ibrahim and Dr. Saiful Huq, a special thanks to them.

I would like to extend my gratitude to the Universiti Tun Hussein Onn Malaysia for awarding a scholarship for this journey, to the Faculty of Electrical and Electronic Engineering for providing facilities and services, and to the Centre for Diploma Studies for allowing me to pursue this PhD study. For my colleagues, especially in the multidiscipline research group (MDRG), thank you for the continuous support and cheers.

Last but not least, my deepest appreciation to my parents, Sha'abani and Katirah, my parents in law, Md Jamal and Leli, my lovely wife, Norezmi, my little daughter, Nurawatif, and to all the family members for their love, prayers, support and understanding that significantly contributed to this achievement. Finally, thank you to everyone and institution who have assisted me in the accomplishment of this thesis.

ABSTRACT

Recently, the cognitive neuroscience research community has been interested in measuring mental workload based on electroencephalogram (EEG) signals. In multichannel EEG studies, it is reported that the signal from the brain's frontal area is associated with mental workload. Hence, using a single or a few EEG channels could be feasible. However, the challenge is to remove the presence of artefact in the EEG signal since not all existing methods in multichannel EEG work well when using a single or a small number of channels due to the limited signal sources. To overcome the limitation, this thesis proposed using the ensemble empirical mode decomposition (EEMD) technique. The EEMD heuristically decomposed the EEG signal in the time domain into a series of intrinsic mode functions (IMF). Here, a new technique is proposed for selecting the significant IMFs based on the peak frequency of power spectral density. To evaluate the performance of the proposed method, a mental arithmetic task and a building structure task are designed to stimulate the mental workload of cognitive and psychomotor activities. A cross-task and a cross-subject classification based on the designed mental workload task have been done. Relative power, Shannon entropy, log energy entropy, skewness and kurtosis were extracted as features. Results show that the EEMD coupled with ANN provides the best overall performance compared to the other classifiers. In cross-task classification, the classification accuracy achieved 90.0% when using the log energy entropy feature. While in cross-subject classification, the accuracy achieved 76.7% and 86.7% for mental arithmetic and building structure tasks, respectively when the Shannon entropy feature was used. In a comparative study, the EEMDANN and log energy entropy features provide better accuracy in cross-task and cross-subject classification than the previous studies. In conclusion, this work has contributed to the EEG-based mental workload evaluation using a small number of EEG channels.

ABSTRAK

Kebelakangan ini, komuniti penyelidikan dalam bidang neurosains kognitif berminat dalam mengukur beban kerja intelektual berdasarkan isyarat EEG. Dalam kajian EEG berbilang saluran, dilaporkan bahawa isyarat di kawasan hadapan otak dikaitkan dengan beban kerja intelektual. Oleh itu, saluran tunggal atau berbilang saluran EEG boleh digunakan. Namun, cabaran untuk menghapuskan kehadiran artifak dalam isyarat EEG adalah sukar kerana tidak semua kaedah sedia ada berfungsi apabila kaedah saluran tunggal digunakan. Bagi mengatasi batasan tersebut, tesis ini mencadangkan penggunaan teknik penguraian mod empirikal (EEMD). EEMD secara heuristik menguraikan isyarat EEG dalam domain masa kepada satu siri fungsi mod intrinsik (IMF). Di sini, teknik baharu dalam memilih IMF penting berdasarkan kekerapan puncak ketumpatan spektrum kuasa telah dicadangkan. Untuk menilai prestasi kaedah yang dicadangkan, tugasan congakan aritmetik dan membina struktur telah direka untuk mendorong beban kerja mental aktiviti kognitif dan psikomotor. Klasifikasi silang tugas dan silang subjek berdasarkan bebanan tugas kerja yang direka bentuk telah dilakukan. Kuasa relatif, entropi Shannon, entropi tenaga log, pencongan dan kurtosis diekstrak sebagai ciri bebanan intelektual. Keputusan menunjukkan bahawa EEMD diganding dengan ANN memberikan prestasi keseluruhan yang terbaik berbanding pengelas yang lain. Ketepatan klasifikasi mencapai 90.0% bagi klasifikasi silang tugas apabila entropi tenaga log digunakan. Dalam pengelasan silang subjek pula, ketepatan masing-masing mencapai 76.7% dan 86.7% untuk tugasan congakan aritmetik dan membina struktur apabila entropi Shannon digunakan. Dalam kajian perbandingan, kaedah EEMDANN dan entropi tenaga log memberikan ketepatan yang lebih baik dalam klasifikasi silang tugas dan silang subjek berbanding kajian terdahulu. Kesimpulannya, kerja ini telah menyumbang kepada pengukuran beban kerja intelektual berasaskan EEG menggunakan sebilangan kecil saluran EEG.

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LIST OF ABBREVIATION

AC	–	Alternative current
ANN	–	Artificial neural network
BS	–	Building structure task
BSS	–	Blind source separations
ECoG	–	Electrocorticography
EEG	–	Electroencephalogram
EEMD	–	Ensemble empirical mode decomposition
EMD	–	Empirical mode decomposition
ERP	–	Event-related potential
fMRI	–	Functional magnetic resonance imaging
FN	–	False negative
FNIRS	–	Functional near-infrared spectroscopy
FP	–	False positive
GUI	–	Graphical user interface
HHT	–	Hilbert Huang transform
Hz	–	Hertz
ICA	–	Independent component analysis
IMF	–	Intrinsic mode function
MA	–	Mental arithmetic task
MEG	–	Magnetoencephalography
NASA	–	National aeronautics and space agency
PET	–	Position emission tomography
PSD	–	Power spectral density
SMEQ	–	Subjective mental effort question
STFT	–	Short-time Fourier transform
TN	-	True negative
TP	-	True positive
WT	-	Wavelet transform

LIST OF SYMBOLS

a	–	white noise amplitude
b	–	lower envelope
b_{high}	–	higher frequency of interest
b_{low}	–	lower frequency of interest
e_{max}	–	local maxima
e_{min}	–	local minima
f_p	–	peak frequency
kurt	–	kurtosis
LogEn	–	Log energy entropy
p_{band}	–	subband average power
P_{max}	–	peak amplitude
p_{total}	–	total average power
r	–	residual
skew	–	skewness
ShEn	–	Shannon entropy
u	–	upper envelope
w_n	–	white noise
x	–	raw EEG signal
Y	–	clean EEG signal
μ	–	Mu band
α	–	Alpha rhythm
β	–	Beta rhythm
γ	–	Gamma rhythm
δ	–	Delta rhythm
ɵ	–	Theta rhythm

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Bloom's taxonomy is a framework or tool for learning objectives, outcomes and assessments. Cognitive and psychomotor domains are two major domains in the taxonomy for ability indicators besides the affective domain. According to Bloom (1956), cognitive ability is defined as thinking level, knowledge and intellectual skills, while psychomotor ability reflects motor coordination and physical skills. Both abilities are interrelated and are the product of maturation and learning. Hence, they reflect an individual strategy for handling a task. Therefore, different individuals may have different mental workloads when performing a same task.

The definition of mental workload is the amount of mental effort a person makes while performing a specific task within a limited time, depending on the person's prior knowledge and physiological state (Cain, 2007, Moray, 2013). Then, the workload is the brain's cognitive processes involved during the task, such as problem-solving, working memory and arithmetic (iMotion, 2015). Traditionally, a mental workload study is typically done by a psychologist through a self-written report or verbal evaluation. Some common evaluation measures that have been used are performance measure, subjective measure and behavioural measure (Witon, 2019). However, such evaluation methods lack real-time mental workload measurement during task execution (So et al., 2017, Miyake, 2001).

Recently, the research community in cognitive neuroscience and biomedical engineering has an ongoing interest in monitoring the mental state directly from the human brain by measuring the mental workload at the physiological level (Chin et al., 2018, Plechawska-Wójcik et al., 2019, Adewale and Panoutsos, 2019, Charles and

Nixon, 2019, Tao et al., 2019). Figure 1.1 shows the number of articles published related to mental workload based on physiological measures from the year 2010 until May 2022 as extracted from the Scopus database. This trend is predicted to continue in the future as the World Health Organization (WHO) targeted a doubling in the output of global research on mental health by 2030 (WHO, 2021).

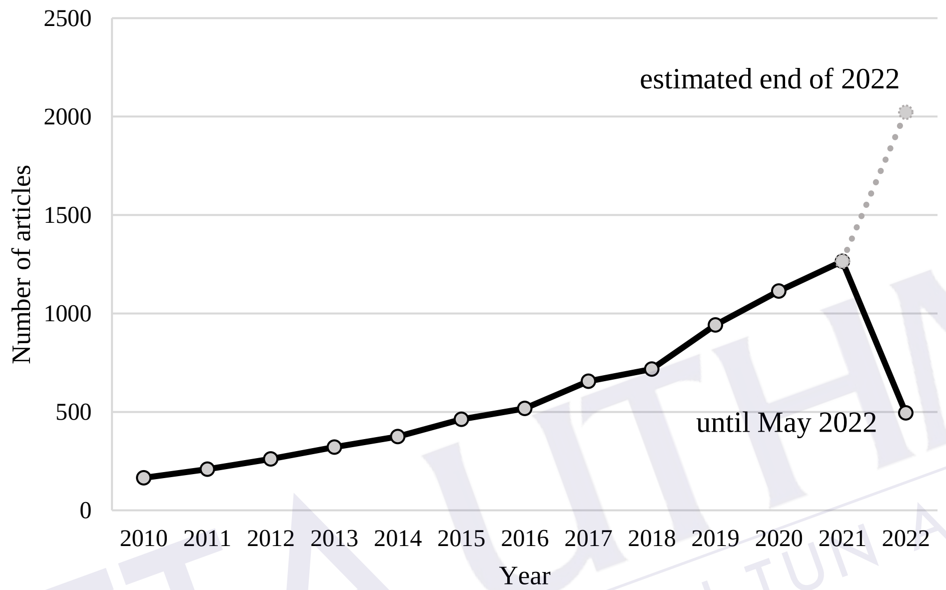

Figure 1.1: Articles published in the mental workload topic based on physiological measures from the year 2010 until May 2022 (retrieved on 21st May 2022)

In the physiological measure approach, most of them used electroencephalogram (EEG) signals (Chen et al., 2017a, Mehla et al., 2020, Hernández-Sabaté et al., 2022), functional magnetic resonance imaging (fMRI) (Causse et al., 2021), magnetoencephalography (MEG) (Ishii et al., 2018), functional near-infrared spectroscopy (fNIRS) (Geissler et al., 2021) and electrocorticography (ECoG) (Calderon et al., 2018). Amongst these techniques, EEG is the most popular technique for assessing the mental workload. This is evidenced by the number of articles found in the Scopus database related to EEG-based mental workload studies as shown in Figure 1.2. The search used the keyword ALL ("mental" AND "workload" AND "<technique>"). It is shown that the EEG-based mental workload studies have the largest number of publications compared to other measurement approaches. From that number, about 2254 articles were found to have implemented artificial neural networks (ANN) using the search keyword ALL ("mental" AND "workload" AND

“EEG” AND “Neural network”), while the rest articles implemented other classifiers such as linear discriminant, k-nearest neighbour, support vector machine etc. One of the reasons the EEG signal has been widely used is due to its non-invasive technique, safety and relatively low cost (Teplan, 2002).

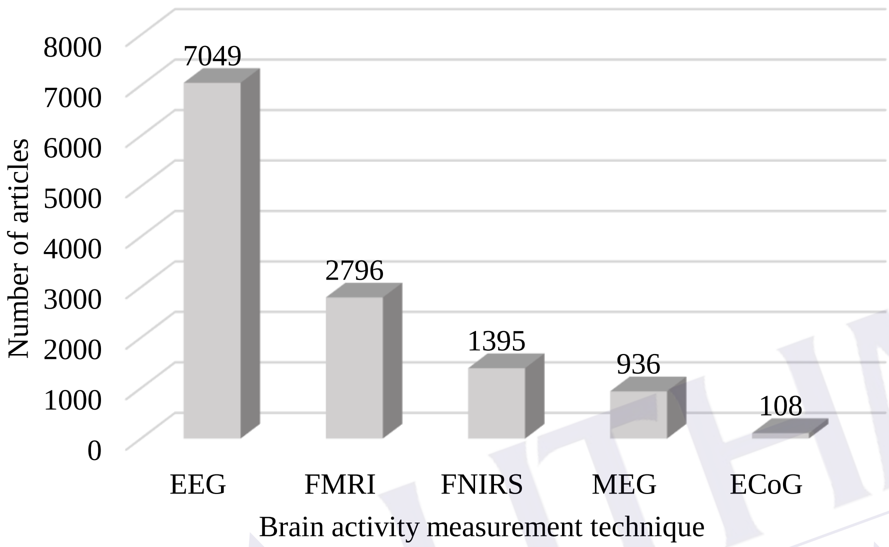

Figure 1.2: Mental workload research based on brain activity measurement techniques in the Scopus database (retrieved on 21st May 2022)

Measuring mental workload using brain activity, especially EEG signals, has engaged with many applications, especially in a working environment, human factors and ergonomics. Combined with the recent technology of portable EEG devices, measuring mental workload can be performed outside of the laboratory environment. The experiment setup becomes flexible, the EEG devices become wearable and wireless, and some devices offer fewer electrodes, allowing researchers to focus on certain brain locations (Casson, 2019). This innovation gives an advantage to the mental workload assessment and is more practical for activities requiring movement or motor coordination such as psychomotor tasks.

The research on mental workload with EEG can be categorised into two bases: studying the cognitive process itself such as semantic or recognition memory tasks (Klimesch et al., 1993, Puma et al., 2018, Radüntz, 2020), and classifying the mental effort based on general task demands such as attentional demands and task difficulty (Plechawska-Wójcik et al., 2019, Ismail and Karwowski, 2020). In most of these studies, a high number of EEG channels have been used. It is reported that the EEG channels that can be associated with mental workload are commonly located in the frontal area (Baldwin, 2003, So et al., 2017, Albuquerque et al., 2018). For that reason, it is hypothesised that the use of a single or smaller number of EEG channels for mental workload classification is feasible. However, the study using a smaller number of EEG channels has not been widely explored yet. Although analysing the EEG signal using a smaller number of EEG channels is a challenging task, it will simplify the experiment setup and avoid subject inconvenience. Consequently, the measurement of mental workload in real environments can be accomplished without hassle.

Therefore, this research focuses on the classification of mental workload levels based on two designated cognitive and psychomotor tasks using EEG signals acquired from two EEG channels in the frontal lobe area. The research described in this thesis is motivated by the many potential applications that may benefit from this approach.

1.2 Motivation

The study of mental workload provides a lot of benefits to many potential applications. Understanding the mental workload instead of only physical performance during task execution allows an insight into the psychological state of the performer. While different people can accomplish the same task with similar performance, their mental workload can be different depending on their prior knowledge, capability and experience factors (Chin et al., 2018, Tao et al., 2019).

In the education field, students' mental workload during a learning process influences their learning efficacy. If an educator can identify students' mental levels by some means, students' performance can be improved. However, a typical classroom has around 30 to 40 students, thus increasing the burden on the educator to continuously monitor students' mental states by observing each student's expressions (Xu and Zhong, 2018). Hence, monitoring the mental state during learning based on EEG signals is a promising approach.

In the workplace, most companies require candidates to complete a pre-employment task to assess candidates' abilities in specific aspects of the job offered, such as mental abilities (i.e. cognitive), physical abilities (i.e. psychomotor) and personality (Black et al., 2019). Having high cognitive and psychomotor ability indicates having the essential job skills and good productivity, thus likely requiring less training to master a new skill. This is important to ensure a potential candidate performs comfortably without stress or depression with minimal supervision. While in a real work situation, the mental workload is measured to facilitate an optimal mental performance for efficient work and safety measures (So et al., 2017).

In other applications, measuring mental workload has also been done for ergonomic and safety reasons. For example, the mental workload was measured in driving performance impairments (Paxion et al., 2014), improvement of safety in maritime transportation (Lim et al., 2018), prevention of operator's underload and overload conditions in air traffic control systems (Aricò et al., 2016) and mitigation of the occurrence of human error in operating aeroplanes (Dehais et al., 2019). With so many applications that benefit from mental workload studies, the study is motivated to utilise EEG signal as a modality in measuring mental workload to obtain a better understanding of human performance.

1.3 Problem statement

Mental workload classification studies have been reported in the literature utilising various signal processing and classification algorithms. Recently, the availability of mobile EEG systems with a single or a few electrode channels has increased the potential to measure brain activities in real environments (Dadebayev et al., 2021). However, the potential of examining mental workload, particularly for cognitive and psychomotor tasks using mobile EEG devices with a single or a small number of channels still needs to be explored.

Analysing EEG signals from a small number of channels has a limitation in terms of the low availability of signal sources. This is because a raw EEG signal usually contains artefacts such as eye blinks, heartbeats and muscle activities (Teplan, 2002) which need to be isolated to produce a clean EEG signal. Numerous machine learning algorithms have been used in mental workload classification problems as found in the literature. Most of those classifiers are combined with other signal pre-processing algorithms to remove or at least reduce the effect of artefact contamination (Islam et al., 2016). However, not all existing methods work well when using low numbers of EEG channels. For example, the regression and adaptive filters are not suitable to be used because both methods require an extra artefact reference channel, which is usually not available in most mobile EEG devices. As an alternative, decomposition techniques such as the independent component analysis (ICA), wavelet transform (WT) and empirical mode decomposition (EMD) have been preferred (Jiang et al., 2019). Yet, ICA requires a high number of EEG channels for it to work properly. Then, WT can decompose a single EEG signal based on a basis function called the mother wavelet function. Nevertheless, WT relies on the chosen basis function to decompose the signal sources of interest (Urigüen and Garcia-Zapirain, 2015).

Fortunately, EMD heuristically decomposes EEG signal in the time domain into a series of intrinsic mode functions (IMF) without prior knowledge of the signal of interest. Basically, the method is used for non-stationary and nonlinear signal decomposition (Wu and Huang, 2009). The original EMD method has mode mixing issues and sensitive to noise. Later, the method has been enhanced by adopting a noise-assisted method called ensemble empirical mode decomposition (EEMD), which significantly improves the original EMD. Therefore, the EEMD method is predicted to be feasible to overcome the aforementioned limitation.

Measuring mental workload using EEG signals requires a task load. The task load must be carefully designed so that the induced brain signal stimulated by the task is related to the desired mental load. Several task loads such as mental arithmetic (So et al., 2017, Plechawska-Wójcik et al., 2019), the n-back task (Yang and Huang, 2018), intelligent test (Friedman et al., 2019) and physical task in real environment (Hatfield et al., 2004, Christie et al., 2017) have been designed in the previous studies. However, those studies do not show the effectiveness of the designed task on stimulating the mental workload of the subject. This is important to quantify the mental effort experienced by the subject during performing the task.

Several methods can be used to measure mental effort such as NASA task load index (NASA-TLX) or subjective mental effort questionnaire (SMEQ). NASA-TLX is a multiple-factor questionnaire to measure several aspects of workload (Witon, 2019). It is commonly used for a long task with multiple sections. Whereas the SMEQ provides a single scale from 0 – 150 with nine labels of difficulty level in a straight line, where 0 means the easiest and 150 the hardest. In EEG research, subjects are recommended to not being interfered when the task is in progress because it has been found to disrupt the performance of the primary task (Kramer et al., 1995). Therefore, a simple subjective measure such as SMEQ is suitable to be used to measure the effectiveness of the given task load.

1.4 Objectives

This thesis aims to classify mental workload levels measured using non-invasive EEG modalities on the frontal lobe region during the performance of cognitive and psychomotor tasks. To achieve the target and solve the stated limitations, the detailed objectives of the research are as follows:

i. To design tasks that can stimulate the mental workload of a cognitive and psychomotor task.
ii. To develop a classification framework based on EEMD and ANN for applications using a small number of EEG channels.
iii. To investigate the relevant EEG features associated with the mental workload.
iv. To validate the proposed method using accuracy and F1-score.

1.5 Scope of research

The research is primarily acquiring EEG signals on the frontal lobe of the brain during specific cognitive and psychomotor tasks. The research was done according to the following scopes:

i. The raw EEG signals are acquired on the frontal lobe area with two electrodes, specifically at the AF3 and AF4 electrode positions.
ii. The Emotiv Insight mobile EEG device was used for EEG signal acquisition.
iii. Thirty subjects aged from 19 to 21 years old were voluntarily involved in the data collection.
iv. A mental arithmetic task and a building structure task were designed to represent the cognitive and psychomotor tasks, respectively.
v. Both tasks were carried out in an isolated space by completely displaying the instruction and questions on a laptop without instructor intervention.
vi. Two states of mental workload, “Low” and “High” are considered for the classification purpose.
vii. MATLAB 2019b software is used in this research with a laptop powered by Intel(R) Core(TM) i5-1035G1 CPU @ 1.00GHz and 8 Gigabytes of RAM.

1.6 Significance of study

This research’s findings will benefit the research community in biomedical engineering and neuroscience, considering the recent needs in mental health study. The research provides a framework for selecting the most relevant components in EEG signal which are associated with the mental workload. Moreover, the feasibility of the framework to be used on a single source of EEG signal analysis, it is predicted to give advantages to the use of mobile EEG devices in numerous applications.

1.7 Thesis outline

Chapter 1 introduces the EEG-based mental workload application and its benefit for future use. The problem statement on the EEG-based mental workload classification is also described here, along with the direction of the research.

Chapter 2 reviews the theoretical background, methodology, analysis, performance measures and previous related works on measuring mental workload using EEG signals. The gap analysis and the proposed approach is stated here.

Chapter 3 overviews the methodology of the study such as the experimental design and procedure. A brief description of the proposed EEG-based mental workload classification using a two EEG channels is presented. The experimental analysis of the proposed classification method is also presented.

Chapter 4 presents the findings on the mental workload effect on the EEG signal. The performance results of the proposed classification method are also presented and discussed.

Chapter 5 summarises the research processes, concludes the research outcomes and states the future recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of the previous works on EEG-based mental workload classification focusing on the utilisation of a single or a small number of EEG channels. The review begins with the background research on mental workload studies, followed by an introduction on the brainwave functions. Accordingly, a brief discussion on the previous related works regarding to mental workload stimulation task, EEG signal processing, feature extraction and classification approach are presented. Finally, the research gap in EEG-based mental workload classification is presented.

2.2 Research background

Mental workload studies have almost been tripled since the 1980s (Young et al., 2015). Previous mental workload studies have been implemented in various applications, especially on the safety and ergonomics of the working environment. Imposed by modern technology, recent challenges in working environments have increased the cognitive demands upon workers. For example, the recent outbreak of the COVID-19 pandemic has impacted the working style and education process where the home-based working has been implemented (Bolisani et al., 2020, Pokhrel and Chhetri, 2021). This situation distracts the mental condition of the workers as the implementation of the online approach is not well prepared by some individuals. Therefore, an evaluation of mental workload is important to ensure the best possible individual performance.

REFERENCES

Abiri, R., Borhani, S., Sellers, E.W., Jiang, Y. & Zhao, X. A comprehensive review of EEG-based brain–computer interface paradigms. *Journal of Neural Engineering*. 2019. 16 (1): 011001.

Adewale, Q. & Panoutsos, G. Mental Workload Estimation Using Wireless EEG Signals. *bioRxiv*. 2019. 755033.

Ahmad, M.I., Keller, I., Robb, D.A. & Lohan, K.S. A framework to estimate cognitive load using physiological data. *Personal Ubiquitous Computing*. 2020. 1-15.

Albuquerque, I., Tiwari, A., Gagnon, J.-F., Lafond, D., Parent, M., Tremblay, S. & Falk, T. (2018). On the analysis of EEG features for mental workload assessment during physical activity. *The 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC),* Miyazaki, Japan. IEEE, 538-543.

Ali, H., Salleh, M.N.M., Saedudin, R., Hussain, K. & Mushtaq, M.F. Imbalance class problems in data mining: a review. *Indonesian Journal of Electrical Engineering Computer Science*. 2019. 14 (3): 1560-1571.

Alonso, L.F.N. & Gil, J.G. Brain Computer Interfaces, a Review. *Sensors*. 2012. 12 (2): 1211.

Antonenko, P., Paas, F., Grabner, R. & Van Gog, T. Using electroencephalography to measure cognitive load. *Educational Psychology Review*. 2010. 22 (4): 425-438.

Aricò, P., Borghini, G., Di Flumeri, G., Colosimo, A., Bonelli, S., Golfetti, A., Pozzi, S., Imbert, J.-P., Granger, G. & Benhacene, R. Adaptive automation triggered by EEG-based mental workload index: a passive brain-computer interface application in realistic air traffic control environment. *Frontiers in human neuroscience*. 2016. 10: 539.

Arpaia, P., Moccaldi, N., Prevete, R., Sannino, I. & Tedesco, A. A wearable EEG instrument for real-time frontal asymmetry monitoring in worker stress analysis. *IEEE Transactions on Instrumentation Measurement*. 2020. 69 (10): 8335-8343.

Aydın, S., Saraoğlu, H.M. & Kara, S. Log energy entropy-based EEG classification with multilayer neural networks in seizure. *Annals of biomedical engineering.* 2009. 37 (12): 2626.

Ayenu-Prah, A. & Attoh-Okine, N. A criterion for selecting relevant intrinsic mode functions in empirical mode decomposition. *Advances in Adaptive Data Analysis.* 2010. 2 (01): 1-24.

Babu, T.A., Gadde, S., Ravi, S., Rao, K.V.V., Mamillu, Y. & Krishna, D. (2022). Analysis of Mental Task Ability in Students based on Electroencephalography Signals. *2022 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES),* Kerala, India. IEEE, 274-278.

Baldwin, C.L. Neuroergonomics of mental workload: New insights from the convergence of brain and behaviour in ergonomics research. *Theoretical Issues in Ergonomics Science.* 2003.

Belakhdar, I., Kaaniche, W., Djmel, R. & Ouni, B. (2016). A comparison between ANN and SVM classifier for drowsiness detection based on single EEG channel. *2016 2nd International Conference on Advanced Technologies for Signal and Image Processing (ATSIP).* IEEE, 443-446.

Berrar, D. (2019). Cross-Validation. *In:* Ranganathan, S., Gribskov, M., Nakai, K. & Schönbach, C. (eds.) *Encyclopedia of Bioinformatics and Computational Biology.* Oxford: Academic Press.

Bertrand, A. & Moonen, M. (2014). Distributed eye blink artifact removal in a wireless EEG sensor network. *2014 IEEE international conference on acoustics, speech and signal processing (ICASSP).* IEEE, 5849-5853.

Bhattacharyya, D., Chowdhury, B., Chatterjee, T., Pal, M. & Majumdar, D. Selection of character/background colour combinations for onscreen searching tasks: An eye movement, subjective and performance approach. *Displays.* 2014. 35 (3): 101-109.

Bishop, C.M. & Nasrabadi, N.M. (2006). *Pattern recognition and machine learning,* New York, Springer.

Black, S., Gardner, D.G., Pierce, J.L. & Steers, R. (2019). *Organizational Behavior,* OpenStax.

Bloom, B. Taxonomy of educational objectives. Vol. 1: Cognitive domain. *New York: McKay.* 1956. 20-24.

Bolisani, E., Scarso, E., Ipsen, C., Kirchner, K. & Hansen, J.P. Working from home during COVID-19 pandemic: lessons learned and issues. *Management Marketing. Challenges for the Knowledge Society*. 2020. 15 (s1): 458-476.

Borowska, M. Entropy-based algorithms in the analysis of biomedical signals. *Studies in Logic, Grammar Rhetoric*. 2015. 43 (1): 21-32.

Boutana, D., Benidir, M. & Barkat, B. (2010). On the selection of intrinsic mode function in EMD method: application on heart sound signal. *3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies*, Rome, Italy. IEEE, 1-5.

Brookes, M.J., Wood, J.R., Stevenson, C.M., Zumer, J.M., White, T.P., Liddle, P.F. & Morris, P.G. Changes in brain network activity during working memory tasks: a magnetoencephalography study. *Neuroimage*. 2011. 55 (4): 1804-1815.

Brouwer, A.-M., Hogervorst, M.A., Van Erp, J.B., Heffelaar, T., Zimmerman, P.H. & Oostenveld, R. Estimating workload using EEG spectral power and ERPs in the n-back task. *Journal of neural engineering*. 2012. 9 (4): 045008.

Cain, B. (2007). A review of the mental workload literature. Defence Research And Development Toronto (Canada).

Calderon, J., Yang, Y., Inman, C., Willie, J. & Berman, G. (2018). Decoding human behavior from complex neural interactions. *APS March Meeting Abstracts*, Los Angeles, California. S06. 006.

Casson, A.J. Wearable EEG and beyond. *Biomedical Engineering Letters*. 2019. 9 (1): 53-71.

Casson, A.J., Abdulaal, M., Dulabh, M., Kohli, S., Krachunov, S. & Trimble, E. (2018). Electroencephalogram. *Seamless Healthcare Monitoring*. Springer.

Causse, M., Lepron, E., Mandrick, K., Peysakhovich, V., Berry, I., Callan, D. & Rémy, F. Facing successfully high mental workload and stressors: An fMRI study. *Human Brain Mapping*. 2021.

Charles, R.L. & Nixon, J. Measuring mental workload using physiological measures: A systematic review. *Applied ergonomics*. 2019. 74: 221-232.

Chaumon, M., Bishop, D.V. & Busch, N.A. A practical guide to the selection of independent components of the electroencephalogram for artifact correction. *Journal of neuroscience methods*. 2015. 250: 47-63.

Chen, C.-S., Chien, T.-S., Lee, P.-L., Jeng, Y. & Yeh, T.-K. Prefrontal Brain Electrical Activity and Cognitive Load Analysis Using a Non-linear and Non-Stationary Approach. *IEEE Access*. 2020. 8: 211115-211124.

Chen, J., Taylor, J.E. & Comu, S. Assessing task mental workload in construction projects: A novel electroencephalography approach. *Journal of Construction Engineering Management*. 2017a. 143 (8): 04017053.

Chen, X., Xu, X., Liu, A., Mckeown, M.J. & Wang, Z.J. The use of multivariate EMD and CCA for denoising muscle artifacts from few-channel EEG recordings. *IEEE Transactions on Instrumentation and Measurement*. 2017b. 67 (2): 359-370.

Chin, Z.Y., Zhang, X., Wang, C. & Ang, K.K. (2018). EEG-based discrimination of different cognitive workload levels from mental arithmetic. *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 1984-1987.

Cho, S., Shahriar, M.R. & Chong, U. Identification of significant intrinsic mode functions for the diagnosis of induction motor fault. *The Journal of the Acoustical Society of America*. 2014. 136 (2): EL72-EL77.

Christie, S., Di Fronso, S., Bertollo, M. & Werthner, P. Individual alpha peak frequency in ice hockey shooting performance. *Frontiers in Psychology*. 2017. 8: 762.

Conway, A.R., Kane, M.J., Bunting, M.F., Hambrick, D.Z., Wilhelm, O., Engle, R.W.J.P.B. & Review. Working memory span tasks: A methodological review and user's guide. 2005. 12 (5): 769-786.

Correa, M.a.G. & Leber, E.L. (2011). Noise removal from EEG signals in polisomnographic records applying adaptive filters in cascade. *Adaptive Filtering Applications*. INTECH Open Access Publisher.

Dadebayev, D., Goh, W.W., Tan, E.X. & Sciences, I. EEG-based emotion recognition: Review of commercial EEG devices and machine learning techniques. *Journal of King Saud University-Computer*. 2021.

Daneman, M. & Carpenter, P.A. Individual differences in working memory and reading. *Journal of verbal learning verbal behavior*. 1980. 19 (4): 450-466.

De Cheveigné, A. & Arzounian, D. Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data. *Neuroimage*. 2018. 172: 903-912.

De Rooij, M. & Weeda, W. Cross-validation: A method every psychologist should know. *Advances in Methods Practices in Psychological Science*. 2020. 3 (2): 248-263.

Decoster, J., Gallucci, M. & Iselin, A.-M.R. Best practices for using median splits, artificial categorization, and their continuous alternatives. *Journal of experimental psychopathology*. 2011. 2 (2): 197-209.

Dehais, F., Duprès, A., Blum, S., Drougard, N., Scannella, S., Roy, R.N. & Lotte, F. Monitoring pilot's mental workload using ERPs and spectral power with a six-dry-electrode EEG system in real flight conditions. *Sensors*. 2019. 19 (6): 1324.

Dursun, M., Özşen, S., Güneş, S., Akdemir, B. & Yosunkaya, Ş. Automated elimination of EOG artifacts in sleep EEG using regression method. *Turkish Journal of Electrical Engineering & Computer Sciences*. 2019. 27 (2): 1094-1108.

Eggemeier, F. & Wilson, G. (1991). Workload assessment in multi-task environments. Multiple task performance. DL Damos. London, GB. Taylor & Francis, Ltd.

Emotiv. (2020). *Insight User Manual* [Online]. Available: https://emotiv.gitbook.io/insight-manual/ [Accessed 24 May 2022].

Fasil, O. & Rajesh, R. (2020). Empirical Mode Decomposition of EEG Signals for the Effectual Classification of Seizures. *Advances in Neural Signal Processing*. IntechOpen.

Fatimah, B., Pramanick, D. & Shivashankaran, P. (2020). Automatic detection of mental arithmetic task and its difficulty level using EEG signals. *11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*. IEEE, 1-6.

Fawcett, T. An introduction to ROC analysis. *Pattern Recognition Letters*. 2006. 27 (8): 861-874.

Friedman, N., Fekete, T., Gal, K. & Shriki, O. EEG-Based Prediction of Cognitive Load in Intelligence Tests. 2019. 13 (191).

Geissler, C.F., Schneider, J. & Frings, C. Shedding light on the prefrontal correlates of mental workload in simulated driving: a functional near-infrared spectroscopy study. *Scientific Reports*. 2021. 11 (1).

Gentili, R.J., Jaquess, K.J., Shuggi, I.M., Shaw, E.P., Oh, H., Lo, L.C., Tan, Y.Y., Domingues, C.A., Blanco, J.A. & Rietschel, J.C. Combined assessment of attentional reserve and cognitive-motor effort under various levels of challenge with a dry EEG system. *Psychophysiology*. 2018. 55 (6): e13059.

Ghojogh, B. & Crowley, M. Linear and quadratic discriminant analysis: Tutorial. *arXiv preprint arXiv:.02590*. 2019.

Grispino, A.S., Petracca, G.O. & Dominguez, A.E. Comparative Analysis of Wavelet and EMD in the Filtering of Radar Signal Affected by Brown Noise. *IEEE Latin America Transactions*. 2013. 11 (1): 81-85.

Grozdanovic, M., Marjanovic, D., Janackovic, G.L. & Djordjevic, M. The impact of character/background colour combinations and exposition on character legibility and readability on video display units. *Transactions of the Institute of Measurement and Control*. 2017. 39 (10): 1454-1465.

Gupta, V., Priya, T., Yadav, A.K., Pachori, R.B. & Acharya, U.R. Automated detection of focal EEG signals using features extracted from flexible analytic wavelet transform. *Pattern Recognition Letters*. 2017. 94: 180-188.

Haas, L. Hans Berger (1873–1941), Richard Caton (1842–1926), and electroencephalography. *Journal of Neurology, Neurosurgery & Psychiatry*. 2003. 74 (1): 9-9.

Halder, S., Bensch, M., Mellinger, J., Bogdan, M., Kübler, A., Birbaumer, N. & Rosenstiel, W. Online artifact removal for brain-computer interfaces using support vector machines and blind source separation. *Computational Intelligence Neuroscience*. 2007. 2007:82069.

Hart, P.E., Stork, D.G. & Duda, R.O. (2000). *Pattern classification*, Wiley Hoboken.

Hassanat, A.B., Abbadi, M.A., Altarawneh, G.A. & Alhasanat, A.A. Solving the problem of the K parameter in the KNN classifier using an ensemble learning approach. *International Journal of Computer Science and Information Security*. 2014. 12 (8): 33-39.

Hatfield, B.D., Haufler, A.J., Hung, T.-M. & Spalding, T.W. Electroencephalographic studies of skilled psychomotor performance. *Journal of Clinical Neurophysiology*. 2004. 21 (3): 144-156.

Hawes, Z., Sokolowski, H.M., Ononye, C.B. & Ansari, D. Neural underpinnings of numerical and spatial cognition: An fMRI meta-analysis of brain regions associated with symbolic number, arithmetic, and mental rotation. *Neuroscience & Biobehavioral Reviews*. 2019. 103: 316-336.

Hernández-Sabaté, A., Yauri, J., Folch, P., Piera, M.À. & Gil, D. Recognition of the Mental Workloads of Pilots in the Cockpit Using EEG Signals. *Applied Sciences*. 2022. 12 (5): 2298.

Hjorth, B. EEG analysis based on time domain properties. *Electroencephalography Clinical Neurophysiology*. 1970. 29 (3): 306-310.

Hoedemaeker, M. (2002). Summary Description of Workload Indicators: WP1 Workload Measures. Human Machine Interface and the Safety of Traffic in Europe Growth Project. GRD1-2000-25361. HASTE. Institute for Transport Studies. Leeds, UK ….

Hogervorst, M.A., Brouwer, A.-M. & Van Erp, J.B.F. Combining and comparing EEG, peripheral physiology and eye-related measures for the assessment of mental workload. *Frontiers in Neuroscience*. 2014. 8: 322.

Hollnagel, E. Prolegomenon to cognitive task design. *Handbook of cognitive task design*. 2003. 3-15.

Huang, N.E. (2014). *Hilbert-Huang transform and its applications*, World Scientific.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.-C., Tung, C.C. & Liu, H.H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Journal Proceedings of the Royal Society of London. Series A: Mathematical, Physical Engineering Sciences*. 1998. 454 (1971): 903-995.

iMotion. (2015). Top 6 Most Common Applications for Human EEG Research. Available from: https://imotions.com/blog/top-6-common-applications-human-eeg-research/ [Accessed 10th February 2019].

Ishii, A., Ishizuka, T., Muta, Y., Tanaka, M., Yamano, E. & Watanabe, Y. The neural effects of positively and negatively re-experiencing mental fatigue sensation: a magnetoencephalography study. *Experimental Brain Research*. 2018. 236 (6): 1735-1747.

Islam, M.K., Rastegarnia, A. & Yang, Z. Methods for artifact detection and removal from scalp EEG: A review. *Neurophysiologie Clinique/Clinical Neurophysiology*. 2016. 46 (4): 287-305.

Islam, M.R., Rahim, M.A., Akter, H., Kabir, R. & Shin, J. (2018). Optimal IMF selection of EMD for sleep disorder diagnosis using EEG signals. *Proceedings of the 3rd International Conference on Applications in Information Technology*. 96-101.

Ismail, L.E. & Karwowski, W. Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis. *Plos One*. 2020. 15 (12): e0242857.

Ives-Deliperi, V.L. & Butler, J.T. Relationship between EEG electrode and functional cortex in the international 10 to 20 system. *Journal of Clinical Neurophysiology*. 2018. 35 (6): 504-509.

Jaquess, K.J., Lo, L.-C., Oh, H., Lu, C., Ginsberg, A., Tan, Y.Y., Lohse, K.R., Miller, M.W., Hatfield, B.D. & Gentili, R.J. Changes in mental workload and motor performance throughout multiple practice sessions under various levels of task difficulty. *Neuroscience*. 2018. 393: 305-318.

Jasper, H.H. The ten twenty electrode system of the international federation. *Electroencephalography and Clinical Neuroph siology*. 1958. 10: 371-375.

Jiang, X., Bian, G.-B. & Tian, Z. Removal of artifacts from EEG signals: a review. *Sensors*. 2019. 19 (5): 987.

Junsheng, C., Dejie, Y. & Yu, Y. Research on the intrinsic mode function (IMF) criterion in EMD method. *Mechanical systems signal processing*. 2006. 20 (4): 817-824.

Kaleem, M., Guergachi, A. & Krishnan, S. Comparison of Empirical Mode Decomposition, Wavelets, and Different Machine Learning Approaches for Patient-Specific Seizure Detection Using Signal-Derived Empirical Dictionary Approach. *Frontiers in Digital Health*. 2021. 3.

Karabiber Cura, O., Kocaaslan Atli, S., Türe, H.S. & Akan, A. Epileptic seizure classifications using empirical mode decomposition and its derivative. *BioMedical Engineering OnLine*. 2020. 19 (1): 10.

Kim, D.-W. & Im, C.-H. (2018). EEG Spectral Analysis. *In:* Im, C.-H. (ed.) *Computational EEG Analysis: Methods and Applications*. Springer Singapore.

Kim, K., Duc, N.T., Choi, M. & Lee, B. EEG microstate features according to performance on a mental arithmetic task. *Scientific Reports*. 2021. 11 (1): 343.

Kirchner, W.K. Age differences in short-term retention of rapidly changing information. *Journal of experimental psychology*. 1958. 55 (4): 352.

Klimesch, W., Schimke, H. & Pfurtscheller, G. Alpha frequency, cognitive load and memory performance. *Brain topography*. 1993. 5 (3): 241-251.

Klonowski, W. Everything you wanted to ask about EEG but were afraid to get the right answer. *Nonlinear Biomedical Physics*. 2009. 3 (1): 2.

Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *International Joint Conference on Artificial Intelligence (IJCAI)*, Montreal, Canada. Morgan Kaufmann Publishers Inc, 1137-1143.

Kosti, M.V., Georgiadis, K., Adamos, D.A., Laskaris, N., Spinellis, D. & Angelis, L. Towards an affordable brain computer interface for the assessment of programmers' mental workload. *International Journal of Human-Computer Studies*. 2018. 115: 52-66.

Kotan, S. & Akan, A. (2018). A new intrinsic mode function selection method based on power spectral density. *Medical Technologies National Congress* Magusa, Cyprus. IEEE, 1-4.

Kotan, S., Van Schependom, J., Nagels, G. & Akan, A. (2019). Comparison of IMF selection methods in classification of multiple sclerosis EEG data. *Medical Technologies Congress*, Izmir, Turkey. IEEE, 1-4.

Kramer, A.F., Trejo, L.J. & Humphrey, D. Assessment of mental workload with task-irrelevant auditory probes. *Biological Psychology*. 1995. 40 (1): 83-100.

Krishnaveni, V., Jayaraman, S., Aravind, S., Hariharasudhan, V. & Ramadoss, K. Automatic identification and removal of ocular artifacts from EEG using wavelet transform. *Measurement science review*. 2006. 6 (4): 45-57.

Kutafina, E., Heiligers, A., Popovic, R., Brenner, A., Hankammer, B., Jonas, S.M., Mathiak, K. & Zweerings, J. Tracking of Mental Workload with a Mobile EEG Sensor. *Sensors*. 2021. 21 (15): 5205.

Labate, D., La Foresta, F., Occhiuto, G., Morabito, F.C., Lay-Ekuakille, A. & Vergallo, P. Empirical mode decomposition vs. wavelet decomposition for the extraction of respiratory signal from single-channel ECG: A comparison. *IEEE Sensors Journal*. 2013. 13 (7): 2666-2674.

Li, X., Song, D., Zhang, P., Zhang, Y., Hou, Y. & Hu, B. Exploring EEG Features in Cross-Subject Emotion Recognition. *Frontiers in Neuroscience*. 2018. 12 (162).

Liang, Z., Wang, Y., Sun, X., Li, D., Voss, L.J., Sleigh, J.W., Hagihira, S. & Li, X. EEG entropy measures in anesthesia. *Frontiers Computer Neuroscience*. 2015. 9 (16).

Lim, W.L., Liu, Y., Harihara Subramaniam, S.C., Liew, S.H.P., Krishnan, G., Sourina, O., Konovessis, D., Ang, H.E. & Wang, L. (2018). EEG-Based Mental Workload and Stress Monitoring of Crew Members in Maritime Virtual

Simulator. *In:* Gavrilova, M. L., Tan, C. J. K. & Sourin, A. (eds.) *Transactions on Computational Science XXXII: Special Issue on Cybersecurity and Biometrics.* Berlin, Heidelberg: Springer Berlin Heidelberg.

Ling, C.X. & Sheng, V.S. (2010). Class Imbalance Problem. *In:* Sammut, C. & Webb, G. I. (eds.) *Encyclopedia of Machine Learning.* Boston, MA: Springer US.

Liu, Y., Ayaz, H. & Shewokis, P.A. Mental workload classification with concurrent electroencephalography and functional near-infrared spectroscopy. *Brain-Computer Interfaces.* 2017. 4 (3): 175-185.

Liu, Y., Lim, W.L., Hou, X., Sourina, O. & Wang, L. (2015). Prediction of human cognitive abilities based on EEG measurements. *International Conference on Cyberworlds (CW),* Visby, Sweden. IEEE, 161-164.

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A. & Yger, F. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. *Journal of neural engineering.* 2018. 15 (3): 031005.

Luque-Casado, A., Perales, J.C., Cárdenas, D. & Sanabria, D. Heart rate variability and cognitive processing: The autonomic response to task demands. *Biological Psychology.* 2016. 113: 83-90.

Mahmoud, R., Shanableh, T., Bodala, I.P., Thakor, N.V. & Al-Nashash, H. Novel classification system for classifying cognitive workload levels under vague visual stimulation. *IEEE Sensors Journal.* 2017. 17 (21): 7019-7028.

Malviya, L., Mal, S. & Lalwani, P. (2021). EEG data analysis for stress detection. *2021 10th IEEE international conference on communication systems and network technologies (CSNT),* Bhopal, India. IEEE, 148-152.

Marchand, C., De Graaf, J.B. & Jarrassé, N. Measuring mental workload in assistive wearable devices: a review. *Journal of Neuroengineering Rehabilitation.* 2021. 18 (1): 1-15.

Marinescu, A.C., Sharples, S., Ritchie, A.C., Sánchez López, T., Mcdowell, M. & Morvan, H.P. Physiological Parameter Response to Variation of Mental Workload. *Human Factors.* 2018. 60 (1): 31-56.

Martinez, M. & Stiefelhagen, R. (2018). Taming the cross entropy loss. *German Conference on Pattern Recognition*. Springer, 628-637.

Mehla, V.K., Singhal, A. & Singh, P. (2020). EMD-based discrimination of mental arithmetic tasks from EEG signals. *IEEE 17th India Council International Conference (INDICON)*, 10-13 Dec. 2020. 1-4.

Mijović, B., De Vos, M., Gligorijević, I., Taelman, J. & Van Huffel, S. Source separation from single-channel recordings by combining empirical-mode decomposition and independent component analysis. *IEEE Transactions on Biomedical Engineering.* 2010. 57 (9): 2188-2196.

Miyake, S. Multivariate workload evaluation combining physiological and subjective measures. *International journal of psychophysiology.* 2001. 40 (3): 233-238.

Mohammadi, M., Al-Azab, F., Raahemi, B., Richards, G., Jaworska, N., Smith, D., De La Salle, S., Blier, P. & Knott, V. Data mining EEG signals in depression for their diagnostic value. *BMC Medical Informatics and Decision Making.* 2015. 15 (1): 108.

Molinaro, A.M., Simon, R. & Pfeiffer, R.M. Prediction error estimation: a comparison of resampling methods. *Bioinformatics.* 2005. 21 (15): 3301-3307.

Moray, N. (2013). *Mental workload: Its theory and measurement*, Springer Science & Business Media.

Naumann, L., Schultze-Kraft, M., Dähne, S. & Blankertz, B. (2016). Prediction of difficulty levels in video games from ongoing EEG. *International Workshop on Symbiotic Interaction*. Springer, Cham, 125-136.

Paas, F., Renkl, A. & Sweller, J. Cognitive load theory and instructional design: Recent developments. *Educational Psychologist.* 2003. 38 (1): 1-4.

Patel, R., Janawadkar, M.P., Sengottuvel, S., Gireesan, K. & Radhakrishnan, T.S. Suppression of eye-blink associated artifact using single channel EEG data by combining cross-correlation with empirical mode decomposition. *IEEE Sensors Journal*. 2016. 16 (18): 6947-6954.

Pathak, D.K., Kalita, S.K. & Bhattacharya, D.K. Hyperspectral image classification using support vector machine: a spectral spatial feature based approach. *Evolutionary Intelligence*. 2022. 15 (1): 1809–1823.

Paxion, J., Galy, E. & Berthelon, C. Mental workload and driving. *Frontiers in Psychology*. 2014. 5 (1344).

Peng, Z., Peter, W.T. & Chu, F. A comparison study of improved Hilbert–Huang transform and wavelet transform: application to fault diagnosis for rolling bearing. *Mechanical systems signal processing.* 2005. 19 (5): 974-988.

Plechawska-Wojcik, M., Borys, M., Tokovarov, M., Kaczorowska, M., Wesolowska, K. & Wawrzyk, M. (2018). Classifying Cognitive Workload Based on Brain Waves Signal in the Arithmetic Tasks' Study. *2018 11th International Conference on Human System Interaction (HSI)*, 4-6 July 2018 Gdańsk, Poland. 277-283.

Plechawska-Wójcik, M., Tokovarov, M., Kaczorowska, M. & Zapała, D. A Three-Class Classification of Cognitive Workload Based on EEG Spectral Data. *Journal of Applied Sciences*. 2019. 9 (24): 5340.

Pokhrel, S. & Chhetri, R. A literature review on impact of COVID-19 pandemic on teaching and learning. *Higher Education for the Future*. 2021. 8 (1): 133-141.

Poorna, S.S., Baba, P.M.V.D.S., Ramya, G.L., Poreddy, P., Aashritha, L.S., Nair, G.J. & Renjith, S. (2016). Classification of EEG based control using ANN and KNN — A comparison. *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, 15-17 Dec. 2016. 1-6.

Puma, S., Matton, N., Paubel, P.-V., Raufaste, É. & El-Yagoubi, R. Using theta and alpha band power to assess cognitive workload in multitasking environments. *International Journal of Psychophysiology*. 2018. 123: 111-120.

Qu, H., Shan, Y., Liu, Y., Pang, L., Fan, Z., Zhang, J. & Wanyan, X. Mental workload classification method based on EEG independent component features. *Applied Sciences*. 2020. 10 (9): 3036.

Radüntz, T. The effect of planning, strategy learning, and working memory capacity on mental workload. *Scientific Reports*. 2020. 10 (1): 1-10.

Rady, H. Classification of multilayer neural networks using cross entropy and mean square errors. *El Shorouk, Journal of the ACM*. 2008.

Rahman, S.M.Z., Tawana, I., Mostafiz, H.R., Chowdhury, T.T. & Shahnaz, C. (2021). Arithmetic Mental Task of EEG Signal Classification Using Statistical Modeling of The DWT Coefficient. *2021 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)*, Rajshahi, Bangladesh. IEEE, 1-4.

Rao, R.P. (2013). *Brain-computer interfacing: an introduction*, Cambridge University Press.

Rasamoelina, A.D., Adjailia, F. & Sinčák, P. (2020). A Review of Activation Function for Artificial Neural Network. *IEEE 18th World Symposium on Applied*

Machine Intelligence and Informatics (SAMI), 23-25 Jan. 2020. IEEE, 281-286.

Rashid, M., Sulaiman, N., P. P. Abdul Majeed, A., Musa, R.M., Ab. Nasir, A.F., Bari, B.S. & Khatun, S. Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review. *Frontiers in Neurorobotics.* 2020. 14 (25).

S. R, H., Mohanty, S.R., Kishor, N. & Singh, D.K. (2018). Comparison of Empirical Mode Decomposition and Wavelet Transform for Power Quality Assessment in FPGA. *2018 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, 18-21 Dec. 2018. 1-6.

Samima, S. & Sarma, M. (2019). EEG-based mental workload estimation. *41st Annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, Berlin, Germany. IEEE, 5605-5608.

Sanei, S. & Chambers, J.A. (2013). *EEG signal processing*, John Wiley & Sons.

Sauro, J. & Dumas, J.S. (2009). Comparison of three one-question, post-task usability questionnaires. *Proceedings of the SIGCHI conference on human factors in computing systems*, Boston. Association for Computing Machinery, 1599-1608.

Shivabalan, K.R., Deb, B., Ramachandran, A. & Goel, S. SMORASO-DT: A Hybrid Machine Learning Classification Model to classify individuals based on Working Memory Load during Mental Arithmetic Task. *Neurology.* 2021. 96 (15).

Silva, I.N.D., Hernane Spatti, D., Andrade Flauzino, R., Liboni, L.H.B. & Reis Alves, S.F.D. (2017). Artificial neural network architectures and training processes. *Artificial neural networks.* Springer.

Simon, R. (2007). Resampling strategies for model assessment and selection. *Fundamentals of Data Mining in Genomics and Proteomics.* Springer.

So, W.K., Wong, S.W., Mak, J.N. & Chan, R.H. An evaluation of mental workload with frontal EEG. *PloS One.* 2017. 12 (4): e0174949.

Sokolova, M. & Lapalme, G. A systematic analysis of performance measures for classification tasks. *Information Processing & Management.* 2009. 45 (4): 427-437.

Spüler, M., Krumpe, T., Walter, C., Scharinger, C., Rosenstiel, W. & Gerjets, P. (2017). Brain-computer interfaces for educational applications. *Informational Environments.* Springer.

Spüler, M., Walter, C., Rosenstiel, W., Gerjets, P., Moeller, K. & Klein, E. EEG-based prediction of cognitive workload induced by arithmetic: a step towards online adaptation in numerical learning. *ZDM Mathematics Education.* 2016. 48 (3): 267-278.

Sreeja, S., Sahay, R.R., Samanta, D. & Mitra, P. Removal of eye blink artifacts from EEG signals using sparsity. *IEEE Journal of Biomedical Health Informatics.* 2017. 22 (5): 1362-1372.

Stancin, I., Cifrek, M. & Jovic, A. A Review of EEG Signal Features and their Application in Driver Drowsiness Detection Systems. *Sensors.* 2021. 21 (11): 3786.

Sternberg, S. Memory-scanning: Mental processes revealed by reaction-time experiments. *American scientist.* 1969. 57 (4): 421-457.

Stoica, P. & Moses, R.L. (2005). *Spectral Analysis of Signals*, Upper Saddle River, NJ, Pearson Prentice Hall.

Suarez-Alvarez, M.M., Pham, D.-T., Prostov, M.Y. & Prostov, Y.I. Statistical approach to normalization of feature vectors and clustering of mixed datasets. *Proceedings of the Royal Society A: Mathematical, Physical Engineering Sciences.* 2012. 468 (2145): 2630-2651.

Sweller, J. Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational psychology review.* 2010. 22 (2): 123-138.

Tang, H., Dai, Z., Jiang, Y., Li, T. & Liu, C. PCG classification using multidomain features and SVM classifier. *BioMed Research International.* 2018. 2018: 14).

Tao, D., Tan, H., Wang, H., Zhang, X., Qu, X., Zhang, T. & Health, P. A systematic review of physiological measures of mental workload. *International journal of environmental research.* 2019. 16 (15): 2716.

Teplan, M. Fundamentals of EEG measurement. *Measurement Science Review.* 2002. 2 (2): 1-11.

Thomas, H. Communication theory and the constellation hypothesis of calculation. *Quarterly Journal of Experimental Psychology.* 1963. 15 (3): 173-191.

Urigüen, J.A. & Garcia-Zapirain, B. EEG artifact removal—state-of-the-art and guidelines. *Journal of Neural Engineering.* 2015. 12 (3): 031001.

Varshney, A., Ghosh, S.K., Padhy, S., Tripathy, R.K. & Acharya, U.R. Automated Classification of Mental Arithmetic Tasks Using Recurrent Neural Network and Entropy Features Obtained from Multi-Channel EEG Signals. *Electronics.* 2021. 10 (9): 1079.

Wallstrom, G.L., Kass, R.E., Miller, A., Cohn, J.F. & Fox, N.A. Automatic correction of ocular artifacts in the EEG: a comparison of regression-based and component-based methods. *International Journal of Psychophysiology.* 2004. 53 (2): 105-119.

Walter, C., Rosenstiel, W., Bogdan, M., Gerjets, P. & Spüler, M. Online EEG-Based Workload Adaptation of an Arithmetic Learning Environment. 2017. 11 (286).

Walter, C., Wolter, P., Rosenstiel, W., Bogdan, M. & Spüler, M. (2014). Towards cross-subject workload prediction. *Proceedings of the 6th International Brain-Computer Interface Conference*.

Wan, X. (2019). Influence of feature scaling on convergence of gradient iterative algorithm. *Journal of physics: Conference series*. IOP Publishing, 032021.

Wang, Q. & Sourina, O. Real-time mental arithmetic task recognition from EEG signals. *IEEE Transactions on Neural Systems Rehabilitation Engineering.* 2013. 21 (2): 225-232.

Wang, Y., Nakanishi, M., Zhang, D. & Applications. EEG-based brain-computer interfaces. *Neural Interface: Frontiers.* 2019. 41-65.

Wang, Z., Wang, C., Wu, G., Luo, Y. & Wu, X. (2017). A control system of lower limb exoskeleton robots based on motor imagery. *Information and Automation (ICIA), 2017 IEEE International Conference on*. IEEE, 311-316.

Weisburd, D., Britt, C., Wilson, D.B. & Wooditch, A. (2020). Describing the Typical Case: Measures of Central Tendency. *In:* Weisburd, D., Britt, C., Wilson, D. B. & Wooditch, A. (eds.) *Basic Statistics in Criminology and Criminal Justice.* Cham: Springer International Publishing.

Who (2021). Comprehensive mental health action plan 2013–2030. World Health Organization.

Witon, A.J. (2019). *EEG-Based Mental States Identification.* University of Kent.

Wu, Z. & Huang, N.E. Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Journal Advances in Adaptive Data Analysis.* 2009. 1 (01): 1-41.

Xiang, J., Maue, E., Fan, Y., Qi, L., Mangano, F.T., Greiner, H. & Tenney, J. Kurtosis and skewness of high-frequency brain signals are altered in paediatric epilepsy. *Brain Communications*. 2020. 2 (1).

Xu, J. & Zhong, B. Review on portable EEG technology in educational research. *Computers in Human Behavior*. 2018. 81, : 340-349.

Yadava, M., Kumar, P., Saini, R., Roy, P.P. & Prosad Dogra, D. Analysis of EEG signals and its application to neuromarketing. *Multimedia Tools Applications*. 2017. 76 (18): 19087-19111.

Yang, C.-Y. & Huang, C.-K. Working-memory evaluation based on EEG signals during n-back tasks. *Journal of Integrative Neuroscience*. 2018. 17: 695-707.

Yin, Z. & Zhang, J. Cross-session classification of mental workload levels using EEG and an adaptive deep learning model. *Biomedical Signal Processing Control*. 2017. 33: 30-47.

Young, M.S., Brookhuis, K.A., Wickens, C.D. & Hancock, P.A. State of science: mental workload in ergonomics. *Ergonomics*. 2015. 58 (1): 1-17.

Zappasodi, F., Marzetti, L., Olejarczyk, E., Tecchio, F. & Pizzella, V. Age-Related Changes in Electroencephalographic Signal Complexity. *Plos One*. 2015. 10 (11): e0141995.

Zarjam, P. (2013). *Estimation of working memory load using EEG signal processing*. The University of New South Wales Sydney.

Zarjam, P., Epps, J., Chen, F. & Lovell, N.H. Estimating cognitive workload using wavelet entropy-based features during an arithmetic task. *Computers in Biology and Medicine*. 2013. 43 (12): 2186-2195.

Zeng, K., Chen, D., Ouyang, G., Wang, L., Liu, X. & Li, X. An EEMD-ICA approach to enhancing artifact rejection for noisy multivariate neural data. *IEEE Transactions on Neural Systems Rehabilitation Engineering*. 2015. 24 (6): 630-638.

Zhang, J., Wang, Y. & Li, S. Cross-subject mental workload classification using kernel spectral regression and transfer learning techniques. *Cognition, Technology Work*. 2017. 19 (4): 587-605.

Zhang, S.X. (2014). *Structured support vector machines for speech recognition*. Doctor of Philosophy, University of Cambridge.

Zhang X, Y.L., Zhang D., Wang X., Sheng Q. Z., Gu, T. Multi-person brain activity recognition via comprehensive EEG signal analysis. *Proc. of the 14th EAI Int.*

Conf. on Mobile and Ubiquitous Systems: Computing, Networking and Services. 2017. 28.

Zyma, I., Tukaev, S., Seleznov, I., Kiyono, K., Popov, A., Chernykh, M. & Shpenkov, O. Electroencephalograms during Mental Arithmetic Task Performance. *Data*. 2019. 4 (1): 14.

APPENDIX J

LIST OF PUBLICATIONS AND AWARDS

Publications:

1. Sha’abani, M. N. A. H., Fuad, N., Jamal, N. and Ismail, M. **kNN and SVM Classification for EEG: A Review**. Proceedings of the 5th International Conference on Electrical, Control & Computer Engineering, 2020. Springer Singapore, 555-565. (Scopus indexed)

2. Sha’abani, M. N. A. H., Fuad, N., Jamal, N., Marwan, M., Abd Wahab, M. H. and Idrus, S. Z. S. **Development of Cognitive and Psychomotor Task for EEG Application with Matlab-based GUI**. IOP Conference Series: Materials Science and Engineering, 2020. IOP Publishing, 012050. (Scopus indexed)

3. Sha'abani, M. N. A. H., Fuad, N. and Jamal, N. 2021. **Eye Blink Artefact Removal of Single Frontal EEG Channel Algorithm using Ensemble Empirical Mode Decomposition and Outlier Detection.** Malaysian Journal of Fundamental Applied Sciences, Vol. 17, pp. 731-741. (Scopus & ISI indexed)

4. Sha’abani, M. N. A. H., Fuad, N., Jamal, N. and Engku Mat Nasir, E. M. N. **Selection of Intrinsic Mode Function in Ensemble Empirical Mode Decomposition Based on Peak Frequency of PSD for EEG Data Analysis.** Proceedings of the 3rd International Conference on Trends in Computational and Cognitive Engineering, 2022. Springer, Singapore, 213-221. (Scopus indexed)

Award:

1. Best Innovative Paper Award in the 3rd International Conference on Trends in Computational and Cognitive Engineering, 2022 (Track: Cognitive Science and Computational Biology).

APPENDIX K

VITA

The author was born on 31st March 1986 in Selangor, Malaysia. He went to Sekolah Menengah Kebangsaan Jenjarom and Sekolah Menengah Kebangsaan Telok Datok for his secondary school. He pursued his degree at the Universiti Teknikal Malaysia Melaka (UTeM) and graduated with a Bachelor of Engineering (Honours) in Mechatronic Engineering in 2010. Later, he received his Master of Science in Electrical Engineering from the same university in 2014. After graduation, he worked as a research engineer at Virtual Instrument & System Innovation Sdn. Bhd. between 2014 to 2015. Then, he joined Universiti Tun Hussein Onn Malaysia (UTHM) as a full-time lecturer in 2015. During this time, he taught several courses including computer programming, microcontrollers, control systems as well as robotics and automation at the Department of Electrical Engineering at the Centre for Diploma Studies. Currently, he pursues his study in the doctorate program at UTHM under the Faculty of Electrical and Electronic Engineering. His research focuses on evaluating human abilities based on brainwaves for the related cognitive task. His current research interest are biomedical engineering and artificial intelligence.