BIUST Teaching, Research, & Innovation Symposium 2023 (TRDAIS 2023)
Botswana International University of Science and Technology
Palapye, Botswana, 18 - 19 September 2023

ISSN: 2521-2293

An Interpretation of the Transitions in EEG Signals Based on the Five Frequency Bands with Increasing Alcohol Content in the Human Body

Kaloso M. Tlotleng and Rodrigo S. Jamisola Jr
Department of Mechanical, Energy and Industrial Engineering
Botswana International University of Science and Technology
Palapye, Botswana
kaloso.tlotleng@studentmail.biust.ac.bw, jamisolar@biust.ac.bw

Berdakh Abibullaev
Department of Robotics and Mechatronics
Nazarbayev University
Astana, Kazakhstan
berdakh.abibullaev@nu.edu.kz

***Abstract*—We present an interpretation of the transitions of the brain signals harnessed from an electroencephalogram (EEG) headset attached to the user while increasing alcohol intake by drinking alcoholic beverages. These transitions can be traced to an individual's cognitive and behavioral changes under the influence of alcohol that may affect the individual's decisions and motor control. The EEG headset is a wireless 32-channel Emotiv Epoc Flex brain wear. The data were recorded during experiments where an individual was given alcoholic beverages to consume within two hours. The individual was given a six-pack of beer with an alcohol content of 6%. We establish the variations of epoched data within a specific timeframe, starting from the first bottle of alcohol intake until the last bottle is finished. We use five frequency bands namely, delta, theta, alpha, beta, and gamma to observe and create visualizations based on the power spectrum of the EEG signals. The data is segmented into time-locked segments called epochs that represent the process of alcohol intake. These results can lead to a better understanding of transitions that occur in brain activity as the amount of alcohol consumption increases within a fixed timeframe.**

***Index Terms*—Electroencephalogram (EEG) signals, alcohol consumption, 32-channel headset, frequency bands, epochs**

I. Introduction

The analysis of electroencephalogram (EEG) signals has become a prominent research area in understanding different brain activities. EEG shows a record of continuous time electrical activity that takes place in the brain [1]. These signals are harnessed using a brain-computer interface (BCI) device that directly records from an individual and stores them in a computer [2]. Based on the type of application, EEG data can be interpreted and the results can be used to reflect an individual's mental activity [3].

In more studies using the application of EEG, [4] explains that brain activity can be monitored to understand the dynamics that occur during cognition. Standard tests and measurements are readily available to identify the different waveforms of the EEG signals. In their study, the power spectral density (PSD) of the theta, alpha, beta, and gamma bands was measured during baseline and cognitive tests.

A study by [5] further explains the significance of EEG analysis over the subjective assessment approach. The research concludes that the latter is not reliable in developing clinical diagnosis as it is prone to patient and expert bias. Furthermore, the study demonstrates that EEG signals can be interpreted by focusing on the analysis of the power spectrum of the five brain rhythms.

All these studies show that based on the type of application for EEG analysis, PSD still remains a powerful tool in interpreting the activity of the brain. PSD is a method of EEG data analysis in which the power intensity of the brain signals is measured across the frequency bands [6]. There are many risk factors that impact the normal function of the brain, that include the excessive use of alcohol. Consuming alcoholic beverages has been proven to disrupt normal brain activity and if it is taken more than 48g per day or 144g then it can be regarded as risky [7]. The changes caused by alcohol intake on signal activity can be analyzed by observing its power spectra. This information can be obtained in the frequency bands of the brain that include, delta, theta, alpha, theta, and gamma. These rhythms are classified based on their range of frequency as follows: delta (0.5-4Hz), theta (4-7Hz), alpha (8-13Hz), beta (13-36Hz), and gamma (36Hz and above) [8].

Section 2 of this paper describes the proposed methodology of our study and Section 3 introduces the materials and methods used. Section 4 focuses mainly on results while Section 5 outlines the analysis and interpretations of our results. The last section discusses future recommendations in relation to this study.

II. Methodology

The flowchart in Fig. 1 depicts the logical sequence of our proposed methodology. The first step is EEG data recording which includes recording using the Emotiv Epoc Flex brain wear. In this step, the volunteers were given a six-pack of beer with 6% of alcohol and the experiment took a maximum of two hours. The second step includes preprocessing the raw EEG data by first importing the data in CSV format, then detecting and dropping the bad channels, and finally filtering the data. Two types of filtering were applied that includes notch filtering and band-pass filtering. In the third step, epoching was applied

ISSN: 2521-2293

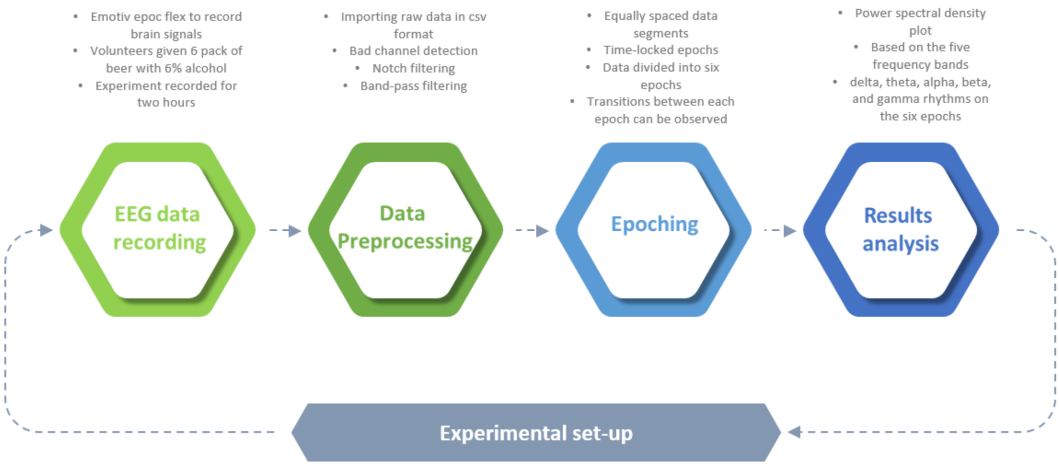

Fig. 1. *The proposed methodology of our study showing all the steps. It depicts the logical sequence followed from the recording of the EEG data until the analysis of the results. We use a power spectral density plot for all five frequency bands that are, delta, theta, alpha, beta, and gamma. The variations of these rhythms are observed in the six epochs.*

by creating six equally spaced data segments. These are time-locked such that the transitions between each epoch can be observed. The final step of the methodology includes the analysis of the results by spectral density plot based on the five frequency bands. These delta, theta, alpha, beta, and gamma rhythms were observed across all six epochs.

III. Materials and Methods

In this section, we outline the process we used to derive the required output, as outlined in the methodology below:

A. Experimental setup and device

Data were recorded using a wireless 32-channel Emotiv Epoc Flex EEG headset. During the experiment, the individual was given alcoholic beverages to consume within two hours. They were given a six-pack of beer with an alcohol content of 5.5% The BCI experiments were approved by the Ministry of Health and Wellness and, the Human Ethics Research Committee. The study participants include male volunteers aged between 22-44 years who are alcoholics. Each individual signed a consent form indicating that he agreed to participate in the experiments. The method of recruitment was random and participants were briefed on the experimental setup. The Alcohol Use Disorder Identification Test was administered to the volunteers to evaluate their frequency of use of alcohol.

The Emotiv Epoc Flex Headset was positioned based on the 10-20 standard electrode placement as shown in Fig.2.

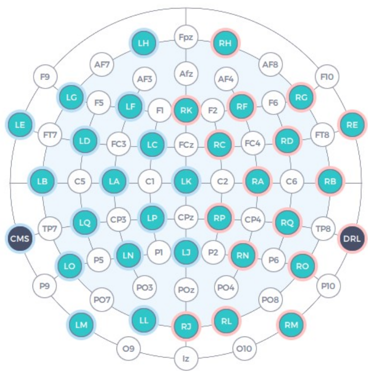

Fig. 2. *In the figure, the highlighted green positions represent the electrode placement using the 10-20 standard electrode placement. It also shows the number of channels from which the EEG data was recorded. They are 32 positions representing the 32-channel headset.*

B. Data Preprocessing

This step involves transforming our data into a format that is easier to manipulate and analyze. Artifact removal is carried out such that we can have clean EEG data separated from the noisy data [9]. This is because EEG data can be easily contaminated by various artifacts that include, muscle movement, eye blinks, and measuring instruments. It is desirable to filter out this type of data [10].

1) Importing raw data: The data was imported in a CSV format through the use of the MNE library which is python based. It provides a way to convert any type of data into a format that can be used by the library [11]. Only data from the 32-channels was retained and all other columns were dropped.

ISSN: 2521-2293

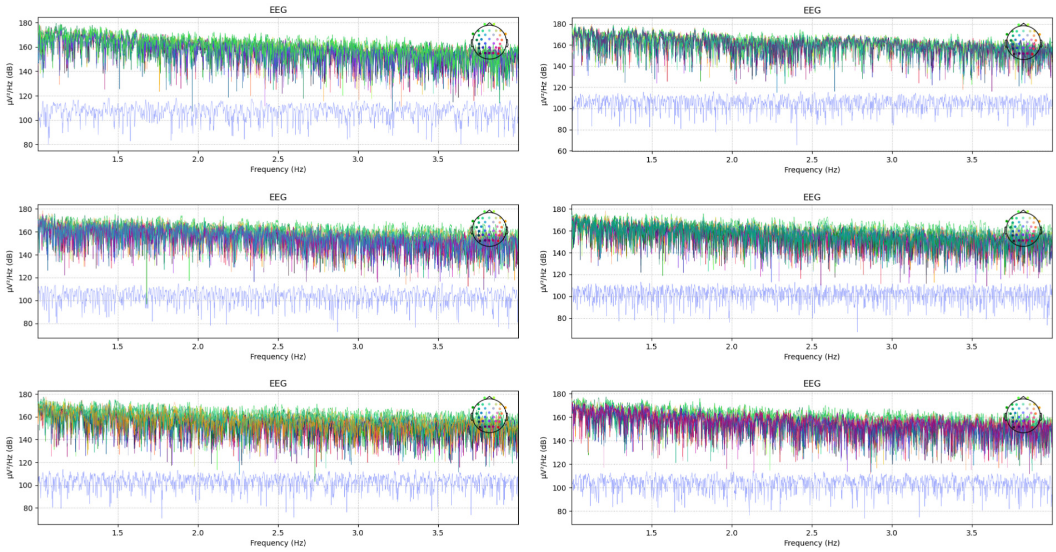

Fig. 3. *The power spectral density plots for the six epochs of the delta band are shown in Fig.3. The frequency range for this band lies between 1Hz and 4Hz. We can observe that the power of the delta band stays constant across all the epochs.*

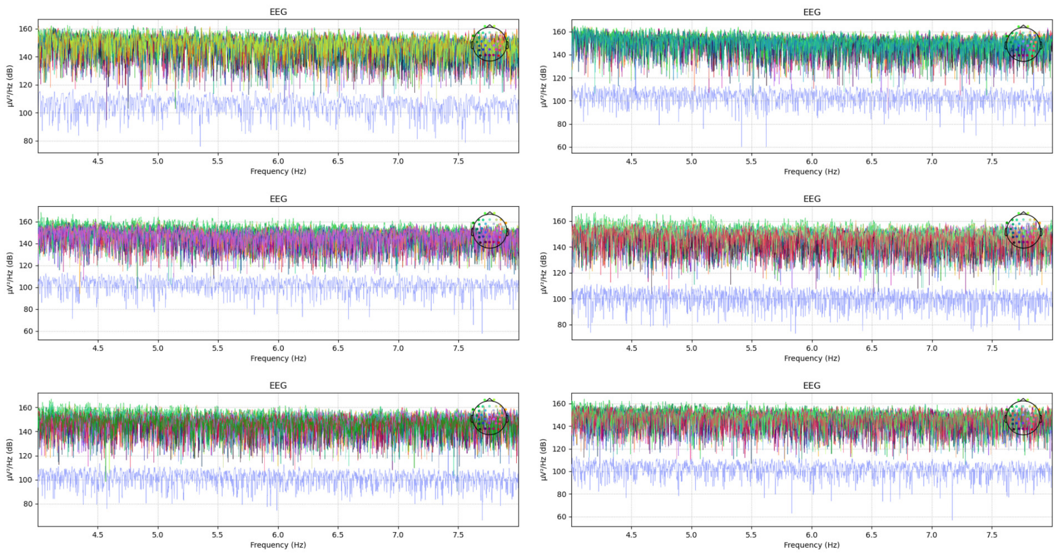

Fig. 4. *The graph in Fig.4 represents the power spectral density of the theta band across the six epochs. This frequency band ranges between 4Hz and 8hz. The power spectrum is constant in all six epochs.*

2) Bad channel detection: These are channels that do not provide enough information to be considered for analysis. They may be caused by various reasons that include, poor contact between the scalp and the electrode, poor electrode

ISSN: 2521-2293

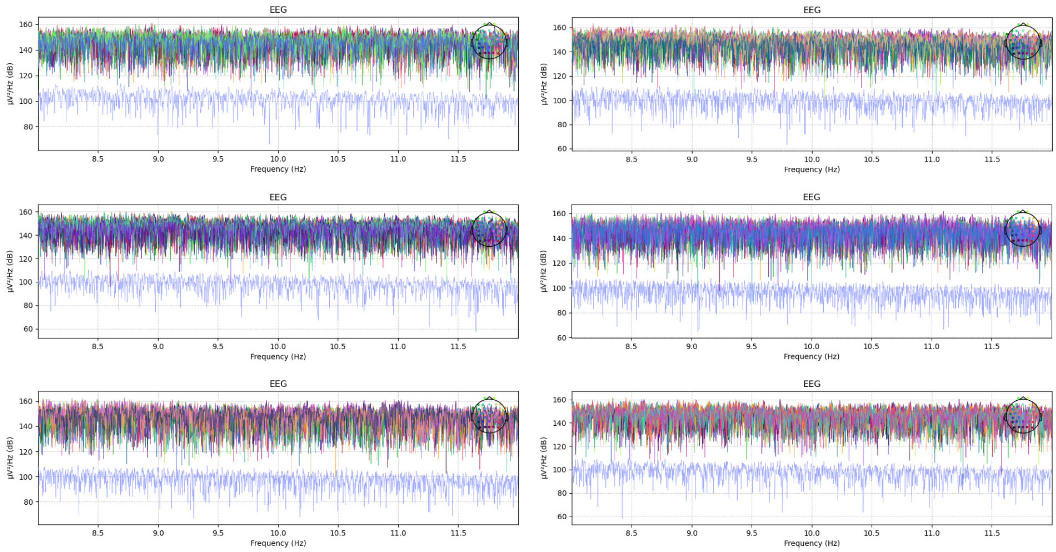

Fig. 5. *The graph in Fig.5 depicts the power spectral density plot for the alpha band across the six epochs. This band ranges between 8Hz and 12Hz. The power in this rhythm is constant across all six epochs.*

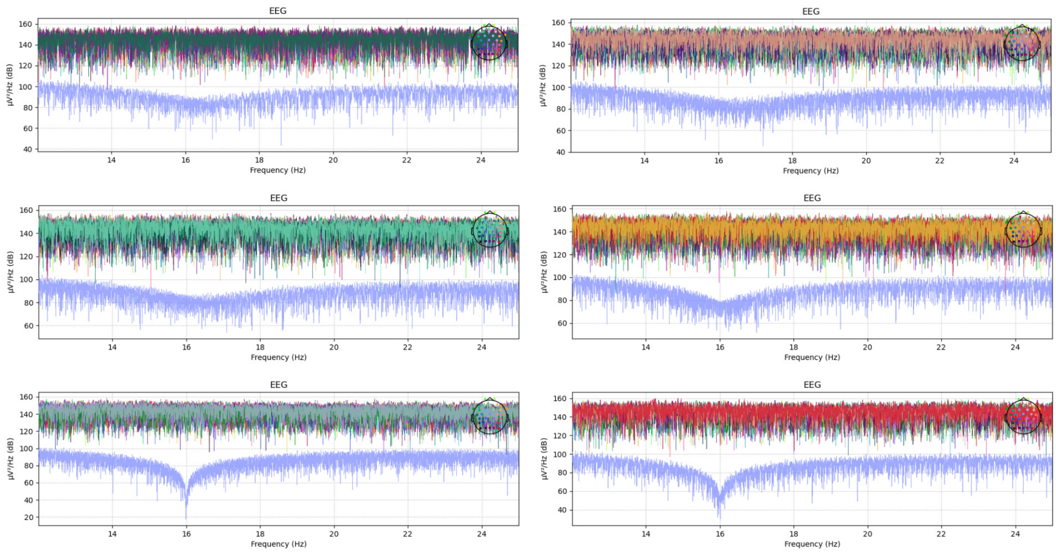

Fig. 6. *In the beta band the visualizations are shown in this graph on Fig.6. Its frequency ranges between 12Hz and 25Hz. The power in this band can be observed to have a slight reduction in power at 16Hz.*

placement, and malfunction. These may affect the interpretation and analysis of the EEG data [12]. No bad channels were spotted in our data.

ISSN: 2521-2293

3) Notch Filtering: This step is very crucial to remove the power line or electrical noise in our EEG data [13]. The artifacts are usually around 50Hz or 60Hz. A notch filter was introduced to reject all the frequencies from 60Hz and above.

4) Band-pass Filtering: In a band-pass filter, minimum and maximum frequencies are chosen such that any signal that falls outside the range will be rejected. It can help eliminate noise from eye blinks, muscle movements, and probable electrocardiography data [1]. We applied a band-pass filter to keep frequencies between 1Hz and 55Hz.

5) Epoching: This process allows us to create segments of data that are equally spaced. It divides the data into equal epochs that are time-locked such that we can analyze the transitions that occur from one segment to the other. The data was segmented between six equally spaced epochs that correspond to the increasing amounts of alcohol intake. That is, they represent the time a participant started drinking until the time they finished drinking. Within each epoch, we obtain the results for the power spectra of the five frequency bands and interpret these changes.

IV. Results

In this section, we present the visualizations from the power spectral density of each epoch. We show the results of the changes in the frequency bands starting with delta, then theta, alpha, beta, and lastly gamma. We observe the transitions of these rhythms from the first epoch to the last epoch.

A. Delta band

This frequency band is mostly associated with deep sleep and is only active when the body is fully at rest in that state. It is the smallest rhythm with a frequency range from 1Hz to 4Hz [14].

B. Theta band

The theta band is found mostly in frequencies ranging from 4Hz and 8Hz. It is also associated with learning and inhibitory control processes [15]. It can be generated and recorded across all the parts of the cortex.

C. Alpha band

The alpha rhythm is found within the frequency band from 8Hz to 12Hz and is mostly associated with sensory and memory functions [16]. Its power spectrum is mostly suppressed during body activities with eyes open.

D. Beta band

This frequency band is mostly associated with sensory-motor control processing and tasks [17]. It is usually generated in the frontal regions of the brain and ranges between 12Hz to 25Hz.

E. Gamma band

This rhythm is mostly associated with very high frequencies ranging from 25Hz upwards. It is still an active research area and therefore it is still unclear where it is generated [18].

V. Interpretation of Results

Based on these visualizations, we can observe obvious changes in the power spectra from epoch one to epoch six in all rhythms shown in Fig.3 to Fig.7. In figures 3 to 5 we can observe the color changes in the graph. Each signal color corresponds to an eeg channel. The change in the color in the graph means that some channels are becoming more prominent than others for their signal color to dominate the graph. We can interpret this as some parts of the brain are suppressed due to alcohol consumption. And this suppression increases as the alcohol content increases. It is observed further that the power spectrum of the graph has no observable changes.

In Fig.6 to Fig7 the same observed change of colors in the graph is shown. However, for some channels, there are observed changes in the power of the signals as shown in the lower set of signals that dips. This dipping of the signal increases with increasing alcohol content.

Based on these results, we can interpret that, the volunteer has higher alcohol tolerance. We can also conclude that the individual is projecting symptoms of alcohol use disorder. According to [19], increased spectral power in the beta band is expected from people who are alcoholics. In our results, the participant had a slight reduction in the spectral power of the beta rhythm which is in contrast to the expected results. This implies that at the time the volunteer had the last bottle of alcohol, there were no induced effects, and the body could potentially have more consumption.

VI. Future work

In the future, we plan to increase the data visualization by presenting the data per channel or combining the signals for several channels. We also plan to improve the filtering to further remove white noise. Some presentations will also be shown for the brain signal topography map. Feature extraction is to be implemented and the results will be clustered using unsupervised machine learning. We will compare the results for all seventeen volunteers.

References

[1] A. Khosla, P. Khandnor, and T. Chand, "A comparative analysis of signal processing and classification methods for different applications based on eeg signals," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 2, pp. 649–690, 2020.

[2] M. C. Guerrero, J. S. Parada, and H. E. Espitia, "Eeg signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks," *Heliyon*, vol. 7, no. 6, p. e07258, 2021.

[3] S. Ullah and Z. Halim, "Imagined character recognition through eeg signals using deep convolutional neural network," *Medical & Biological Engineering & Computing*, vol. 59, no. 5, pp. 1167–1183, 2021.

[4] J. G. Foy and M. R. Foy, "Dynamic changes in eeg power spectral densities during nih-toolbox flanker, dimensional change card sort test and episodic memory tests in young

ISSN: 2521-2293

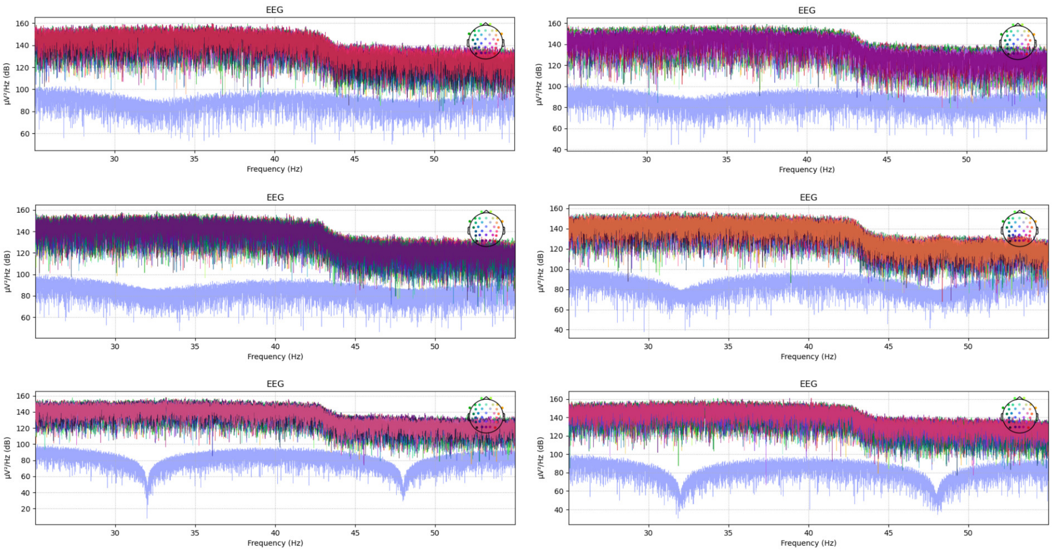

Fig. 7. *The graph for the power spectral density of the gamma band is shown in Fig.7. It ranges between 25Hz and 55Hz. The results show a distinctive structure in relation to the power of the rhythm.*

adults," *Frontiers in human neuroscience*, vol. 14, p. 158, 2020.

[5] J. J. Newson and T. C. Thiagarajan, "Eeg frequency bands in psychiatric disorders: a review of resting state studies," *Frontiers in human neuroscience*, vol. 12, p. 521, 2019.

[6] M. N. Alam, M. I. Ibrahimy, and S. Motakabber, "Feature extraction of eeg signal by power spectral density for motor imagery based bci," in *2021 8th International Conference on Computer and Communication Engineering (ICCCE)*. IEEE, 2021, pp. 234–237.

[7] W. Mumtaz, P. L. Vuong, L. Xia, A. S. Malik, and R. B. Abd Rashid, "Automatic diagnosis of alcohol use disorder using eeg features," *Knowledge-Based Systems*, vol. 105, pp. 48–59, 2016.

[8] A. Anuragi and D. S. Sisodia, "Alcohol use disorder detection using eeg signal features and flexible analytical wavelet transform," *Biomedical Signal Processing and Control*, vol. 52, pp. 384–393, 2019.

[9] S.-P. Kim, "Preprocessing of eeg," in *Computational EEG Analysis*. Springer, 2018, pp. 15–33.

[10] X. Jiang, G.-B. Bian, and Z. Tian, "Removal of artifacts from eeg signals: a review," *Sensors*, vol. 19, no. 5, p. 987, 2019.

[11] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen, and M. S. Hämäläinen, "MEG and EEG data analysis with MNE-Python," *Frontiers in Neuroscience*, vol. 7, no. 267, pp. 1–13, 2013.

[12] V. Tuyisenge, L. Trebaul, M. Bhattacharjee, B. Chanteloup-Forêt, C. Saubat-Guigui, I. Mîndruţă, S. Rheims, L. Maillard, P. Kahane, D. Taussig *et al.*, "Automatic bad channel detection in intracranial electroencephalographic recordings using ensemble machine learning," *Clinical Neurophysiology*, vol. 129, no. 3, pp. 548–554, 2018.

[13] S. Leske and S. S. Dalal, "Reducing power line noise in eeg and meg data via spectrum interpolation," *Neuroimage*, vol. 189, pp. 763–776, 2019.

[14] F. Bröhl and C. Kayser, "Delta/theta band eeg differentially tracks low and high frequency speech-derived envelopes," *Neuroimage*, vol. 233, p. 117958, 2021.

[15] C. Pscherer, M. Mückschel, L. Summerer, A. Bluschke, and C. Beste, "On the relevance of eeg resting theta activity for the neurophysiological dynamics underlying motor inhibitory control," *Human Brain Mapping*, vol. 40, no. 14, pp. 4253–4265, 2019.

[16] B. Scally, M. R. Burke, D. Bunce, and J.-F. Delvenne, "Resting-state eeg power and connectivity are associated with alpha peak frequency slowing in healthy aging," *Neurobiology of aging*, vol. 71, pp. 149–155, 2018.

[17] H. Díaz, F. M. Cid, J. Otárola, R. Rojas, O. Alarcón, and L. Cañete, "Eeg beta band frequency domain evaluation for assessing stress and anxiety in resting, eyes closed, basal conditions," *Procedia Computer Science*, vol. 162, pp. 974–981, 2019.

[18] M. Sameer, A. K. Gupta, C. Chakraborty, and B. Gupta, "Epileptical seizure detection: Performance analysis of

ISSN: 2521-2293

gamma band in eeg signal using short-time fourier transform," in *2019 22nd international symposium on wireless personal multimedia communications (WPMC)*. IEEE, 2019, pp. 1–6.

[19] K. E. Courtney and J. Polich, "Binge drinking effects on eeg in young adult humans," *International journal of environmental research and public health*, vol. 7, no. 5, pp. 2325–2336, 2010.