Trait depressivity prediction with EEG signals via LSBoost

1st Shenghuan Zhang
Dept. of Computer Science
University of Otago
Dunedin, New Zealand
zhangsh@cs.otago.ac.nz

2nd Brendan McCane
Dept. of Computer Science
University of Otago
Dunedin, New Zealand
mccane@cs.otago.ac.nz

3rd Phoebe S-H Neo
Dept. of Psychology
University of Otago
Dunedin, New Zealand
phoebe.neo@otago.ac.nz

4th Shabah M. Shadli
Dept. of Psychology
University of Otago
Dunedin, New Zealand
shabah.shadli@otago.ac.nz

5th Neil McNaughton
Dept. of Psychology
University of Otago
Dunedin, New Zealand
neil.mcnaughton@otago.ac.nz

Abstract—Purpose: This study aims to identify EEG biomarkers that predict the level of depressive personality (where extreme scores indicate disorder), as opposed to the presence or absence of a depressive state or a depression diagnosis.

Methods: Fourier features were extracted from 2-second epochs of resting state EEG and used by LSBoost to maximise the correlation with depressive trait tendencies (PID-5 depressivity index).

Results: Our method accounted for 25.75% of the variance in PID-5 scores, albeit in females only. The recording channel C3 and frequencies in the gamma band were the most important contributors to the prediction. The findings are consistent with previous psychological studies and suggest that our method is a feasible strategy for developing quantitative EEG biomarkers for trait depressivity in a neuropsychologically interpretable form. We have also shown that there might be different markers for depressivity between males and females.

Index Terms—EEG, depressivity, LSBoost

I. Introduction

The prevalence rates of depression range from 2.2 to 10.4% worldwide [1] and the economic burden of depression was estimated to be approximately $US210 billion dollars in the United States in 2010 [2]. Yet the biological causes of depression are largely unknown, and clinical diagnosis is based on symptoms rather than underlying causes. Consequently, the NIMH has called for the development of biomarkers to enhance the diagnosis of mental health disorders [3].

Electroencephalography (EEG) signals are a potentially rich source of biomarkers and have been previously used to characterize different physiological states, such as dementia [4], schizophrenia [5], [6] and obsessive-compulsive disorder [7], [8]. However, effective treatment of depression needs the diagnosis to take into account its severity, its sub-types, and the associated neural basis. Hence, highly accurate but binary classification, and black-box biomarkers that are not easily interpretable biologically, will add limited value to the clinical decision, and are unlikely to be well-accepted amongst clinicians. In this paper we use LSBoost regression [9] and Fourier EEG features to predict trait depressivity (a measure that varies smoothly in the population with only high values associated with clinical disorder) and also to highlight potential interpretable biomarkers extracted from EEG signals.

II. Related Work

During the past years, EEG studies on depression have shown that EEG data can be used to effectively distinguish depressed patients and healthy controls. One method, called the spectral asymmetry index, calculates the difference between the higher and lower EEG frequency bands; and provided effective features to differentiate depressed patients with 77% classification accuracy [10] for 17 depressed patients and 17 controls. Mohammadi et al. [11] used linear discriminant analysis to map the features into a new feature space, genetic algorithms to select the most important features and decision trees for classification. Participants included 53 major depressed patients and 43 non-depressed healthy controls and produced an accuracy of 80%. Likewise, Hosseinifard et al. [12] used several feature extraction methods and machine learning techniques to classify 45 depressed patients and 45 normal subjects. This study achieved a classification accuracy of 90%, using a combination of feature extraction methods (detrended fluctuation analysis, Higuchi fractal dimension, correlation dimension and lyapunov exponent) and a Linear Regression classifier.

Unlike previous work, which sees depression as a binary disease, our focus is to identify biomarkers that are sensitive to depressive trait tendencies. We use LSBoost [9] to perform regression against the PID-5 scale [13] that includes scores through the range of healthy as well

978-1-7281-6926-2/20/$31.00 ©2020 IEEE

as depressed individuals. The PID-5 was developed to improve the capturing of symptoms only specific to the disease. We expect it to be more specific than the simple contrasts of healthy controls with patients in the previous work, which will include non-specific differences between the two groups. Being a trait rather than a state measure, biomarkers of PID-5 are also more stable features as they capture the depressivity tendency of a person regardless of the current mood. For features, we used the EEG power spectrum at 0.5Hz intervals at conventional EEG electrode sites spaced evenly across the top of the head. Such an approach has two main advantages. It allows for a direct and purer measurement of depressive severity which can be used to both guide appropriate treatments and measure their effectiveness; and it also highlights which features are most important for measuring depressivity, which could lead to effective and neuropsychologically interpretable biomarkers.

III. Materials and Methods

A. Experiment for Data Acquisition

1) Participants: Data were obtained from 73 right-handed participants (44 females, 29 males; aged 18-37 years with a mean of 21.56 years). All procedures were approved by the University of Otago Ethics Committee (approval number: H15/005). All participants were recruited through the University of Otago Student Job Search. Informed consent was provided before participating in the experiment. No participant reported any medical or psychological treatment for depression, anxiety or other type of emotional disorder in the last 12 months.

2) Procedure: Prior to EEG testing, each participant spent 10-15 minutes to complete a computer-delivered questionnaire program containing scales from the Personality Inventory for DSM-5 (duration 10-15 minutes). The experimenter then measured each participant's head circumference and marked Fp1 and Fp2 according to the International 10-20 system [14] using a black marker. Electrode gel (Electro-Cap International, Eaton, OH, USA) was inserted into 20 electrodes via a blunt square-tipped 16-gauge needle (Precision Glide, Needle, Becton Dickinson, Franklin Lakes, NJ, USA); impedance reduced to $<5K\Omega$ by gentle abrasion of the scalp with the tip of the needle; and brief relaxation-induced alpha rhythm and deliberate eye-blink traces assessed by the experimenter to ensure good recording, with adjustments as necessary (preparation time $\sim$ 30 minutes).

A relaxation test was then performed by instructing the participants to remain relaxed, with their eyes open and then closed for one-minute intervals, the order was O-C-O-C-C-O-C-O (C: eyes closed, O: eyes open). Resting EEG was recorded throughout this period (8 minutes duration). This database includes 18 primary recorded channels: Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4 and P8, which were referenced to CPz when recording, and the average of 'A1' and 'A2' was used to re-reference (see Fig. 1). The sampling rate for analysis was 256Hz.

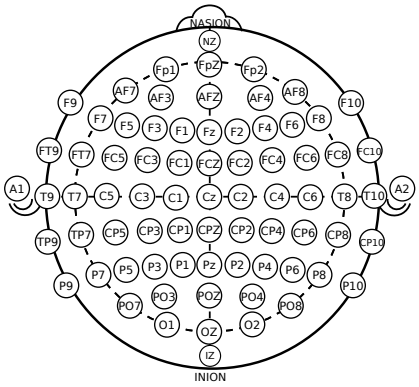

Fig. 1. The extended International 10-20 system position of scalp electrodes. Electrodes are placed at 5%, 10% and 20% spacings relative to standard skull measurements (e.g. nasion-inion). Figure is CC0 from https://commons.wikimedia.org/wiki/File:International_10-20_system_for_EEG-MCN.svg. Abbreviations: A = Auxiliary (Ear lobe, shown, or mastoid, in our experiments), C = central, P = parietal, F = frontal, Fp = frontal polar, O = occipital.

3) PID-5 depressivity scores: The Personality Inventory for DSM-5 (PID-5) questionnaire includes 14 questions related to depressivity on a 4-point scale (Score 0-3) representing the depressivity level [15], [16]. The scores are summed across these questions to generate the PID-5 depressivity score (PID-5-d). Low values mean far from clinical. Medium is normal for the middle of the population and high is in the clinical range. A score above a particularly high threshold can be taken as clinical [17], [18]. In our database, the highest PID-5-d score is 27, the lowest is 0. Fig. 2 shows the PID-5-d score's distribution for females and males, separately. The participants of this database were not clinical patients, so there were more low PID-5 depressivity score participants than high score ones.

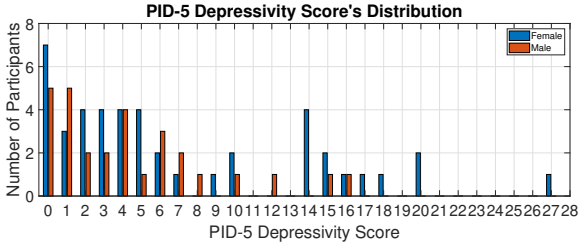

Fig. 2. The figure illustrates the PID-5 depressivity scores' distribution of our data samples. We can see that most cases have low scores, with a small number of cases having high scores.

B. Data Preprocessing

Data preprocessing was used to improve signal quality and included six steps: baseline drift removal, mains noise removal, eye blink removal, data splitting, and

rejecting extremely contaminated epochs automatically and manually.

1) Baseline Drift Removal: Baseline drift can be caused by variations in temperature, instrumentation bias and so on [19]. To remove baseline drift, a 1Hz high-pass filter was applied to the raw signal.

2) Mains Noise Removal: EEG signals are contaminated by mains power from electrical equipment. The mains power causes a local peak in the EEG signal around the frequency of electricity. Our dataset recorded EEG data from several channels synchronously, therefore, mains power should have a fixed phase all through the record and be synchronous across all channels whereas real brain signals are not the same phase as each other and should not be synchronous. Therefore, to remove the mains noise, a phase-fixed method was designed to evaluate the component of mains noise in EEG signal and removed. This method is reported in [20].

3) Eye Blink Removal: Eye blinks affect EEG signals but are not hypothesised to be related to depression. We use the method proposed in [21] to remove the effects of eye blinks from the signal.

4) Data Splitting (Open/Closed): Since EEG recording is related to eye state [22], the eyes-open data and eyes-closed data are treated separately. The first and last second of each eye state recording were discarded leaving 232 seconds of EEG for each eye state (4 minutes each minus 8 seconds for transition). Each recording was then split into 1-second-length epochs.

5) Rejection of Contaminated Epochs: Because of head movements and other interference, sometimes extremely high EEG values are recorded, therefore epochs with amplitudes greater than 500 μV or less than -500 μV were discarded.

After all automatic processing, each data sample was visually inspected, and contaminated epochs that had been missed by the algorithms were rejected. The main types of EEG artefacts (e.g. Rapid eye movement, chewing artefact, and tongue movement) are listed in [23] and the records were visually searched for this and then discarded.

C. Feature Extraction

To reduce spectral leakage, a Hanning window was applied to each channel in each epoch (2-second-length epoch with 1 second overlap) and the discrete Fourier transform used to extract frequency features. Since our sampling rate (F_s) is 256 Hz and the length (N) of each epoch is 512 time points (2 second $\times$ 256 Hz), the frequency resolution (F_s/N) is 0.5Hz. This results in 256 frequency components from 0.5 to 128Hz (the DC component is discarded). Finally, the square of each component (power spectrum) is log transformed to normalize error variance and used to compute a feature. Since there are 18 channels and 256 frequency samples per channel, each epoch is represented as a 4608 dimensional vector. Generally, EEG signals are divided into five different frequency bands, their frequency range is from 1 Hz to 80 Hz [24]. Therefore, the segment from 1 to 80 Hz of the vector was selected to be the feature vector with a length of 2862 (18×159). For this paper, each dimension is considered a feature.

D. Feature Selection and Regression

As stated in the introduction, our research goals are twofold: to develop an automatic, quantitative method for measuring depressivity based on biomarkers; and that those biomarkers are easily interpretable biologically. Therefore we need to use methods that use relatively few features and those features should be interpretable. Using Fourier features deals with the latter problem, but produces thousands of features. We have chosen the LSBoost algorithm [9] to deal with the former. At each step, LSBoost fits a new weak learner to the difference between the observed response and the aggregated prediction of all previous weak learners to minimize mean-squared error.

There are approximately 200 epochs per participant for each of the eyes-open and eyes-closed experiments. The ground truth target score for each participant is their PID-5-d score, which is a single number. For regression training purposes, we assume that each epoch from the same participant has the same target value. This is based on the definition of depressivity as a trait, i.e. a property of the brain that does not vary with time and that depressivity as a trait can give rise to persistent (or frequently occurring), rather than intermittent, distinctive brain states [25]–[28]. Nevertheless, at identification time, we do not expect each epoch to produce the same LSBoost score, and so we simply average the scores for all epochs to assign a score to a new participant. As is common with boosting algorithms, we choose decision stumps with a single feature as the weak learner. LSBoost therefore chooses the most significant features to fit to the target value. Here we use up to 100 weak learners. Adding more features/weak learners did not improve regression results. We call the depressivity score predicted by LSBoost the ML-d score.

E. Experimental Design

Barry et al. [29] demonstrated that the eyes closed and eyes open states provide EEG measures differing in topography and power levels. When the eyes are closed, cortical activation is decreased [30]. Because the alpha power is usually more dominant when the eyes are closed [31], [32] and the previous depression study usually focussed on the alpha band, some research only used the eyes closed data [33]–[35].

There are also many reports of gender differences in the causes of depression, and gender differences in the EEG of depressed people. Halbreich et al. [36] suggested that the differences in mechanisms of depressive symptoms between male and female might be related to the central nervous system. Bryden [37] reported that gender may modulate hemispheric EEG asymmetry, while [38] suggested that

EEG asymmetry may only relate to depression in young females rather than males. Ahmadlou et al. [39] found significant differences between male and female adults with major depressive disorder in relative convergence of *delta* band EEG in the intraleft temporal and frontoleft temporal lobe. Males and females with depression also appear to have different slow-wave activities during non-rapid eye movement sleep [40]–[42].

Therefore, to demonstrate the eye states and gender states difference, in our research, the data was split into three categories relating to eye condition (open, closed, all), and three categories relating to gender (male, female, gender-mixed), resulting in nine experiments in total. The "all" conditions include both open and closed epochs, and the "gender-mixed" condition includes male and female participants. There were 44 females and 29 males in the sample.

For each experiment, k-fold cross validation was used to pick training and testing data sets. Each fold consisted of 4 participants except for the last fold in the male experiments which had 5 participants. Therefore, for male group, $k = 7$; for female group, $k = 11$; for gender-mixed group, $k = 18$. For a given training or test run, all epochs from a single participant were used in either the training set or the test set. Pearson's correlation coefficient (R) between the ML-d and PID-5-d score was used to evaluate the effectiveness of ML-d. R-values between 0.4 and 0.6 would normally be considered indicative of a moderate positive correlation.

IV. Results and discussion

A. R-values

Table I shows the correlation (R^2) between PID-5-d and ML-d scores, and the statistical significance of the correlation (p). We can see from the table that for the female group, the best result (25.75%) was obtained by using all eye states epochs. This result is also the best one of all experiments. Figure 3 shows the scatter plots of the ML-d score and the matched PID-5-d score for Experiment 1.3. For the male group, no results were statistically significant. For the gender-mixed group, the best result (18.28%) was obtained by using eyes open epochs.

B. Genders

The results obtained by our experiments show that for different genders, the performance of the male group is much worse than the female and the gender-mixed groups (Gender, F (2,8) = 163.26, p < 0.001). However, the main possible reasons are we only have 29 data sets in the male group and the PID-5-d range of the male group in our dataset was narrow. Therefore, it cannot easily demonstrate a gender difference or lack thereof.

The results also show that the performance of the gender-mixed group is worse than the female group. To an extent, this result confirmed the existence of a gender difference. The different EEG patterns from different genders lower the model's depressivity prediction ability at least for regression models.

TABLE I
Correlation values between PID-5-d and ML-d for each of the experimental conditions.

Gender	*Eyes*	*Ex*	R^2	p
Female	Open	E1.1	24.52%	0.0006
	Closed	E1.2	22.51%	0.0011
	All	E1.3	25.75%	0.0004
Male	Open	E1.4	1.57%	0.5179
	Closed	E1.5	2.84%	0.3820
	All	E1.6	1.97%	0.4675
Gender-Mixed	Open	E1.7	18.28%	0.0002
	Closed	E1.8	16.31%	0.0004
	All	E1.9	14.37%	0.0009

Values in the table are R^2-values and the corresponding p-values of each experiment. In this set of experiments, R-values were all positive and can be got back by taking the square root of the R^2-values. Here, 'Ex' refers to 'Experiment'.

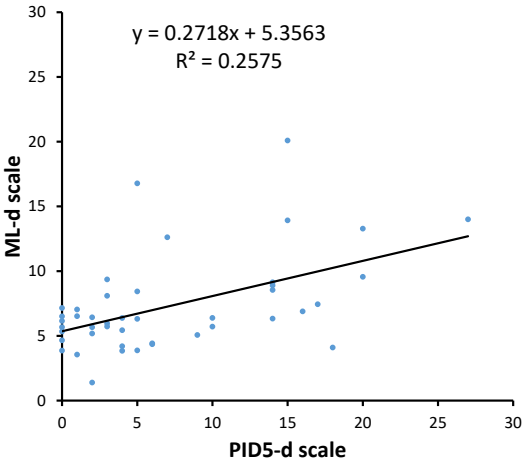

Fig. 3. Figure shows the scatter plots of the ML-d score and the matched PID-5-d score of the experiment E1.3 which is the best result of all experiments.

C. Eye states

There is good evidence that EEG signals are different for eyes-open and eyes-closed conditions [29], [31]. However, the results obtained from our research show that the same depressivity features are present in both states. This is consistent with PID-5 being a measure of a trait and suggests that our methods have identified trait-like EEG features that are stable across different states. This may provide a benefit for designing EEG collecting experiments because participants don't need to be constrained to close their eyes. However, in recent EEG collecting experiment, the participants were required to open and close their eyes for one-minute intervals. In future, these two methods would need to be directly compared in case eye closure changes the eyes open EEG during relaxation testing.

D. Features

The LSBoost method has a good characteristic that it can compute features' importance by summing all estimates over all weak learners in the ensemble. The highest value indicates that this feature is the most important one [43]. After establishing an ensemble, a vector of weight values that indicates the relevant importance of each feature was obtained. The vector was then normalised between 0 to 1. The highest value in the vector indicates the most important feature. Because we implemented experiments with k-fold cross-validation, in each experiment, we established k ensembles. Therefore, we averaged the weight values across the k ensembles in the experiment to get the final rank of features' importance.

According to the components of FFT's feature vector, each point of a feature vector contains two types of information: frequency and channel. The importance of different frequencies and channels were sorted by weight values separately.

1) Channels: The distribution of important channels is shown in Figure 4. The figure shows that the most important channels of the female group are C3 and T8; the most important channels of the gender-mixed group are C3 and T7.

These results, taken together, shows a specific location – C3 – which is the most important for prediction of depressive trait tendencies.. This result is consistent with a previous research [44] which investigated neuromodulatory effects of repetitive transcranial magnetic stimulation (rTMS) on resting EEG and their clinical and cognitive correlates in depressed patients. Their results showed that after rTMS, depressed patients demonstrated significant increases of resting theta–gamma coupling (TGC) at channel C3.

Our research also found that the EEG of channel T7 and T8 may be important for predicting depressivity. This result is consistent with recent research by [45]. They also found temporal electrodes were important.

2) Frequency: The distribution of important frequencies is shown in Figure 5. The figure shows that the most important frequencies are around 50Hz. For the female group, there are also peaks around 10Hz and 35Hz; for the gender-mixed with eyes open group, as well as 50Hz, the importance frequencies also distributed in 10Hz, 20Hz, 30Hz, and 40Hz. 30Hz, 35Hz, 40Hz, and 50Hz are within the *gamma* band. The *Gamma* band is linked to memory, attention, and cognition. 10Hz is within the *alpha* band. This band is a frequently-used band for psychological study. 20Hz which only occurs in the gender-mixed group belongs to the *beta* band. The R^2-values obtained by the male group are all non-significant, therefore, the important features of the male group are not discussed here.

In previous EEG research on depression, the *alpha* band (8–13Hz) has been most used e.g., [33], [35], [46], [47]. Consistent with this, we found that signals in the region of 10Hz, which is in the *alpha* band, contributed

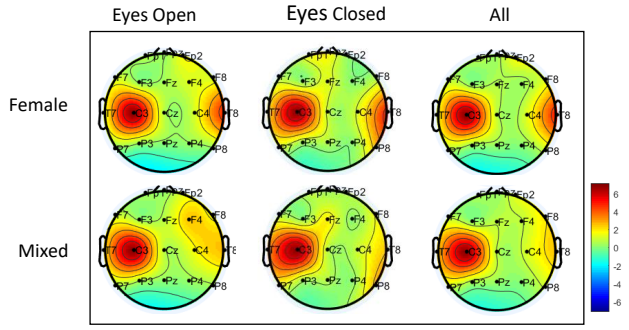

Fig. 4. This figure shows the distribution of importance of different channels on the scalp. From the figure, we can see that the most important channels of the female group are C3, T7 and T8; the most important channels of the gender-mixed group are C3 and T7.

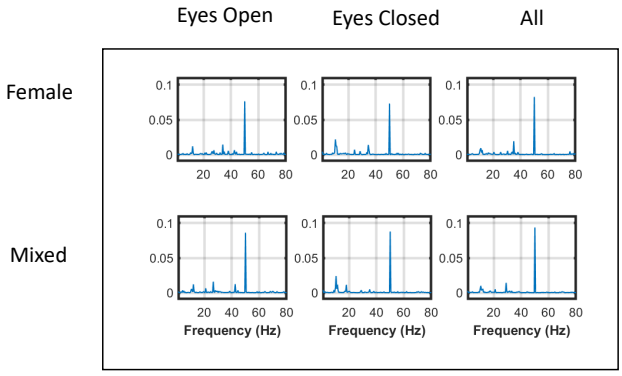

Fig. 5. This figure shows the distribution of importance of different frequencies. From the figure, we can see that the most important frequencies are around 50Hz. For the female group, there are also peaks around 10Hz and 35Hz; for the gender-mixed of eyes open group, except for 50Hz, the importance frequencies also distributed in 10Hz, 20Hz, 30Hz, and 40Hz.

to depressivity prediction. There is little research on the relationship between the *beta* band and depression. Merkl et al. [48] found difference in the *beta* band between depressed patients' reported with emotional empathy for negative stimuli and patients reported to have no empathy. Sheikhani et al. [49] reported that the signal obtained from the *beta* band can be used to distinguish Autism disorders from controls. We found that signals around 20Hz, which is in the *beta* band, are also useful to predict depressivity.

Previous study indicated that the *gamma* band is suitable for EEG-based emotion classification [50]. Webb

et al. [51] found that the EEG of the *gamma* band was highly associated with three promising endophenotypes of depression. The results from [45] also showed that the EEG of the *gamma* band is a good indicator for classifying depressed patients and controls. From the results of our research, the *gamma* band (around 30Hz, 35Hz, 40Hz, 50Hz, 70Hz) was found to be an important band for measuring depressivity. This result is consistent with previous research.

3) Channels across Frequency: The highest weighted single point of each feature vector in different conditions (different genders and different eye states) was also picked. The highest weighted points obtained in all conditions all referred to 50Hz at C3. This means that the 50 Hz resting EEG signal detected at C3 is the most important signal for predicting depressivity. This result is also consistent with the previous research [44] that resting theta–gamma EEG at channel C3 is highly related to depression.

V. Conclusion

In this paper, we introduced a method to predict depressivity scores using EEG signals via the LSBoost algorithm. We are able to produce a measure that is moderately correlated with a trait measure of depressive tendencies. It is important to point out that the PID-5 is a rather blunt tool linked to multiple different types of depression and it would generally not be expected to be able to produce correlations much higher than those reported here. In our lab, the same dataset used in this research with an additional 28 participants was tested using traditional EEG alpha asymmetry and HFD (Higuchi's fractal dimension) with stepwise regression. The correlations obtained by the traditional EEG alpha asymmetry method were very low and showed no significant correlation between alpha asymmetry and depressivity. The best R^2-value was obtained by HFD and was 4%. In previous research, Stewart and Allen [52] reported a longitudinal pilot study where they examined the relationship between resting frontal EEG asymmetry and BDI (Beck Depression Inventory) scores, the highest R^2-values obtained by their female group was only 11%; the result reported by Carvalho et al. [53] showed that the highest R^2-values between frontal alpha asymmetry and BDI was only 8.41%. Our results are based on the PID5-d scale which covers the normal range (maps to personality, not just sickness), while BDI is a clinical scale for depression. Therefore, our method seems more suitable for detecting depressivity as a trait than the previously reported ones.

Furthermore, our method gives insights into neural correlates of depressivity, both in terms of brain location and signal frequency. We have produced results indicating that the *gamma* band and especially the 50Hz brain signal is important for measuring depressivity. 50Hz is in the range of the mains power noise. However, we had taken a lot of care to remove the mains noise, while retaining 50Hz EEG; and mains noise would be consistent across all patients and therefore not correlated with depressivity. Therefore, this result clearly relates to the 50Hz brain signal rather than the mains power noise. The most important brain location related to depressivity was also narrowed to C3, T7 and T8. We have also shown that there might be different markers for depressivity between males and females – although this could reflect the different ranges of their PID-5-d values.

In the future, we plan to increase the experimental size and also investigate new methods for learning the correlations such as convolutional neural networks.

References

[1] P. Nabbe, J. Y. Le Reste, M. Guillou-Landreat, M. A. Munoz Perez, S. Argyriadou, A. Claveria, M. I. Fernandez San Martin, S. Czachowski, H. Lingner, C. Lygidakis, A. Sowinska, B. Chiron, J. Derriennic, A. Le Prielec, B. Le Floch, T. Montier, H. Van Marwijk, and P. Van Royen, "Which dsm validated tools for diagnosing depression are usable in primary care research? a systematic literature review," Eur Psychiatry, vol. 39, pp. 99–105, 2017. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/27992813

[2] P. E. Greenberg, A.-A. Fournier, T. Sisitsky, C. T. Pike, and R. C. Kessler, "The economic burden of adults with major depressive disorder in the united states (2005 and 2010)," The Journal of clinical psychiatry, vol. 76, no. 2, pp. 155–162, 2015.

[3] W. K. Goodman, "Research on biomarkers for mental disorders," https://www.nimh.nih.gov/funding/grant-writing-and-application-process/concept-clearances/2009/research-on-biomarkers-for-mental-disorders.shtml, 2009.

[4] J. Jeong, "Nonlinear dynamics of eeg in alzheimer's disease," Drug Development Research, vol. 56, no. 2, pp. 57–66, 2002.

[5] T. Elbert, W. Lutzenberger, B. Rockstroh, P. Berg, and R. Cohen, "Physical aspects of the eeg in schizophrenics," Biological psychiatry, vol. 32, no. 7, pp. 595–606, 1992.

[6] Y. Li, S. Tong, D. Liu, Y. Gai, X. Wang, J. Wang, Y. Qiu, and Y. Zhu, "Abnormal eeg complexity in patients with schizophrenia and depression," Clin Neurophysiol, vol. 119, no. 6, pp. 1232–41, 2008. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/18396454

[7] S. Aydin, N. Arica, E. Ergul, and O. Tan, "Classification of obsessive compulsive disorder by eeg complexity and hemispheric dependency measurements," International journal of neural systems, vol. 25, no. 03, p. 1550010, 2015.

[8] S. Akdemir Akar, S. Kara, S. Agambayev, and V. Bilgic, "Nonlinear analysis of eegs of patients with major depression during different emotional states," Comput Biol Med, vol. 67, pp. 49–60, 2015. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/26496702

[9] J. H. Friedman, "Greedy function approximation: a gradient boosting machine," Annals of statistics, pp. 1189–1232, 2001.

[10] M. Bachmann, J. Lass, and H. Hinrikus, "Single channel eeg analysis for detection of depression," Biomedical Signal Processing and Control, vol. 31, pp. 391–397, 2017.

[11] M. Mohammadi, F. Al-Azab, B. Raahemi, G. Richards, N. Jaworska, D. Smith, S. de la Salle, P. Blier, and V. Knott, "Data mining eeg signals in depression for their diagnostic value," BMC medical informatics and decision making, vol. 15, no. 1, p. 108, 2015.

[12] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from eeg signal," Comput Methods Programs Biomed, vol. 109, no. 3, pp. 339–45, 2013. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/23122719

[13] American Psychiatric Association et al., Diagnostic and statistical manual of mental disorders (DSM-5). American Psychiatric Pub, 2013.

[14] F. Sharbrough, "American electroencephalographic society guidelines for standard electrode position nomenclature," J clin Neurophysiol, vol. 8, pp. 200–202, 1991.

[15] D. L. Zabelina, D. Condon, and M. Beeman, "Do dimensional psychopathology measures relate to creative achievement or divergent thinking?" Frontiers in psychology, vol. 5, p. 1029, 2014.

[16] American Psychiatric Association et al., "Online assessment measures: The personality inventory for dsm-5 (pid-5)-adults," 2016.

[17] A. Fossati, R. F. Krueger, K. E. Markon, S. Borroni, and C. Maffei, "Reliability and validity of the personality inventory for dsm-5 (pid-5): predicting dsm-iv personality disorders and psychopathy in community-dwelling italian adults," Assessment, vol. 20, no. 6, pp. 689–708, 2013. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/24065702

[18] K. E. Markon, L. C. Quilty, R. M. Bagby, and R. F. Krueger, "The development and psychometric properties of an informant-report form of the personality inventory for dsm-5 (pid-5)," Assessment, vol. 20, no. 3, pp. 370–83, 2013. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/23612961

[19] A. G. Reddy and S. Narava, "Artifact removal from eeg signals," International Journal of Computer Applications, vol. 77, no. 13, pp. 17–19, 2013.

[20] S. Zhang, B. McCane, P. S.-H. Neo, and N. McNaughton, "Removing mains power artefacts from eeg – a novel template-based method," bioRxiv doi: 10.1101/2020.01.27.911586.

[21] S. Zhang, J. McIntosh, S. M. Shadli, P. S. Neo, Z. Huang, and N. McNaughton, "Removing eye blink artefacts from eeg-a single-channel physiology-based method," J Neurosci Methods, vol. 291, pp. 213–220, 2017. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/28860078

[22] O. Rösler and D. Suendermann, "A first step towards eye state prediction using eeg," Proc. of the AIHLS, 2013.

[23] J. Britton, L. C. Frey, J. Hopp, P. Korb, M. Koubeissi, W. Lievens, E. Pestana-Knight, and E. St Louis, Electroencephalography (EEG): An introductory text and atlas of normal and abnormal findings in adults, children, and infants.Appendix 4. Common Artifacts During EEG Recording. American Epilepsy Society, Chicago, 2016.

[24] G. Buzsáki, Rhythms of the Brain. Oxford University Press, 2006.

[25] H. S. Mayberg, "Modulating dysfunctional limbic-cortical circuits in depression: towards development of brain-based algorithms for diagnosis and optimised treatment," British medical bulletin, vol. 65, no. 1, pp. 193–207, 2003.

[26] M. D. Greicius, B. H. Flores, V. Menon, G. H. Glover, H. B. Solvason, H. Kenna, A. L. Reiss, and A. F. Schatzberg, "Resting-state functional connectivity in major depression: abnormally increased contributions from subgenual cingulate cortex and thalamus," Biological psychiatry, vol. 62, no. 5, pp. 429–437, 2007.

[27] K. Mizoguchi, H. Shoji, R. Ikeda, Y. Tanaka, and T. Tabira, "Persistent depressive state after chronic stress in rats is accompanied by hpa axis dysregulation and reduced prefrontal dopaminergic neurotransmission," Pharmacology Biochemistry and Behavior, vol. 91, no. 1, pp. 170–175, 2008.

[28] Z. Bhagwagar, E. Rabiner, P. Sargent, P. Grasby, and P. Cowen, "Persistent reduction in brain serotonin 1a receptor binding in recovered depressed men measured by positron emission tomography with [11 c] way-100635," Molecular psychiatry, vol. 9, no. 4, p. 386, 2004.

[29] R. J. Barry, A. R. Clarke, S. J. Johnstone, C. A. Magee, and J. A. Rushby, "Eeg differences between eyes-closed and eyes-open resting conditions," Clinical Neurophysiology, vol. 118, no. 12, pp. 2765–2773, 2007.

[30] D. G. Gilbert, F. J. McClernon, N. E. Rabinovich, C. Sugai, L. C. Plath, G. Asgaard, Y. Zuo, J. Huggenvik, and N. Botros, "Effects of quitting smoking on eeg activation and attention last for more than 31 days and are more severe with stress, dependence, drd2 a1 allele, and depressive traits," Nicotine & Tobacco Research, vol. 6, no. 2, pp. 249–267, 2004.

[31] K. A. Lindgren, C. L. Larson, S. M. Schaefer, H. C. Abercrombie, R. T. Ward, T. R. Oakes, J. E. Holden, S. B. Perlman, R. M. Benca, and R. J. Davidson, "Thalamic metabolic rate predicts eeg alpha power in healthy control subjects but not in depressed patients," Biological psychiatry, vol. 45, no. 8, pp. 943–952, 1999.

[32] G. Bruder, R. Fong, C. Tenke, P. Leite, J. Towey, J. Stewart, P. McGrath, and F. Quitkin, "Regional brain asymmetries in major depression with or without an anxiety disorder: A quantitative electroencephalographic study," Biological Psychiatry, vol. 41, no. 9, pp. 939–948, 1997, cited By 226.

[33] E. Baehr, J. P. Rosenfeld, R. Baehr, and C. Earnest, "Comparison of two eeg asymmetry indices in depressed patients vs. normal controls," International Journal of Psychophysiology, vol. 31, no. 1, pp. 89–92, 1998.

[34] V. Knott, C. Mahoney, S. Kennedy, and K. Evans, "Eeg power, frequency, asymmetry and coherence in male depression," Psychiatry Research: Neuroimaging, vol. 106, no. 2, pp. 123–140, 2001.

[35] A. Kemp, K. Griffiths, K. Felmingham, S. A. Shankman, W. Drinkenburg, M. Arns, C. R. Clark, and R. Bryant, "Disorder specificity despite comorbidity: resting eeg alpha asymmetry in major depressive disorder and post-traumatic stress disorder," Biological Psychology, vol. 85, no. 2, pp. 350–354, 2010.

[36] U. Halbreich and L. A. Lumley, "The multiple interactional biological processes that might lead to depression and gender differences in its appearance," Journal of Affective Disorders, vol. 29, no. 2-3, pp. 159–173, 1993.

[37] M. Bryden, "Laterality: Functional asymmetry in the intact," Brain. Academic Press, New York, 1982.

[38] D. Smit, D. Posthuma, D. Boomsma, and E. De Geus, "The relation between frontal eeg asymmetry and the risk for anxiety and depression," Biological psychology, vol. 74, no. 1, pp. 26–33, 2007.

[39] M. Ahmadlou, H. Adeli, and A. Adeli, "Spatiotemporal analysis of relative convergence of eegs reveals differences between brain dynamics of depressive women and men," Clinical EEG and neuroscience, vol. 44, no. 3, pp. 175–181, 2013.

[40] C. F. Reynolds III, D. J. Kupfer, M. E. Thase, E. Frank, D. B. Jarrett, P. A. Coble, C. C. Hoch, D. J. Buysse, A. D. Simons, and P. R. Houck, "Sleep, gender, and depression: an analysis of gender effects on the electroencephalographic sleep of 302 depressed outpatients," Biological Psychiatry, vol. 28, no. 8, pp. 673–684, 1990.

[41] R. Armitage, R. Hoffmann, M. Trivedi, and A. J. Rush, "Slow-wave activity in nrem sleep: sex and age effects in depressed outpatients and healthy controls," Psychiatry research, vol. 95, no. 3, pp. 201–213, 2000.

[42] R. Armitage and R. F. Hoffmann, "Sleep eeg, depression and gender," Sleep medicine reviews, vol. 5, no. 3, pp. 237–246, 2001.

[43] The MathWorks, Inc., "Predictor importance," https://au.mathworks.com/help/stats/compactregressionensemble.predictorimportance.html, 2018, [Online; accessed 21-Sep-2018].

[44] Y. Noda, R. Zomorrodi, T. Saeki, T. K. Rajji, D. M. Blumberger, Z. J. Daskalakis, and M. Nakamura, "Resting-state eeg gamma power and theta–gamma coupling enhancement following high-frequency left dorsolateral prefrontal rtms in patients with depression," Clinical Neurophysiology, vol. 128, no. 3, pp. 424–432, 2017.

[45] S.-C. Liao, C.-T. Wu, H.-C. Huang, W.-T. Cheng, and Y.-H. Liu, "Major depression detection from eeg signals using kernel eigen-filter-bank common spatial patterns," Sensors, vol. 17, no. 6, p. 1385, 2017.

[46] R. A. Segrave, N. Cooper, R. Thomson, R. J. Croft, D. Sheppard, and P. Fitzgerald, "Individualized alpha activity and frontal asymmetry in major depression," Clinical EEG and Neuroscience, vol. 42, no. 1, pp. 45–52, 2011.

[47] E. Gordon, D. M. Palmer, and N. Cooper, "Eeg alpha asymmetry in schizophrenia, depression, ptsd, panic disorder, adhd and conduct disorder," Clinical EEG and neuroscience, vol. 41, no. 4, pp. 178–183, 2010.

[48] A. Merkl, W.-J. Neumann, J. Huebl, S. Aust, A. Horn, J. K. Krauss, I. Dziobek, J. Kuhn, G.-H. Schneider, M. Bajbouj et al., "Modulation of beta-band activity in the subgenual anterior cingulate cortex during emotional empathy in treatment-resistant

depression," Cerebral Cortex, vol. 26, no. 6, pp. 2626–2638, 2015.

[49] A. Sheikhani, H. Behnam, M. R. Mohammadi, M. Noroozian, and P. Golabi, "Connectivity analysis of quantitative electroencephalogram background activity in autism disorders with short time fourier transform and coherence values," in 2008 Congress on Image and Signal Processing, vol. 1. IEEE, 2008, pp. 207–212.

[50] M. Li and B.-L. Lu, "Emotion classification based on gamma-band eeg," in Engineering in medicine and biology society, 2009. EMBC 2009. Annual international conference of the IEEE. IEEE, 2009, pp. 1223–1226.

[51] C. A. Webb, D. G. Dillon, P. Pechtel, F. K. Goer, L. Murray, Q. J. Huys, M. Fava, P. J. McGrath, M. Weissman, R. Parsey et al., "Neural correlates of three promising endophenotypes of depression: evidence from the embarc study," Neuropsychopharmacology, vol. 41, no. 2, p. 454, 2016.

[52] J. L. Stewart and J. J. Allen, "Resting frontal brain asymmetry is linked to future depressive symptoms in women," Biological Psychology, vol. 136, pp. 161–167, 2018.

[53] A. Carvalho, H. Moraes, H. Silveira, P. Ribeiro, R. A. Piedade, A. C. Deslandes, J. Laks, and M. Versiani, "Eeg frontal asymmetry in the depressed and remitted elderly: Is it related to the trait or to the state of depression?" Journal of affective disorders, vol. 129, no. 1-3, pp. 143–148, 2011.