SIGNAL PROCESSING PROJECT REPORT

EEG-BASED MAJOR DEPRESSIVE DISORDER DETECTION USING FEATURES EXTRACTION

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1 Introduction

Electroencephalogram (EEG) is a recorded measured electromagnetic signal which is generated by neuronal activity in the brain. It captures both slowly and rapidly changing dynamics of brain activations at a millisecond time resolution (Gramfort, et al., 2013). Using EEG one can investigate a neuronal activity and use the results of the analysis in various applications like health issues, diagnosis, treatment, etc. EEG is also used to detect and treat mental issues, which has impacted the psychological field in a positive way. In this paper we will look into how EEG feature analysis can help in Major Depressive Disorder (MDD) diagnosis.

The main problem which this paper was inspired by is lack of early diagnostic and effective therapeutic solutions for youth mental health.

The main concept discussed and used in a research is so-called Event-Related Potential (ERP), which allow for non-invasive recordings of cerebral activity with a temporal resolution on the order of milliseconds (Cai Nan, et al., 2018). ERP lasts for about a second and represents the reaction on a certain stimuli. P300 (third positive peak) is a secondary component of ERP. It is a positive-going waveform that occurs between 300 and 500 ms after stimulus onset. To access P300 component an oddball task should be set. It is usually represented in either audio or visual form. The stimuli has to be unexpected one, like hearing a silence and then observing rough sounds out from nowhere without knowing it would occur. Interesting fact, P300 can even save your life!

The P300 component has two main subcomponents: the P3a and P3b. The P3a has a more frontal distribution and is a component associated with the response to the distracter stimuli (Cai Nan, et al., 2018).

2 Data Description

The data used in a project consists of 61 unique EEG raw files with 50% of Healthy Control data and 50% of patients with MDD. Each file is an EEG recording with 22 channels. Sampling frequency is 256 Hz and lowpass equals to 80 Hz and highpass equals 0.5 Hz for a recording system itself.

EEG acquisition was performed based on three experimental physiological conditions. The first one was 5-minute recording of resting state with Eyes Closed (EC). The second one was

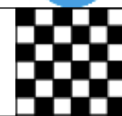
Name Stimuli	***Number of Occurrence***	***Shape of Stimuli***
Standard	314	
Distractor	45	
Target	41	

Figure 1: Oddball Task – Visual 3-Stimulus Oddball Task

resting state with Eyes Opened (EO). The last one we used in our experiments is 10-minute recording of Oddball Task with 3 different stimuli. Only one shape occurred on the computer screen at a time. The pictures were shown randomly for each patient. Those were 400 times a single picture appeared on the screen. The participants were asked to wait for the Target shape in the sequence before pressing the keyboard button.

3 Existing Approaches

There were different approaches analysed for P300 usage in depression detection from EEG. Some of the literature only review the approaches based on features extraction from raw EEG without any events, which were useful for the current research as well.

The first and most important task is to find out how to work with P300 and what it actually is.

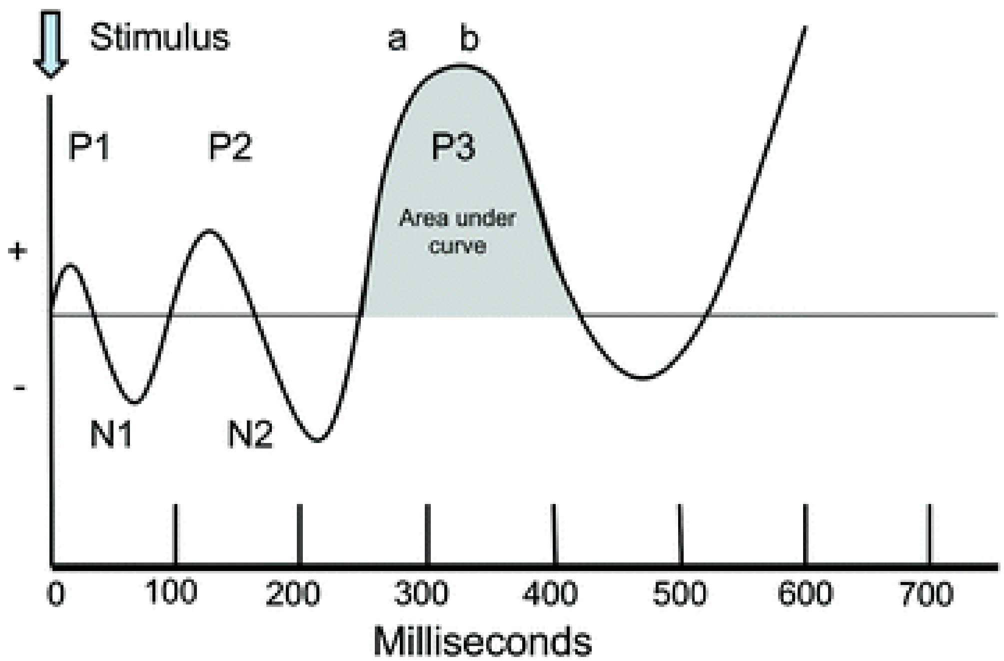


Figure 2: P300 - pattern visualization

On the Fig.2 you could observe a typical template of P300 after a certain stimuli.

3.1 P300 Intensities and Latencies for MDD Detection

The first and the most important paper found is actually the one based on the data set we used. The prepoceessing of the data was a standard band-pass filter, but with somewhat unusual for P300 (as I have read in other papers related to P300 processing) bounds of the filter, which are [0.5, 40] Hz. Then the artifacts like eye blinks, horizontal and vertical eye movement and muscle expansion / contractions, were removed. The filtering and artifacts removal was completed with BESA software.

As for the features extraction and selection, there was an interesting approach of segmenting each channel data into 41 segments based on 250 samples as features to be provided to classification model. Then the matrix from all of those segments was constructed as an input. The dimensionality of the data was really high, so the features provided were ranked by 3 different criteria and then only the top features based on their ranking were selected to train the model.

The authors of this paper concluded the three most important channels for P300 analysis, which are Cz, Pz, Fz.

The classification part used the Logistic Regression as the main model.

3.2 A Novel P300 Classification Algorithm Based on PCA-CNN

Principal Component Analysis (PCA) was used as the main algorithm for removing the noise and artifacts in the data. PCA is widely used in feature extraction and data dimensionality reduction. PCA basically transforms the original signal matrix into covariance matrix through linear transformation and then obtain a new signal matrix by filtering the eigenvalues and eigenvectors of the matrix.

The experiment, or the oddball task used to gather the data in this paper was quite different from the one we are working with. It was based on having a set of letters with low opacity. Then each letter would randomly flash. The subject had to concentrate on a target letter and count the times they see it flashed.

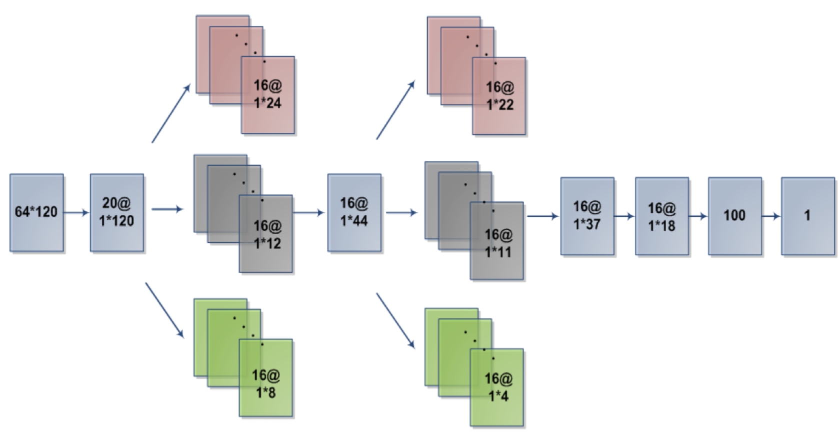


Figure 3: CNN - the framework model of 9-Layer convolutional neural network used for classification

The methods discussed to classify the EEG P300 data was to use Bayesian P300 recognition, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), etc. Thosed were taken from other research papers. In contrast, the Parallel Convolutional Network was used. It contains 9 layers, where L1 represents the data input layer, L2 is the spacial domain convolution layer, L3 and L6 are the parallel convolution layer whcih extract time domain features. L7 is a pooling layer, L8 and L9 are fully connected layer and softmax layer.

4 Data Processing

At first, the Exploratory Data Analysis was performed to see what is actually the data we are dealing with.

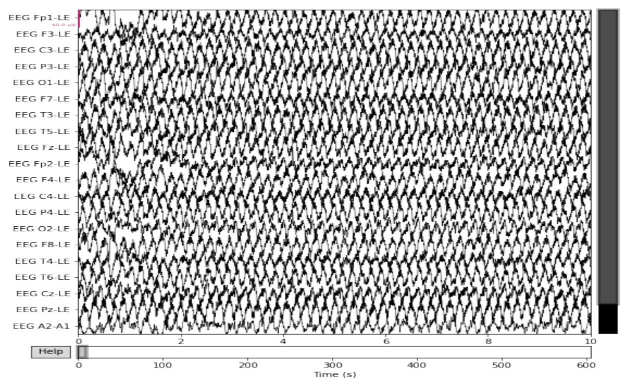


Figure 4: EEG - Raw EEG data of a Healthy Control

As we can observe from the above, this is not the data we would like to work with, hence it is important to reduce the dimensionality of our data. The spatial information is typically exploited by focusing mostly on electrodes located over parietal lobe, where the P300 is known to originate. There is a recommendation to use a set of 8 channels, in positions Fz, Cz, P3, Pz, P4, PO7, Oz, PO8 (Krusienski et al., 2006).

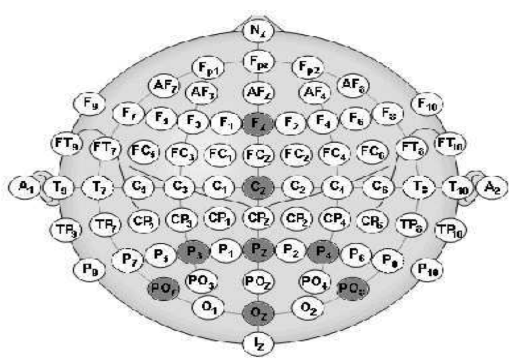


Figure 5: Recommended electrodes for P300

After removing the unwanted channels, we were left with a set of five - Fz, Cz, P3, Pz, P4. On the above figure you can observe the exact placement of the electrodes on a subject's head.

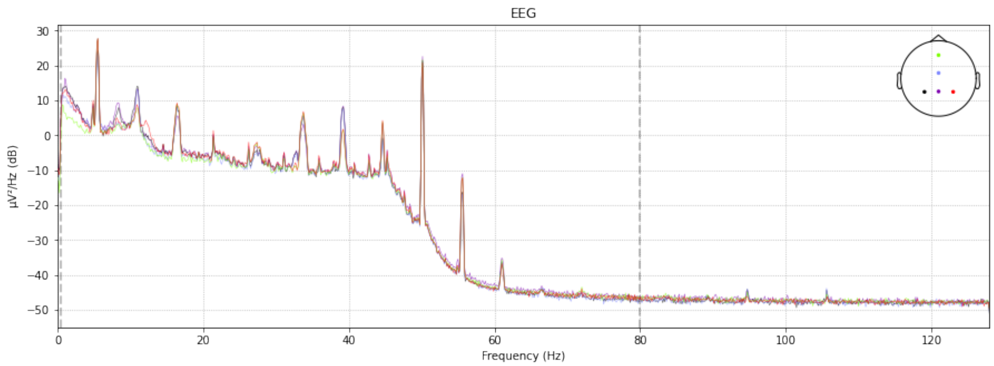


Figure 6: Power Spectrum Density (PSD) of a Healthy Control

If talking about ERP, or P300 specifically, it is efficient to use low-pass or band-pass filtering to extract ERP features without harming the important information in the signal. In our case, we have chosen a band-pass filter with [1, 20] Hz bounds, even though it is mostly [1, 15] or [1, 12] Hz.

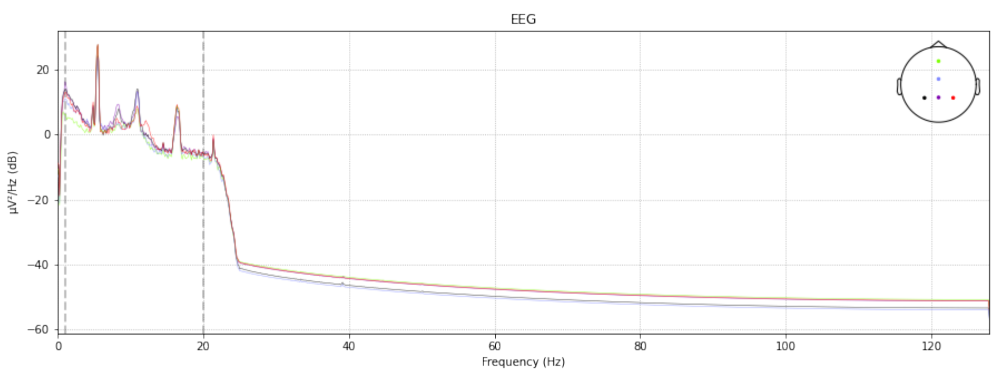


Figure 7: Power Spectrum Density (PSD) of a Healthy Control after a Band-pass filter

Here are some more examples on how the data has changed after filtering.

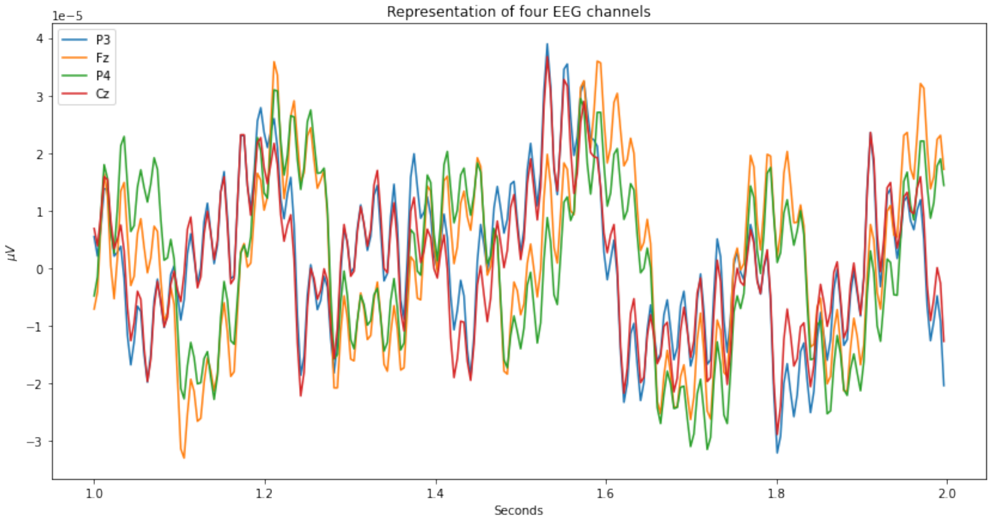


Figure 8: Raw data before filtering

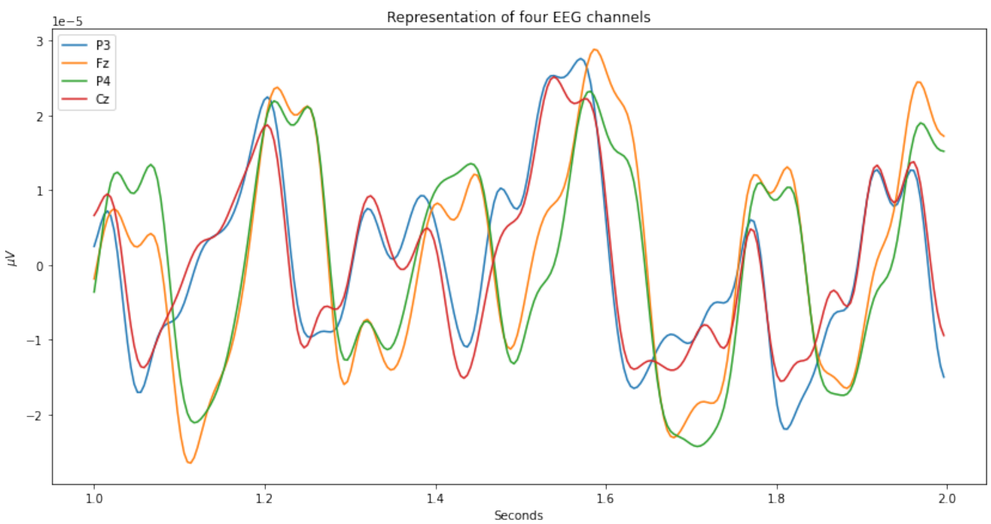


Figure 9: Channels data after filtering

Usually ERP are in a form of slow waves, hence to reduce the dimensionality of data, we also performed downsampling. We performed a so-called discretization of a discrete signal and reduced sample frequency from 256 Hz to 50 Hz.

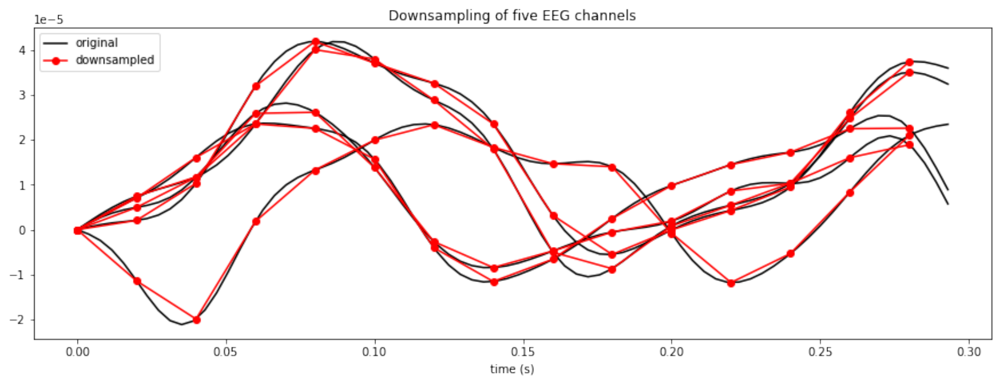


Figure 10: Downsampling of Healthy Control signal from channels

After the downsampling was performed, we needed to also get rid of artefacts. Those could be unwanted noise, muscles or eyes movement, blinking, etc. For this problem we applied Independent Component Analysis (ICA). ICA is a technique for estimating independent source signals from a set of recordings in which the source signals were mixed together in unknown ratios (MNE-Python documentation).

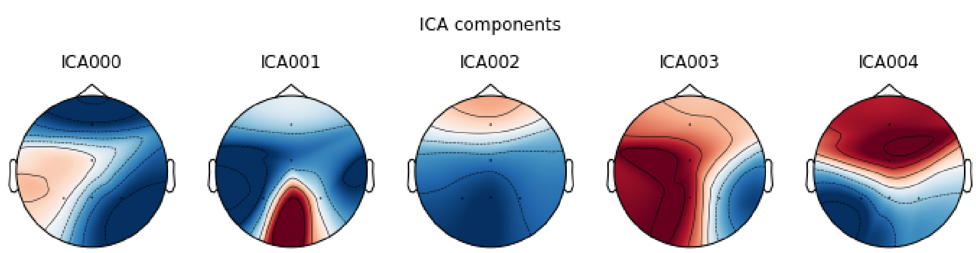


Figure 11: Main ICA properties for five channels (Fz, Cz, P3, Pz, P4)

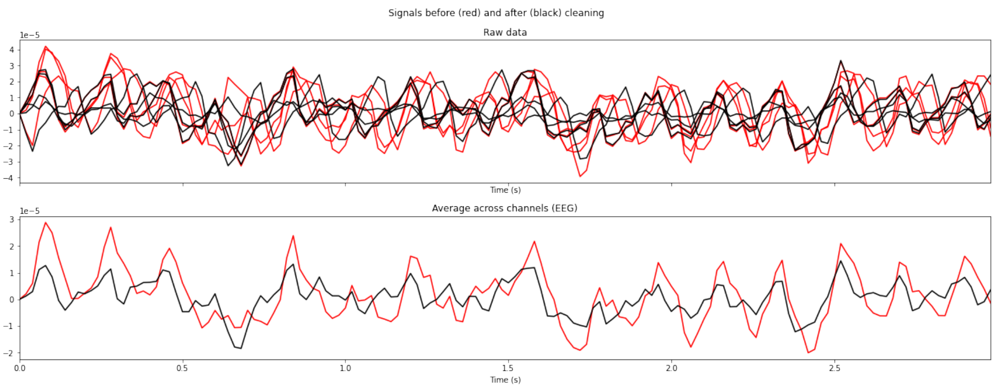


Figure 12: Projected signal plot

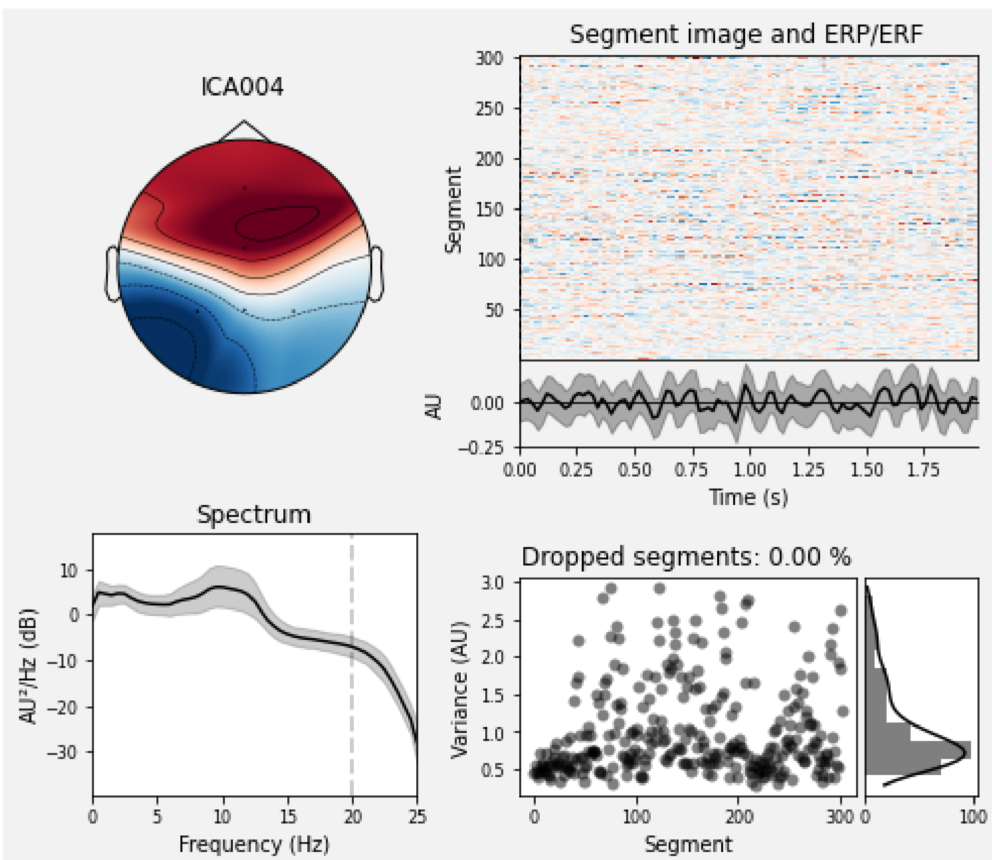


Figure 13: Example plot of ICA processed signal for one channel

After the filtration and data processing was finished, we moved to the step of P300 detection. Since the original data did not contain any STIM channel, which is an EEG channel, but it does not contain any signal, but just event-based information. It consists of unit signals, where one unit represents the True state of if the event has occurred. We did not have any other information provided about target stimuli showing up on a computer screen, so we had to distinguish P300 region by ourselves.

It is kind of a complicated task to do and it usually takes a separate research work on a methodology. Basically, let's just shortly discuss the existing approaches and move forward with personal one.

The most common approaches on distinguishing P300 regions are template matching (no, there is no exact template, that you can match to every P300), which was based on creating the template using a huge dataset of P300. The paper discussing this approached included several techniques on how it can be performed. It mentioned Coherent Averaging, Slope Horizontal Chain Code, etc. The other approach is to train a Neural Network to classify the partitions of a signal into either P300 or no. The best accuracy model we have found with a constructive paper had around 65% of accuracy, which is kind of random guess. Maybe, more time would be needed to research this question more.

So, the approach we used in current analysis is to split a 10-minutes signal into 1 sec intervals with overlap ([0, 50], [1, 51], [2, 52], ...). Then, calculate mean of the signal and see, what are the present peaks in an single interval and whether it is at least as great as a mean value. This method does not ensure we are working with P300 precisely, but it still gives us only an important, or unusual information about part of the signal.

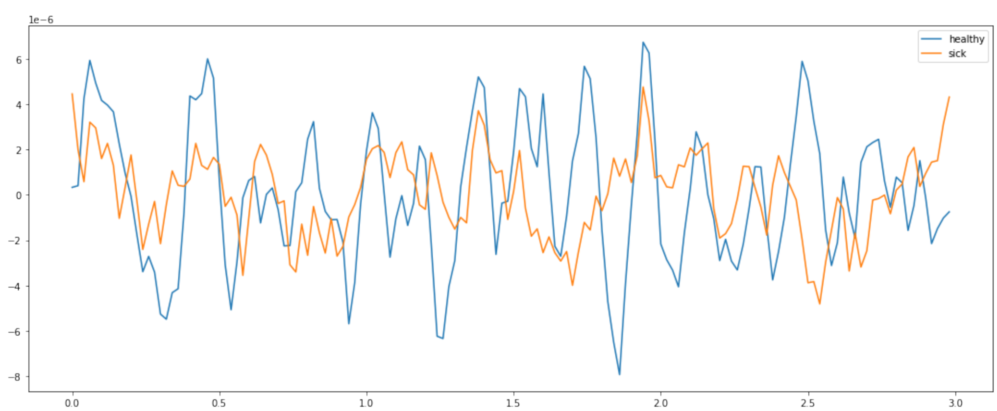


Figure 14: 3-seconds signal showing difference between processed HC and MDD subjects

As a result, we get this data calculated for each and every channel and then by averaging those vectors, we calculate a features vector having 50 values, which are an input for our classification models later on.

5 Classification Models

As for the classification models, we performed training using four different, which are Logistic Regression, Support Vector Machine, K-Nearest Neighbors, and Random Forest Classifier. As an input data, we used those averaged vectors of 50 features. The target variable was represented as (0, 1), where 0 is Healthy Control and 1 is MDD.

After splitting the data into 80% for train and 20% for test, all of the mentioned models above were trained. As mentioned already, the data split is pretty much even (n=29 for Major Depressive Disorder subjects and n=31 for Healthy Control subjects).

As for Logistic Regression, the highest accuracy reached is 54%, which is almost like a random guess. The problem is that Logistic Regression could not catch the tiny beats of difference between signals. It could be a tiny shift by X-axis or a little lower amplitude, but LR could not catch it.

SVM performed a little better and gave 70% of accuracy. This also is not a good result for such a small dataset, so we moved further with KNN. KNN performed with 93% of accuracy. The best model still is a Random Forest Classifier, which has 96.4% of accuracy.

6 Results and Further Steps

The results achieved (96.4% of accuracy) is quite high. We analysed similar problem solutions and have found that researches reached to even higher results using deep neural networks, LSTM, Convolutional Networks and others. The blockers in our case were lack of data, because we only had 61 data samples, which is not so big to train Neural Networks on. Also, there was a big issue with searching for P300 region, which is probably really biased, so it would be great to work with more concrete data set, which contains all of the required information to process the data on P300 like event timing, oddball task broad description, etc. It would also be great to consider collecting personal data about patients, so that a deeper demographic analysis could be done. There could probably be some pattern in ERP with age difference or sex dependence.

7 Literature

1. Sur, S., & Sinha, V. K. (2009). Event-related potential: An overview. Industrial psychiatry journal, 18(1), 70–73. https://doi.org/10.4103/0972-6748.57865

2. Nan, Cai & Wang, Gaohua & Wang, Xiaoping & Liu, Zhongchun & Xiao, Ling & Bai, Hanping & Wu, Shihao. (2018). The P300 component decreases in a bimodal oddball task in individuals with depression: An event-related potentials study. Clinical Neurophysiology. 129. 10.1016/j.clinph.2018.09.012.

3. Picton, Terence. (1992). The P300 Wave of the Human Event-Related Potential. Journal of clinical neurophysiology : official publication of the American Electroencephalographic Society. 9. 456-79. 10.1097/00004691-199210000-00002.

4. Martínez Beltrán, E.T., Quiles Pérez, M., López Bernal, S. et al. Noise-based cyberattacks generating fake P300 waves in brain–computer interfaces. Cluster Comput (2021). https://doi.org/10.1007/s10586-021-03326-z

5. Montserrat Alvarado-González, Edgar Garduño, Ernesto Bribiesca, Oscar Yáñez-Suárez, Verónica Medina-Bañuelos, "P300 Detection Based on EEG Shape Features", Computational and Mathematical Methods in Medicine, vol. 2016, Article ID 2029791, 14 pages, 2016.
https://doi.org/10.1155/2016/2029791

6. Ramele, R., Villar, A. J., & Santos, J. M. (2018). EEG Waveform Analysis of P300 ERP with Applications to Brain Computer Interfaces. Brain sciences, 8(11), 199.
https://doi.org/10.3390/brainsci8110199

7. Colwell, K. A., Ryan, D. B., Throckmorton, C. S., Sellers, E. W., & Collins, L. M. (2014). Channel selection methods for the P300 Speller. Journal of neuroscience methods, 232, 6–15. https://doi.org/10.1016/j.jneumeth.2014.04.009

8. Tripathi, S. M., Mishra, N., Tripathi, R. K., & Gurnani, K. C. (2015). P300 latency as an indicator of severity in major depressive disorder. Industrial psychiatry journal, 24(2), 163–167. https://doi.org/10.4103/0972-6748.181726

9. Mumtaz, Wajid & Malik, Aamir & Ali, Syed Saad & mohd yasin, mohd azhar. (2015). P300 intensities and latencies for major depressive disorder detection. 542-545. 10.1109/ICSIPA.2015.7412250.

10. Li, Feng & Li, Xiaoyu & Wang, Fei & Zhang, Dengyong & Xia, Yi & He, Fan. (2020). A Novel P300 Classification Algorithm Based on a Principal Component Analysis-Convolutional Neural Network. Applied Sciences. 10. 1546. 10.3390/app10041546.

11. Lotte, Fabien. (2014). A Tutorial on EEG Signal Processing Techniques for Mental State Recognition in Brain-Computer Interfaces. 10.1007/978-1-4471-6584-2_7.

12. Gramfort A, Luessi M, Larson E, Engemann DA, Strohmeier D, Brodbeck C, Goj R, Jas M, Brooks T, Parkkonen L, Hämäläinen M. MEG and EEG data analysis with MNE-Python. Front Neurosci. 2013 Dec 26;7:267. doi: 10.3389/fnins.2013.00267. PMID: 24431986; PMCID: PMC3872725.