Deep Learning Analysis of EEG signal to model the impact of Auditory Stimuli on Brain Activity

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1 Introduction

1.1 Abstract

This project aims to integrate traditional signal processing with contemporary deep learning techniques to assess and further quantify the impact of binaural beats on brain signals. It utilizes EEG data collected across 42 electrodes in the presence/ absence of binaural beats on the human scalp (from an ongoing UB study). The methodology extends beyond the traditional signal analysis by trying to map the signal from its original form to latent space that can better understand the inherent structures in EEG-derived functional brain networks.

The novelty in the project lies in the capability to not only differentiate if a brain EEG signal is captured under the presence of binaural beats or not, but also mapping a mathematical vector representation in 2D space. This technique can significantly contribute to quantifying the influence of binaural beats on brain signal into more reasonable parameters like brain rate, power spectral density, etc.

Over recent decades, scholars have predominantly relied on hand-crafted models requiring specialized domain expertise for the interpretation of brain representations associated with EEG, MRI, fMRI recorded datasets. This project endeavors to harness the untapped potential of deep learning methodologies with the objective of elucidating these representations, thereby advancing a contemporary paradigm within this domain.

Our preliminary results suggests traditional non-linear classifier models can learn to differentiate between brain signals with/ without binaural beats on a balanced dataset. However the results when plotted in lower dimension do not a illustrate a visual distinction between the influence of pure-tone and binaural beats on the human brain. This shows that the effect of binaural beats on brain signals might not demonstrate a simple linear difference in brain signals.

The classification accuracy for out of the box sample is as high as 84.5% using XGboost (XGB) classifier when dimensionality is not reduced and 65.6% using Support vector Classifier (SVC) when dimensionality is reduced from 64 to just 2 (through PCA). This underscores a substantial opportunity for the integration of deep learning methodologies in comprehending the impact of auditory stimuli on the human brain. Moreover, the project endures to quantitatively assess the variances induced by the auditory stimuli through utilization of a mathematically formulated brain rate metric, providing insights into the degree of neural activation.

1.2 Background

This deep learning project inherits the EEG data from a recently completed undergraduate study, **Binaural Beats for Focus: Exploring Binaural Beats Parameters for Enhancing Sustained Attention** conducted by the Department of Psychology, University of Buffalo. The provided EEG data has been deidentified to protect the confidentiality of the participants involved. This study, which is still under works for publication, conducted 33-minute cognitive ability sessions in the presence and absence of binaural beats for each participant and recorded their EEG signals via 42 electrodes. The sessions were followed by self-reported questionnaires for the participants, which led them to the conclusion that binaural beats enhance attention span.

2 Literature Survey

The major motivation for undertaking this project was inspired by the study conducted by Yue et al. [1] where they demonstrated the use of Variational Autoencoders (VAEs) to capture complex representations in EEG signals for obesity classification. If non-brain-related diseases can be identified using complex deep networks by understanding the feature space, then the impact of binaural beats should also be visible in the latent space given sufficient data. This holds great significance because it suggests that diseases could potentially be identified using non-intrusive diagnostics like brain EEG signals, even for conditions that previously required intrusive methods.

Similarly, Bethge et al. [3] introduced "EEG2Vec", employing VAEs for emotional state representation from EEG data. Their work illustrates how deep learning models can encode EEG signals into a latent space where learned representations elucidate subtle emotional states, potentially applicable to studying binaural beats' effects. Another challenge on kaggle shows open-source datasets and benchmarks from Anand et al. [7] on GitHub and the Inria-BCI challenge [8] where they show that just from brain signals, it is possible to tell whether a person will give wrong or right answer in a cognitive task.

According to Gao et al. [6], EEG responses to binaural beats across various frequencies suggest that specific EEG frequency bands like alpha and beta waves correspond to relaxation and alertness, respectively which suggests that if brain signal is divided into different waves as explained in section 4.1, it can give important information on a persons cognitive state and alertness.

The current state of the art model to understand the intricacies of brain signal is "Deep-EEG" developed by Mir et al. [2] . It is a framework for diagnosing epileptic seizures from EEG signals, showcasing the versatility of deep learning in neuro-physiological studies. However the model is very basic and doesn't employ the latest Deep Learning techniques.

3 Dataset

The dataset involves raw EEG signal files recorded in BIO SEMI Active Two Brain recorder, and exported in (.BDF) format. The data consists of de-identified data for 40 participants, recorded for 2 sessions of 30 minutes durations, out of which one session had just pure tone, while the other session had binaural beats. The EEG signals have a sampling frequency of 512 Hz. Recording EEG signals using the same experimental setup in a highly controlled environment, reduces disturbances due to external factors and leads to stable results.

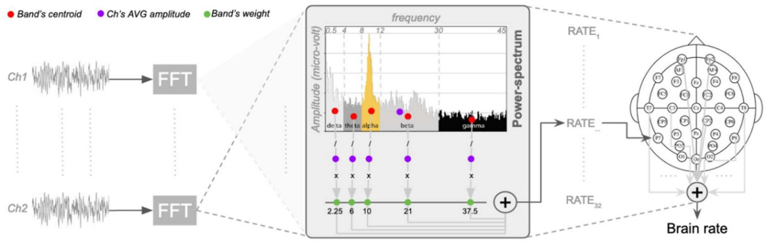

Figure 3.1: EEG Data logging and fetching standard Pipeline

4 Understanding EEG Signals

4.1 Cognitive EEG frequency bands

The electroencephalogram (EEG) signals are divided into different frequency bands, each associated with different types of brain activity, including cognitive processes. The most important frequency bands for finding cognitive brain activity are:

1. Delta Waves (0.5 to 4 Hz): Although primarily associated with deep sleep, delta waves can also be related to certain cognitive processes in some pathological states.

2. Theta Waves (4 to 8 Hz): Theta waves are often linked to memory, learning, and navigation. They are particularly prominent during meditative, drowsy, or sleeping states but also appear during deep emotional experiences and cognitive activities that require concentration and focus.

3. Alpha Waves (8 to 12 Hz): Alpha waves are associated with a state of relaxed alertness and rest. They become prominent when a person is calm and physically and mentally relaxed but still alert. Alpha activity is often related to the brain's idle state or resting state and has been linked to creativity and the reduction of depression

4. Beta Waves (12 to 30 Hz): Beta waves are associated with active, analytical thought and alertness. This frequency band is most commonly observed during active conversation, problem-solving, decision-making, and focused mental activity. High levels of beta activity are associated with stress, anxiety, or excitement.

5. Gamma Waves (30 Hz and above): Gamma waves are associated with higher mental activity, including perception, problem-solving, fear, and consciousness. High-frequency gamma activity is linked to the processing of information from different brain areas simultaneously, essentially integrating thoughts and experiences.

Each of these frequency bands plays a role in different aspects of cognitive processing and brain activity. For cognitive tasks and states of consciousness, alpha, beta, and gamma waves are particularly significant, as they are directly related to how we think, learn, and process information. However, the importance of a specific band can vary depending on the type of cognitive activity being performed.

5 Signal Pre-processing

Signal pre-processing for EEG signals requires that noise or extra high frequency signals are removed from the raw signals. Also it should be noted that not all signals contribute equally to focus, and some channel data can add significant noise to the more important signals. Those electrodes needs to be identified and removed. For this we used SHAP values derived from a trained xgboost model with high accuracy to get the most important features. Before the signal is sent to a ML pipeline it has to go through various signal preprocessing techniques to remove noise, and any unwanted signals. Below are the various preprocessing techniques employed, and the steps:

5.1 Steps:

1. The raw EEG dataset for a single user, for a single session is imported into the EEGLAB on MATLAB.

2. Two marker files: Artifact rejection and ocular correction are also imported for that user. These files are obtained after visualizing the signals on an external software, called Brain Vision Analyzer, which is capable of recognizing the noise in the data due to muscle movements, eye blinks, nose twitches etc.

3. Before applying the marker information for artifact rejection, we visualize the raw EEG data to make sure that the signals are static and ready for preprocessing.

4. However, on visualizing the EEG signals, on a single plot, a trend is observed in the data as seen in figure 5.1. This means that the brain signals aren't as static as required for the analysis. Hence, we decide to re-reference the EEG signals, based on the mastoids (M1 and M2) signals, which are referred to as ground signals, and correspond to the IEO and right earlobe respectively.

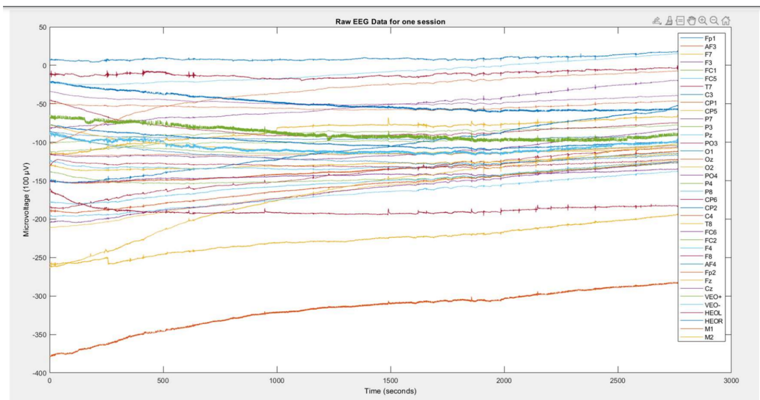

Figure 5.1: Raw EEG Signal

5. During re-referencing, it is important to exclude non-brain activity signals from the analysis. Hence, certain EEG channels like VEO+. VEO-, HEOR, HEOL, B9 and B10 are

excluded from the data, during re-referencing, but not dropped due to their utility during ICA decomposition.

6. The re-referenced signal shows a much better static trend and then gets pre-processed by applying the marker information of artifact rejection and ocular correction.

7. This final signal is then decomposed using Independent Component Analysis, in order to clean out any extra noise

8. The data contained in the final clean signal is written into a .csv file, as channel data matrix and time vector.

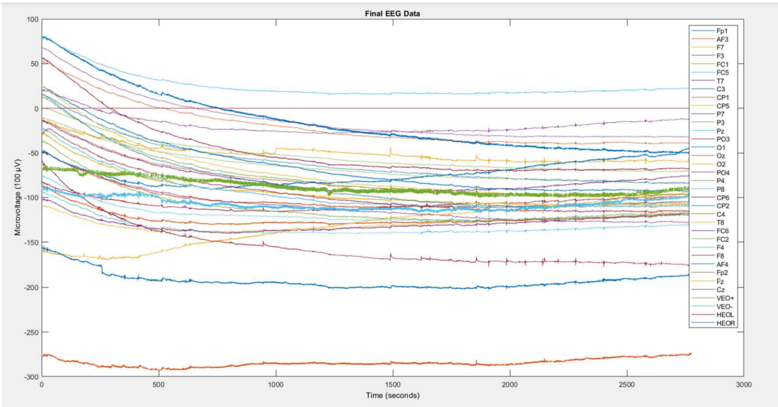

Figure 5.2: Cleaned EEG Signal

6 Model Implementation

6.1 Extract Transform Load

The ETL pipeline utilized various standard techniques employed specially for time series data. The cleaned data received after various FFT transformations using MATLAB is then modelled using Python for analysis. Total there are twelve datasets, two (binaural and non-binaural) sessions for each user in the form of numbers for 42 channels. Following steps are employed in the ETL pipeline:

1. Data for each of the twelve sessions is loaded into pandas dataframe. Rows is clipped into 1013760 (equivalent to 1980 seconds, 512 samples per second) accounting for 33 minute session. Total number of electrodes is 42.

2. Unnecessary electrode data not accounting for cognitive tasks is reduced, giving a final of 32 features for each sample.

3. Since it is a timeseries data, first difference is found for each feature, and normalization individually for each column is performed. This makes the timeseries data stationary, and suitable for modelling.

4. Data for all binaural sessions and non-binaural sessions is combined into two separate dataframes, and a label of 1 (binaural), and 0 (non-binaural) is added.

5. Labelled data is segregated into epochs of length 64 to ensure that each sample has a length of 64 (to store some temporal relationship). Each sample shape is now 64 x 32 (number of continuous samples x number of electrodes).

6. Data is shuffled and separate data generator pipeline using tensorflow is created for train, validation and test.

6.2 Model Architecture

The approach employed here is a Conditional Variational Auto Encoder. To classify a signal into two labels can be performed using traditional ML classification techniques like Logistic regression, Tree based methods, SVC or bagging/ boosting. One may argue that even statistical methods like KL divergence or Z-tests, and A/B testing can help identify if two temporal sequences are statistically different or not. However, the primary argument, and novelty of our project is to quantify the differences, and also understand the inherent complexities of brain signals. For this we used Auto-Encoder approach architecture as defined in detail in Figure 6.1 for three main reasons:

1. The reconstruction loss in AE forces the model to learn the inherent patterns in input data even when the bottleneck latent space is very small in dimension. This can help to understand how many features in input data are actually important, and serves to distinguish between binaural and non-binaural.

2. The use of KL divergence loss adds stochasticity to the input signal which is inherent in EEG signals. Also using a conditional approach in AE reinforces the model to separate

the mean vectors for both the conditions far. This can further help during visualization of both the conditions by separating the two latent spaces more.

3. Dimensionality of latent space can help to experiment with the data more, and provides high flexibility in using that latent space further for classification, and maintaining bias/ variance trade-off.

Each input data sample is of dimension 64X32, and latent space dimension is experimented with both 64 and 32. This reduces dimensionality by a factor of 2. The latent space generated is further used for training classification model (using xgboost and decision tree) to classify the signal as binaural and non-binaural. Further the dimensionality of latent space is reduced to just two, and it is used to classify a signal as binaural and non-binaural. Dimensionality reduction is done to enable visualization of decision boundary.

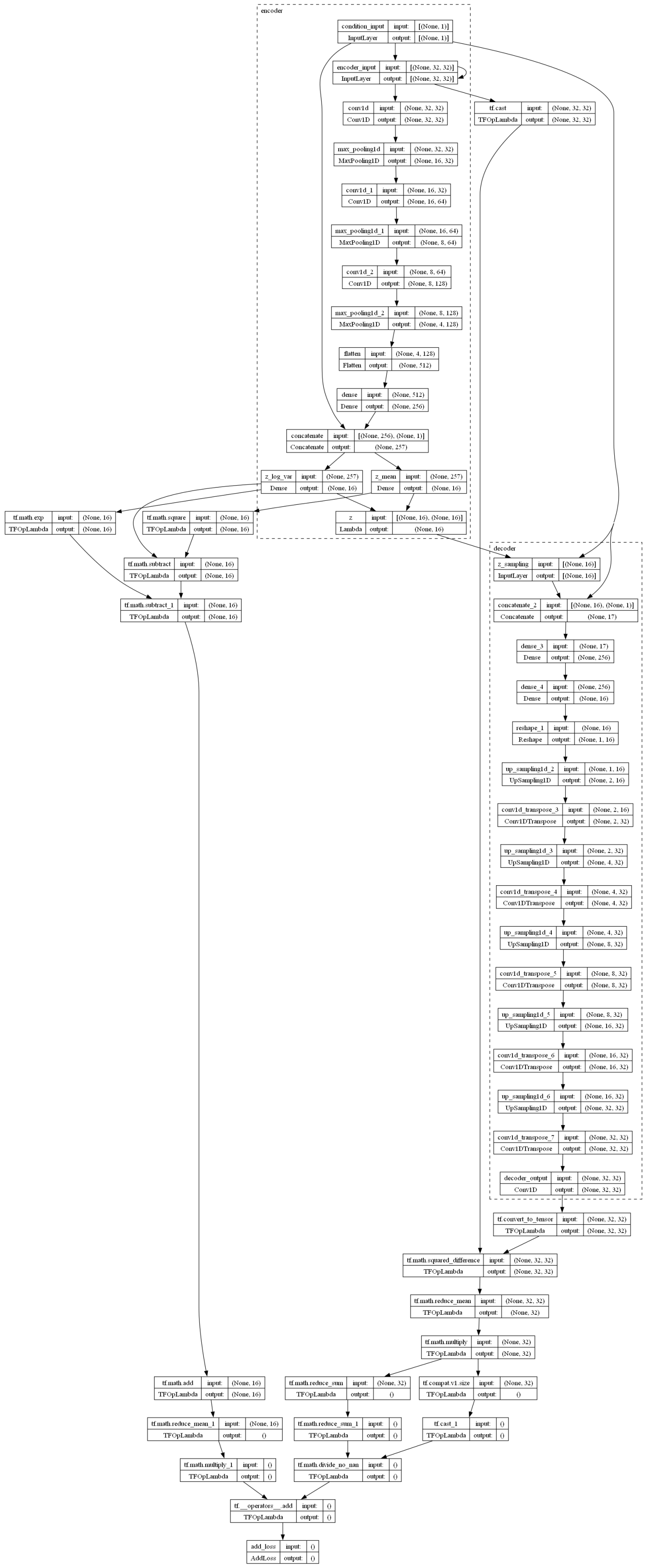

Figure 6.1: Proposed Auto Encoder Model Architecture

7 Results

The results highlighted below show a good classification accuracy of 94.8% on test data with xgb classifier, and 80.9% with linear classifier. Refer figure 7.1. We can use accuracy as a good evaluation parameter because the dataset is balanced. However when dimensionality is reduced using PCA, there is a significant performance drop specially for linear classifier. This is shown in figure 7.4. This hints that the brain signals follow complex patterns and interaction of various electrodes, which makes them difficult for linear separation. However, SVM is still giving a good accuracy at 83.2% using non-linear Radial Basis Function Kernel. The latent spaces boundaries as shown in figure 7.2 also hints at this, the boundary generated by Logistic regressions misses at many points, while decision boundaries by SVM figure 7.3 is better, and is trying to fit many points which are not present at the highest density areas.

But it is clear that with PCA performance is significantly dropping as classification accuracy is much better at 94.8% and 80.9% (xgb and Logistic regression respectively) when compared to 82.9% and 73.9% without and with PCA respectively.

xgb Classifier (Non-Linear classifier)	Test accuracy using xgb classifier on test data is: 0.9488636363636364				
		precision	recall	f1-score	support
	0	0.96	0.94	0.95	1621
	1	0.94	0.96	0.95	1547
	accuracy			0.95	3168
	macro avg	0.95	0.95	0.95	3168
	weighted avg	0.95	0.95	0.95	3168
Logistic Regression (Linear Classifier)	Test accuracy with linear classifier without pca is : 0.8093434343434344				
		precision	recall	f1-score	support
	0	0.94	0.67	0.78	1621
	1	0.73	0.96	0.83	1547
	accuracy			0.81	3168
	macro avg	0.84	0.81	0.81	3168
	weighted avg	0.84	0.81	0.81	3168

Figure 7.1: Test Accuracy using Linear and Non-Linear Classifiers

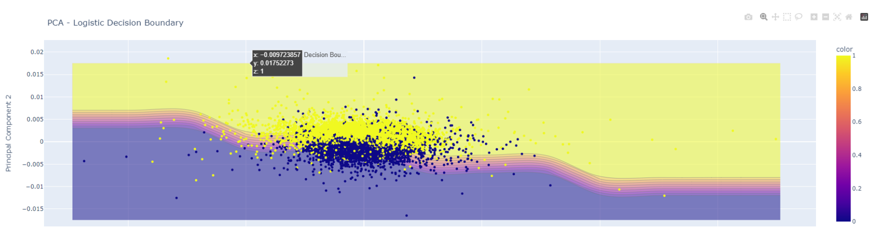

Figure 7.2: Decision boundary for Logistic in 2D

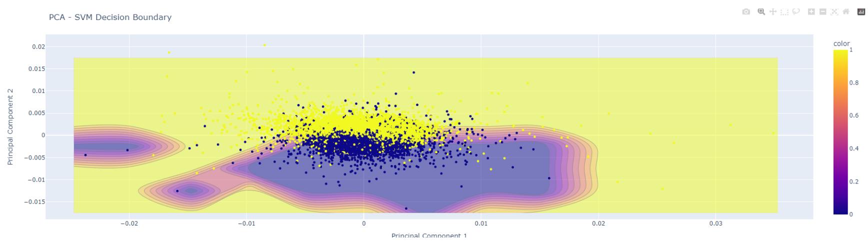

Figure 7.3: Decision boundary for SVM in 2D

```
PCA - Logistic Regression Test accuracy: 0.7395833333333334
              precision    recall  f1-score   support

           0       0.89      0.56      0.69      1621
           1       0.67      0.93      0.78      1547

    accuracy                           0.74      3168
   macro avg       0.78      0.74      0.73      3168
weighted avg       0.78      0.74      0.73      3168

PCA - Random Forest Test accuracy: 0.819760101010101
              precision    recall  f1-score   support

           0       0.83      0.82      0.82      1621
           1       0.81      0.82      0.82      1547

    accuracy                           0.82      3168
   macro avg       0.82      0.82      0.82      3168
weighted avg       0.82      0.82      0.82      3168

PCA - SVM Test accuracy: 0.8323863636363636
              precision    recall  f1-score   support

           0       0.84      0.84      0.84      1621
           1       0.83      0.83      0.83      1547

    accuracy                           0.83      3168
   macro avg       0.83      0.83      0.83      3168
weighted avg       0.83      0.83      0.83      3168

PCA - Decision Tree Test accuracy: 0.7654671717171717
              precision    recall  f1-score   support

           0       0.77      0.77      0.77      1621
           1       0.76      0.77      0.76      1547

    accuracy                           0.77      3168
   macro avg       0.77      0.77      0.77      3168
weighted avg       0.77      0.77      0.77      3168
```

Figure 7.4: Test Accuracy after PCA with 32 latent space dimension

8 Conclusion

It is clear from the data that the model is able to classify the samples with satisfactory accuracy of more than 90%, with non-linear classifiers. However one of the primary goals of the study was to find whether the latent spaces generated are visually separable or not. This could have helped to validate if the influence of binaural beats is distinguishable in lower dimensions or not. However, using our current analysis the latent space has many overlapping patters. This leads us to two main areas of focus which could provide us with more definite results:

1. The model needs to be trained on more than six users and probably on the whole dataset of 40 people. This will improve generalization of the model.

2. Currently the technique used for reducing the dimensionality is PCA, which is not very good at understanding the complex relationships between different features. Since brain data is both temporal as well as spatial, more complex technique like T-SNE and UMAP will be better suited for dimensionality reduction.

However, it is clear from the classification results that there is some inherent differences in the brain signals under the influence of external auditory stimuli like binaural beats under controlled experimental setup. The influence under real life conditions might be different and needs to be studied further.

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