Computational Analysis of EEG Waveforms of Mice in Ketamine-Induced Comas

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Introduction

Electroencephalography (EEG) is a test that measures the electrical activity of neurons in the brain. EEG recordings from patients in waking and sleeping states have been studied to better understand neurological diseases. As part of a larger ongoing project, our team is studying EEG recordings of mice in anesthetically-induced comas so that we can further remove environmental variables. For our project, we are using ketamine as the anesthetic and will be studying the differences between normal 'Wild-Type' (WT) mice and different abnormal mice. Our goal is to use 'white-box' machine learning methods to identify markers that can be used to classify these mice.

Dataset

Data Collection: Over the summer, trials were ran taking three-hour EEG recordings of mice in ketamine-induced comas. Two devices were used for this (EEG1 and EEG2). Due to the nature of the experiment and availability of mice, only 9 trials were completed. Data was collected for 6 WT mice and 3 abnormal mice.

Data Processing: Each mouse sample started at the ketamine injection and ended 150 minutes after. The data was downsampled from 1000Hz to 100Hz. To remedy the limited number of samples available, each recording was split into segments of equal length. Each of these samples were considered separate examples. Various attempts were made to classify the raw EEG data using machine learning methods but this was unsuccessful due to the nature of untransformed data. The data was then converted into Power Spectral Density (PSD) which calculates the signal power at different frequencies. By using this as our feature vector, we can train models that will give us information about the differences between WT and abnormal mice.

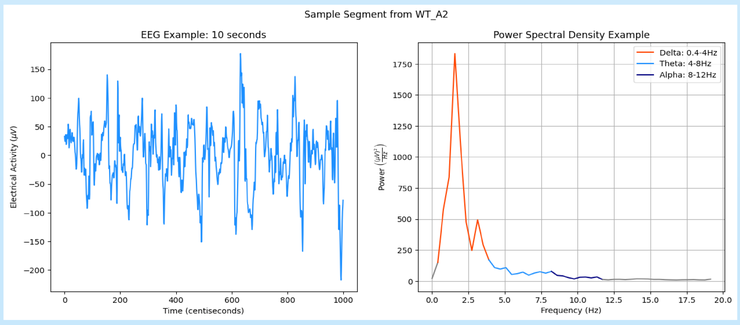

Fig 1: Example of 10 seconds of raw EEG recording followed by the PSD of that sample taken using Welch's method

Methods

Models: The two model types we used to classify segments were Logistic Regression and Decision Trees. Methods from the python library SciPy were used to train both model types.

Feature Selection Problem: The optimal segment length was determined by calculating the accuracy of each model at different time measures. With a minimum example number of 500, the maximum segment length allowed was 108 seconds. 30 trials were conducted at each of the tested lengths. A segment size of 100 seconds was used.

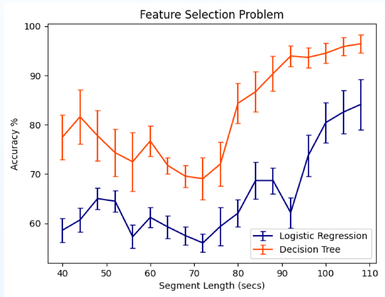

Fig 2: Mean and Standard Deviation of the trained models at segment lengths ranging from 40 to 108 seconds.

Leave-One-Out Validation: To validate that the patterns and markers identified can be generalized, tests were ran classifying the segments where data from all of the mice were used for training except for one of the WT samples. Another result we analyzed here was the difference in accuracy using EEG1 vs EEG2. We hoped to see similar results for both devices, but since they were so different we opted to only using the EEG2 data.

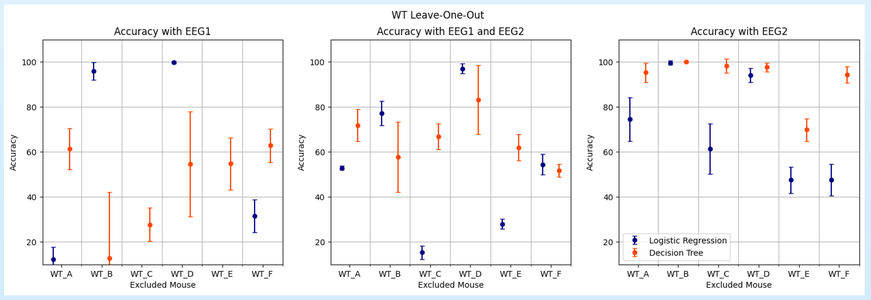

Fig 3: Mean and Standard Deviation using EEG1 and EEG2 data for both models while leaving out the labeled mouse's data. 30 models were trained for each instance.

Model Accuracy: After determining the parameters and datasets to use, 100 models were trained and the means and standard deviations were calculated. Overall, the Decision Tree performed better. Additionally, assuming abnormal mice are treated as the 'positive' case, both models had higher sensitivity vs specificity. At this point, we chose to do further analysis on the decision tree model.

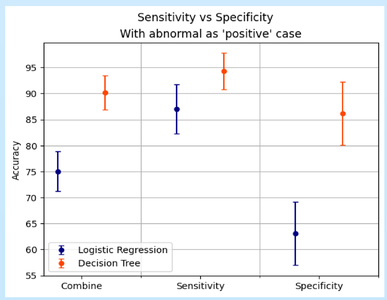

Fig 4: Mean and Standard Deviation of the trained models comparing the overall accuracy with the sensitivity and specificity.

Analysis

The analysis of this project involved studying the trained decision tree models. In all of the decision trees examined, the root node splits segments by their power value at 0.39Hz. The exact threshold value varied throughout models. Additionally, most of the segments with values below the given power threshold were abnormal and most of those above were WT. It is significant that abnormal mice tend to show less activity at this frequency. In general, the types of abnormal mice we used are known to show more low-frequency brain activity. From a biological perspective, is interesting to see that at the lowest examined frequency they showed weaker electrical activity.

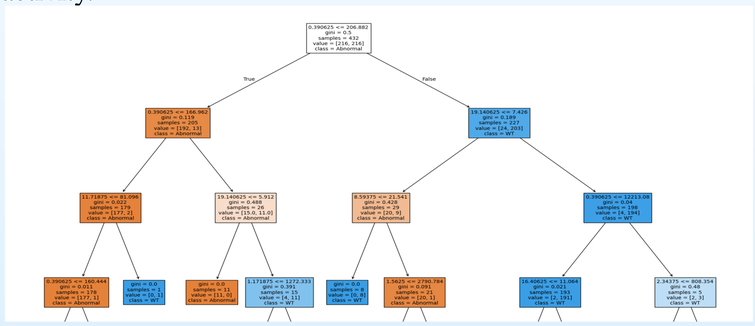

Fig 5: Example of the first few nodes of a decision tree with 98.1% sensitivity and 87.0% specificity.

Next Steps

The next step moving forward is to collect more data from all available mice types to further validate our results and improve the predictive model. We have solid theories from this data, but we will need more to confirm their validity. Once we have enough data, we will be able to train models differentiating between different types of abnormal mice. Additionally, we will begin working with the team using Isoflurane as an anesthetic to train models that will be useful for determining what impacts ketamine has on these results.

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