Case Study 3

DSDA 310: Senior Seminar

Seizure Detection in EEG Data

Report By:

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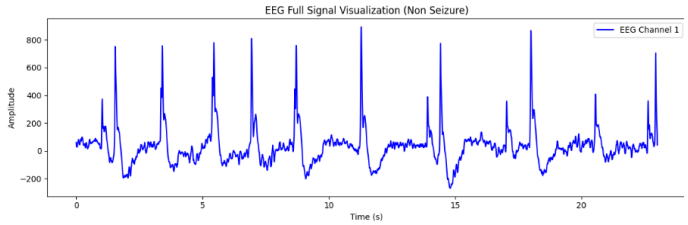
Introduction and Background

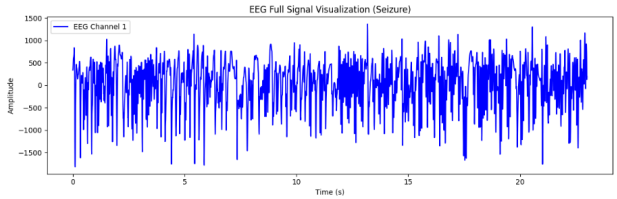
Through this case study we were tasked with determining where seizures potentially occurred within data compiled by Professor Rachel Bergstrom and a team of researchers using EEG (Electroencephalogram) collected throughout 23 seconds per line. A seizure's occurrence can be indicated by a sudden increase in electrical signal occurring at a high frequency and high intensity for a duration of time. Using our model we were able to analyze patterns occurring within the data given to help determine what is and is not a seizure. By training our model to detect patterns and identify which patterns correlate with known patterns we can get a better, more accurate understanding of when a real seizure occurs and where there could potentially be false positives. Due to how time-consuming analysis of EEG data can be when doing it by hand this sort of model building can assist in drastically reducing the amount of time needed to identify the occurrence of a seizure.

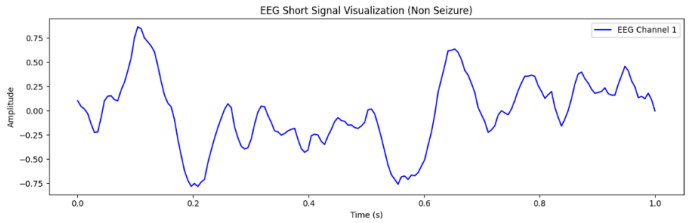
Data Format and Preprocessing

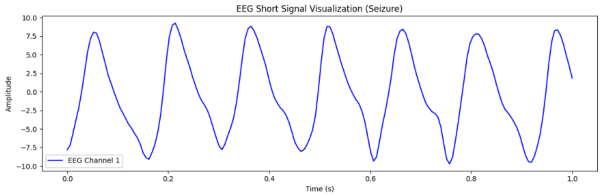
Professor Rachel Bergstrom provided us with four total datasets from Set E of the Bonn dataset, two of which had the readings from the EEG and the other two containing the labels for whether or not a seizure occurred. The first set of readings had full-length signals. This EEG was taken on a frequency of 173.61 Hertz. Each row represents a 23-second clip of the reading. There

are 500 rows total with 400 labeled as “N” for no seizure and 100 labeled “SZ” for seizure. The second dataset’s EEG was also taken on a frequency of 173.61 Hertz. This dataset has 1-second clips of data that overlap by one data point. There are 11,300 rows total, with 9,200 labeled “N” for no seizure and “SZ” for seizure. Below are examples of what seizures and non-seizures look like. All of the datasets were cleaned before they were given to us. The only thing we had to do was normalize the data for the full signal dataset.







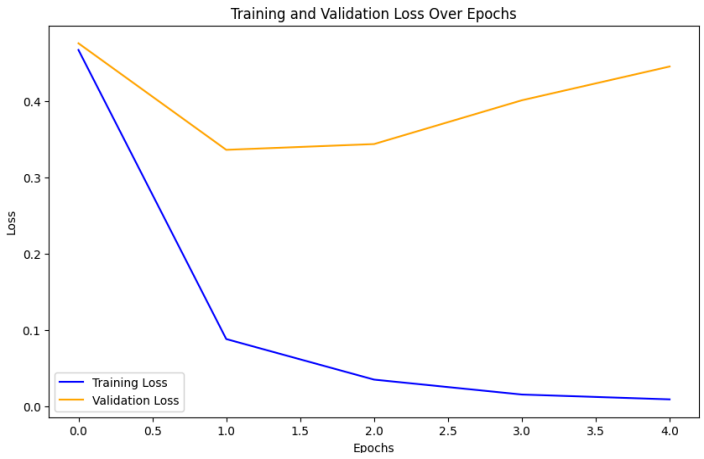


Data Modeling and Analysis

We decided to build a multi-layer perceptron (MLP) model to classify our data. This model takes on input and feeds it through different hidden layers that learn the data pattern by updating different weights over epochs. The model then returns an output of the classification. We used the ReLU and Sigmoid activation functions within our network because these activation functions are better at identifying more complex patterns for classification. Another part of the MLP model is the loss function. The loss function is how the model compares the predicted classes with the actual classes and either rewards or penalizes them based on their accuracy. Since we are only predicting between two classes, the best loss function to use is binary cross

entropy. Since the two datasets are different in their structure, we decided to create two different models, one for each dataset.

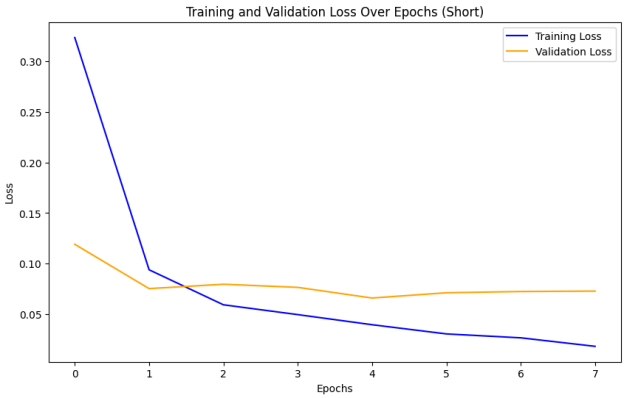
Starting with the full signals, we split the dataset into 90% training, 5% validation, and 5% testing. We trained the model over 50 epochs the first time through. After looking at the graph for the training and validation loss, we noticed that the model wasn't learning anything after the first few epochs. We cut down the number of epochs to five because of this. The graph shows that the loss for the training dataset drops very quickly after the first epoch and stays low. This means that the model learned the training dataset very quickly and isn't learning much after the first epoch. The validation loss dips a little bit after the first epoch and then starts to rise again. This shows us that our model at the second epoch was our best one. The shapes of both the training loss graph and the validation loss graph tell us that our model is overfitting to our data.



After we trained the model, we ran predictions on the test dataset. The model performed well in classifying the non-seizures, getting 22 out of 22 correct. When it comes to predicting seizures though, the model only predicted 1 out of 3 seizures correctly. While the model had an overall accuracy of 92%, it wasn't great at what it was designed to do, detect seizures.

Moving on to the short signal dataset, we split the data into the same ratio for training, validation, and testing as we did for the full signal dataset. After training the model over 50 epochs the first time, the loss graph behaved the same as the original training for the full signal

dataset. We cut the number of epochs down to eight instead of five because this model took a little bit longer to learn than the full signal model. The training loss decreases sharply from the first to the second epoch and then gradually decreases from there on. The validation loss stays relatively even throughout the epochs. This graph shows that the model has overfitted to our data again.



This model performed a lot better than the full signal model in classifying seizures correctly, getting 125 out of 130 predictions correct. The model also predicted 439 out of 445 correct non-seizures. The overall accuracy for this model was about 98%. Even though both datasets had an 80%-20% split for non-seizure to seizure, we believe that the short signal model was better at predicting seizures because there was more data for a seizure in the short signal dataset than in the full signal dataset.

Conclusion

Due to the analysis we conducted on these data sets we were able to determine that our short signals model analysis was able to more accurately identify seizures in comparison to the full signal model since the full signal dataset contained a large amount of data which led to a decrease in the accuracy of the model. The model may be retrained as well to more accurately analyze messier data along with data of differing frequencies than the EEG data we used to train and analyze our current datasets due to receiving data of a consistent frequency for this study. There may also be promise regarding the analysis of the patterns occurring before a known seizure to estimate more accurately when a seizure could occur close to a designated EEG

pattern which could be something to look more into in future work. We would like to thank not only Professor Rachel Bergstrom but also Professor Disha Shende for allowing us to research and analyze this study.