

Case Study 3: Seizure Detection

By Maclaryn Leonard & RJ Pouzar

01 Introduction

02 Case Study Background

03 Data Model

04 Results & Analysis

05 Conclusion

Introduction

This case study was conducted in order to detect when seizures likely occurred within EEG (Electroencephalogram) data collected to view the electrical signals in the brain collected by Professor Rachel Bergstrom along with a team of fellow researchers.

During this study we conducted analysis to determine when seizures most likely occurred throughout the short and full signal datasets.



Case Study Background

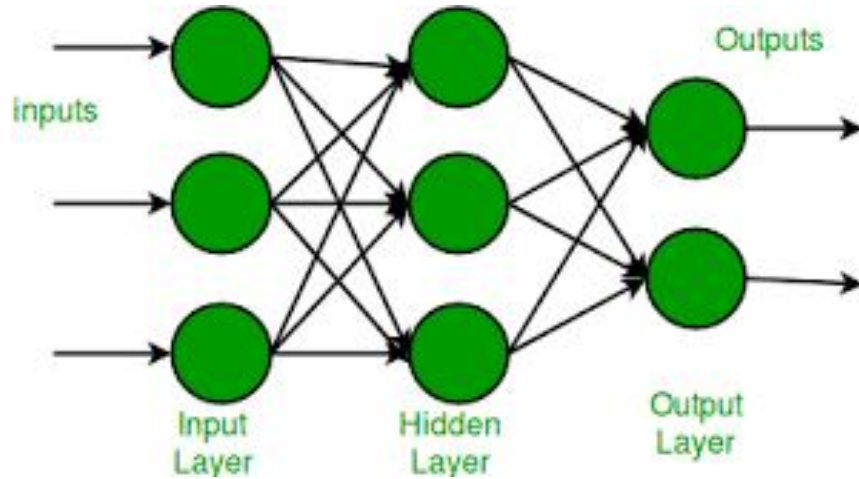
A seizure is shown to be a temporary, abnormal, increase in neural activity with a high frequency and high intensity.

Epilepsy is said to be an initial seizure which is said to lead to a higher likelihood of experiencing seizures later on.

By analyzing patterns within the data sets it becomes easier to predict when seizures occur and how frequently they occur patient to patient to better identify seizures that could stem from epilepsy.

This data analysis can be beneficial to help determine seizures more effectively than the time-consuming analysis by hand.

Data Model

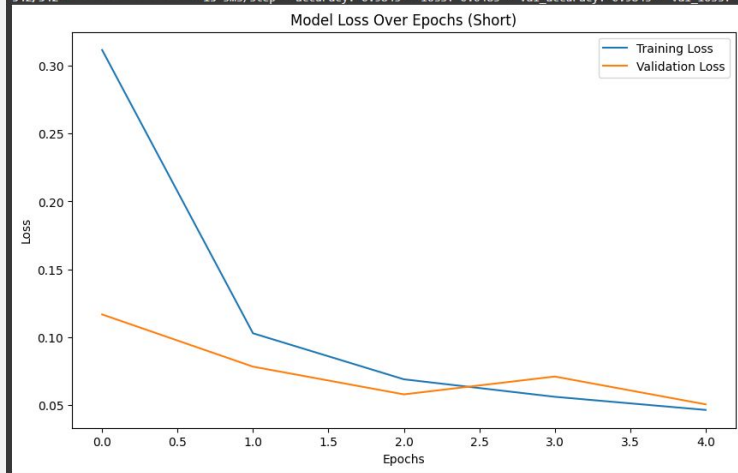


We used a multi-layer perceptron model with a binary cross entropy loss function to classify the different EEG readings from the Bonn dataset.

We chose this model because it is within the domain of what we have learned in our previous classes.

Data Analysis (Short)

```
Epoch 1/5  
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an "input_shape" /  
super().__init__(activity_regularizer=activity_regularizer, **kwargs)  
342/342 _____ 2s 2ms/step - accuracy: 0.8322 - loss: 0.4596 - val_accuracy: 0.9757 - val_loss: 0.1168  
Epoch 2/5  
342/342 _____ 1s 2ms/step - accuracy: 0.9698 - loss: 0.1128 - val_accuracy: 0.9757 - val_loss: 0.0784  
Epoch 3/5  
342/342 _____ 1s 2ms/step - accuracy: 0.9790 - loss: 0.0716 - val_accuracy: 0.9826 - val_loss: 0.0579  
Epoch 4/5  
342/342 _____ 1s 2ms/step - accuracy: 0.9825 - loss: 0.0522 - val_accuracy: 0.9739 - val_loss: 0.0711  
Epoch 5/5  
342/342 _____ 1s 3ms/step - accuracy: 0.9843 - loss: 0.0483 - val_accuracy: 0.9843 - val_loss: 0.0506
```



Our model was able to learn pretty quickly the patterns between the seizures and the non seizures. It learns the pattern pretty much right after the first epoch. The model is prone to overfitting.

With messy data, we can expect the model to have a lower accuracy in both training and testing. Our model will need fine tuning to handle the messy data or we will have to go through the data and clean it in order to see better performance.

Data Results (Short)

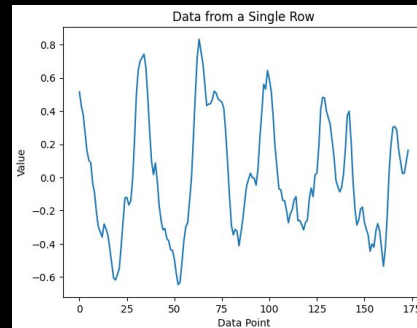
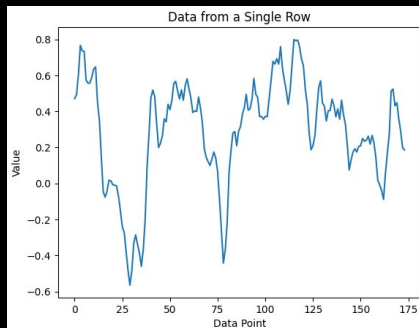


Threshold = 0.9

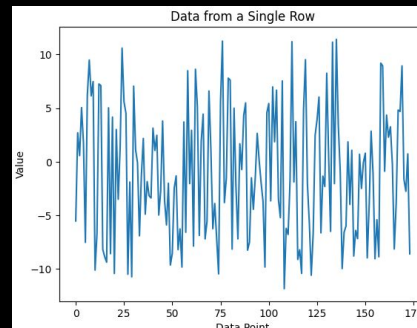
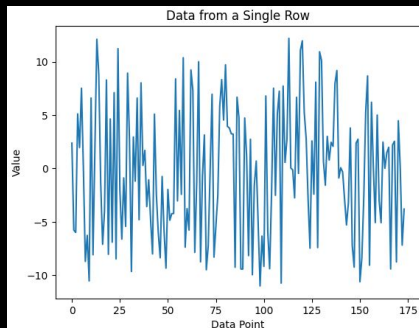
No seizure

Seizure

Actual

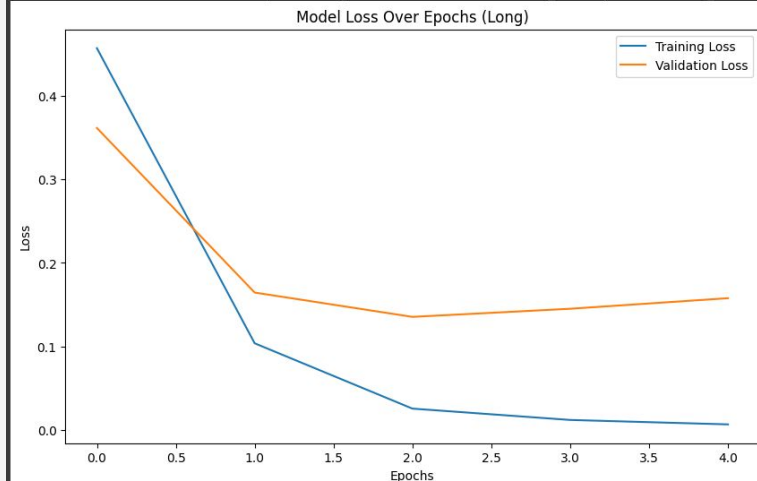


Predicted



Data Analysis (Full)

```
Epoch 1/5  
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`  
super().__init__(activity_regularizer=activity_regularizer, **kwargs)  
15/15 — 1s 18ms/step - accuracy: 0.7119 - loss: 0.5753 - val_accuracy: 0.8400 - val_loss: 0.3615  
Epoch 2/5  
15/15 — 0s 7ms/step - accuracy: 0.9912 - loss: 0.1129 - val_accuracy: 0.9600 - val_loss: 0.1645  
Epoch 3/5  
15/15 — 0s 7ms/step - accuracy: 1.0000 - loss: 0.0293 - val_accuracy: 0.9600 - val_loss: 0.1353  
Epoch 4/5  
15/15 — 0s 7ms/step - accuracy: 1.0000 - loss: 0.0130 - val_accuracy: 0.9600 - val_loss: 0.1451  
Epoch 5/5  
15/15 — 0s 7ms/step - accuracy: 1.0000 - loss: 0.0078 - val_accuracy: 0.9600 - val_loss: 0.1577
```



Our model was able to learn pretty quickly the patterns between the seizures and the non seizures. It learns the pattern pretty much right after the first epoch. The model is prone to overfitting.

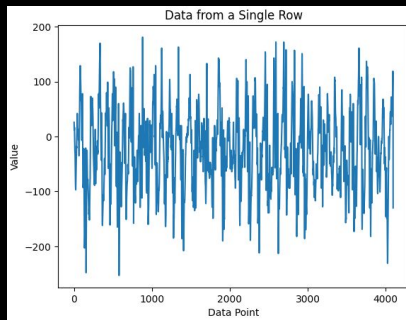
With messy data, we can expect the model to have a lower accuracy in both training and testing. Our model will need fine tuning to handle the messy data or we will have to go through the data and clean it in order to see better performance.

Data Results (Full)

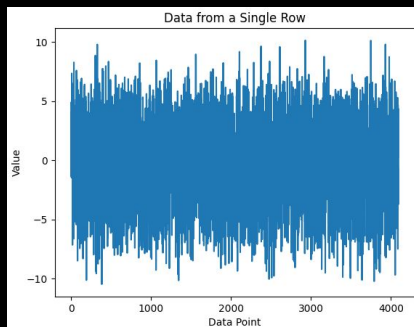


Threshold = 0.9, 0.0086 No seizure

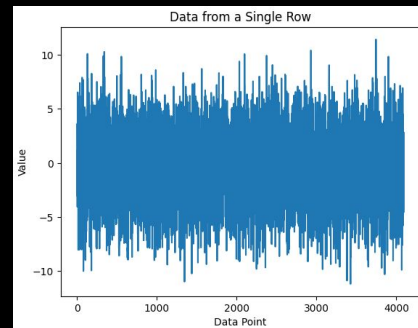
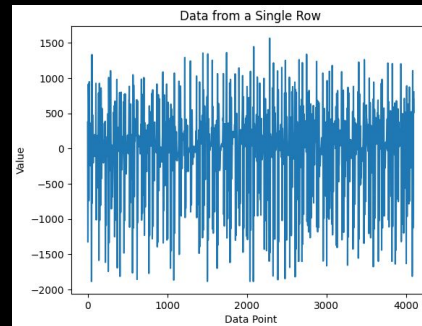
Actual



Predicted



Seizure



Key Insights

The main takeaway that can be seen from our data analysis is that the short data is better for predicting what a brainwave from a brain that is currently seizing might look like. The full dataset seems to have too many data points for our model to show what either type of brainwave might look like.

Our model was trained on data that was taken on a frequency of 173.61 Hz. This means that data taken on other frequencies won't work as well with our model.

Future Work

Future developments to our model could look like:

- Incorporating data taken on different frequencies, classifying the data based on its original label (decision tree), or cleaning more data to add to the training and testing datasets.
- We could also try to create a model that would be able to differentiate between a brain that could potentially lead to an individual experiencing seizures and a brain that would not.



Thank you for listening
and to Rachel Bergstrom
and team for the data!

Questions?