EEG Classification Model

IE6400 – Foundations for Data Analytics Eng

Project Two Report

Group 2

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Introduction and Background Information

Electroencephalogram (EEG) data processing using machine learning algorithms has become a promising field in recent years, especially in the fields of neuroscience and medical diagnostics. The temporal and frequency-specific patterns found in EEG data are indicative of neurological disorders like epilepsy. The goal of this research is to create a strong classification model that can identify various categories in EEG data, with an emphasis on diagnosing epileptic seizures. The chosen datasets for this project have a crucial role in offering a wide and inclusive collection of EEG recordings. The CHB-MIT EEG Database covers various seizure types and non-seizure data, presenting a diverse range of challenges that reflect real-life situations. In addition to this, the Bonn EEG Dataset focuses specifically on EEG recordings associated with epileptic seizures, enabling a more focused investigation into seizure detection capabilities.

The commencement of the expedition involves a thorough data preprocessing stage, wherein we acquire, extract, and thoroughly investigate the structure and attributes of the datasets. Approaches like managing missing values, reducing noise, and potentially augmenting the data are utilized to improve the caliber and comprehensibility of the EEG signals. After completing the data preprocessing stage, the project proceeds to the essential process of feature extraction. The EEG signals are analyzed to extract relevant features from both the time and frequency domains. This step plays a crucial role in identifying distinctive patterns that will enhance the capability of our classification model to differentiate between different neurological states.

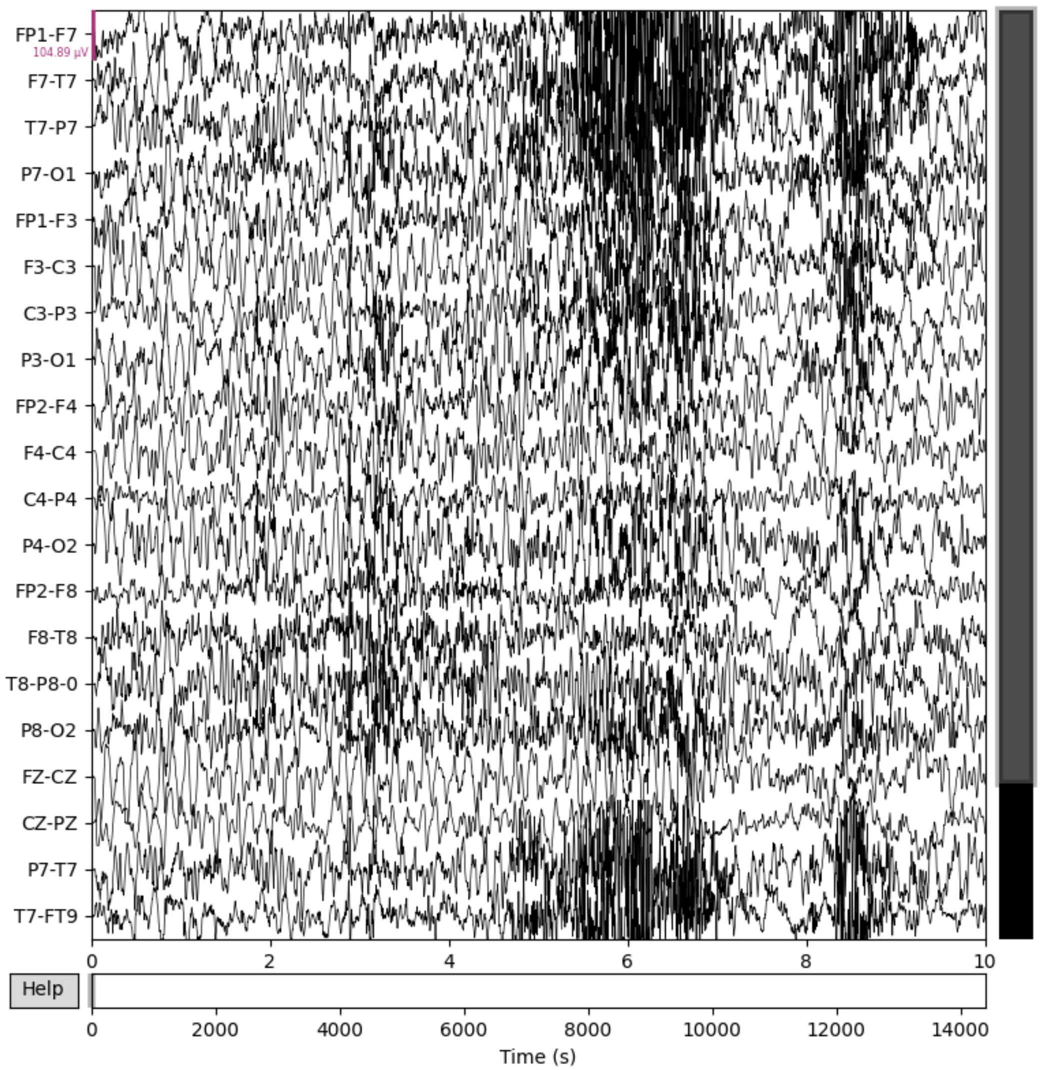
To guarantee the effectiveness of the model, the data is carefully divided into training, validation, and test sets. Advanced machine learning or deep learning architectures, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), are utilized in the subsequent stages of model selection, training, and evaluation. Special attention is given to techniques like dropout and early stopping to prevent overfitting, ensuring the model's robustness and ability to generalize. During the evaluation phase, a range of relevant metrics, including accuracy, precision, recall, and F1-score, are employed to assess the model's performance on the validation set. The hyperparameters of the model are fine-tuned iteratively to optimize its capabilities.

In the final stage, the model undergoes rigorous testing on an independent test set to confirm its ability to generalize unseen data. The results and insights are visually presented through plots and graphs, providing a comprehensive illustration of the EEG data and the model's predictions.

By combining data science, machine learning, and neuroscience, we set out on a mission to make a significant contribution to the comprehension and detection of neurological disorders, specifically epilepsy, through the utilization of EEG data analysis.

Data preprocessing and feature Extraction methods

We are using a .edf file for this project. '.edf', European Data Format (EDF) is a standard file format designed for exchange and storage of medical time series. The visualization of a sample .edf file is done using matplotlib library as shown below:



This dataset contains 916 hours of scalp EEG recordings from 24 individuals sampled at 256 Hz.

In the data frame we have extracted 342 features, one label which stated if the given feature is a seizure or not and file number. Next, we dropped all the columns with null count more than 50 and we are left with 207 features, one label and one filename column. After converting it into csv file we get a count of seizure and non-seizure as

label
non-seizure 545
seizure 141
Name: count, dtype: int64

Now we created a data frame with four columns: file number, seizure number, seizure start time and seizure end time. This data frame is grouped by filename and file number is merged with this data frame on file number and all the null values are replaced by 0. This final data frame is used on models.

Model architecture and training details

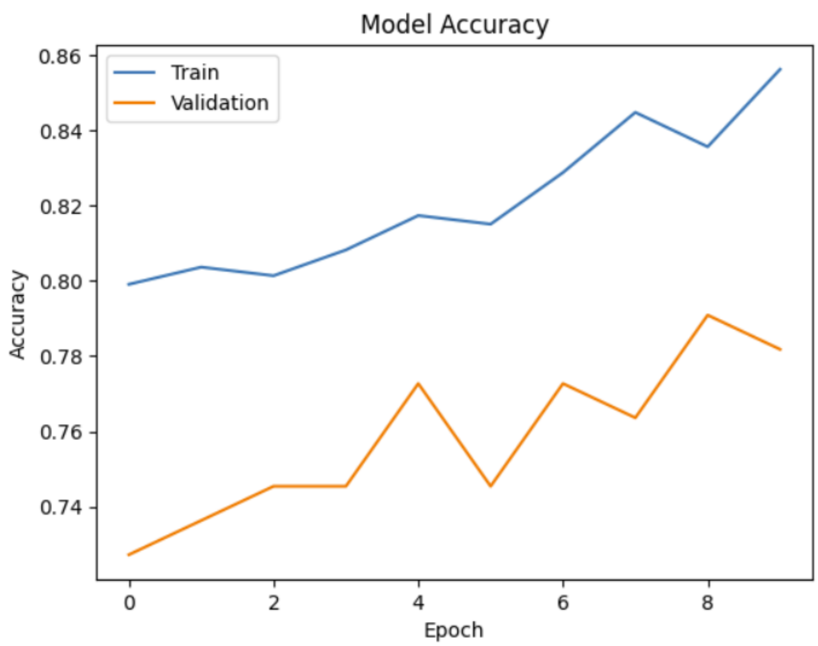
Machine learning model is made using logistic regression and then convolution neural network. Logistic Regression is a fundamental machine learning algorithm, particularly well-suited for binary classification tasks. It is a linear model that predicts the probability of an instance belonging to a specific class. By combining input features linearly and applying the sigmoid activation function, it outputs a probability score. During training, the algorithm adjusts its parameters, or weights, using techniques like gradient descent to minimize the logistic loss function. Logistic Regression is commonly employed as a baseline model for binary classification and offers interpretability through the examination of feature weights.

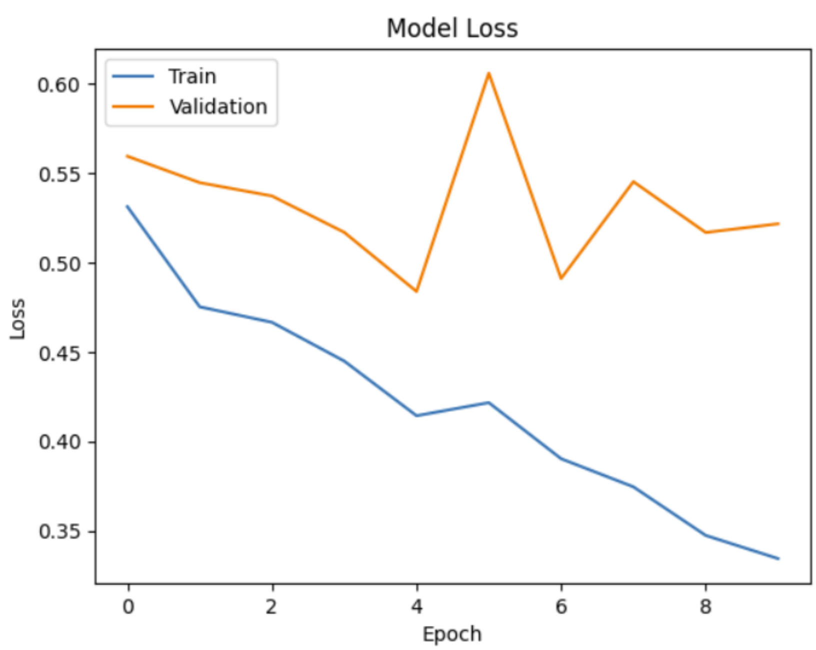
In our project we have split the data into 80% training and 20% testing data. Standardization is applied to the feature sets using StandardScaler to ensure that all features have the same scale. This step is crucial for some machine learning algorithms, including logistic regression. As for evaluation accuracy, confusion matrix, and classification report are computed using scikit-learn metrics. Confusion matrix shows the count of true positive, true negative, false positive, and false negative predictions. The output includes the accuracy, confusion matrix, and a detailed classification report summarizing the model's performance on the test set.

```
Accuracy: 0.99
Confusion Matrix:
[[113   0]
 [  1  24]]
Classification Report:
              precision    recall  f1-score   support

 non-seizure       0.99      1.00      1.00       113
     seizure       1.00      0.96      0.98        25

    accuracy                           0.99       138
   macro avg       1.00      0.98      0.99       138
weighted avg       0.99      0.99      0.99       138
```

Convolutional Neural Networks (CNNs): Convolutional Neural Networks, on the other hand, are a type of deep learning model designed for tasks involving structured grid data, such as images. Their architecture includes convolutional layers for detecting local patterns, pooling layers for down sampling, and fully connected layers for high-level feature combination. CNNs excel in tasks like image classification and object detection, automatically learning hierarchical features from the input data. Their strength lies in capturing translation invariance and hierarchies of features, making them pivotal in computer vision applications.

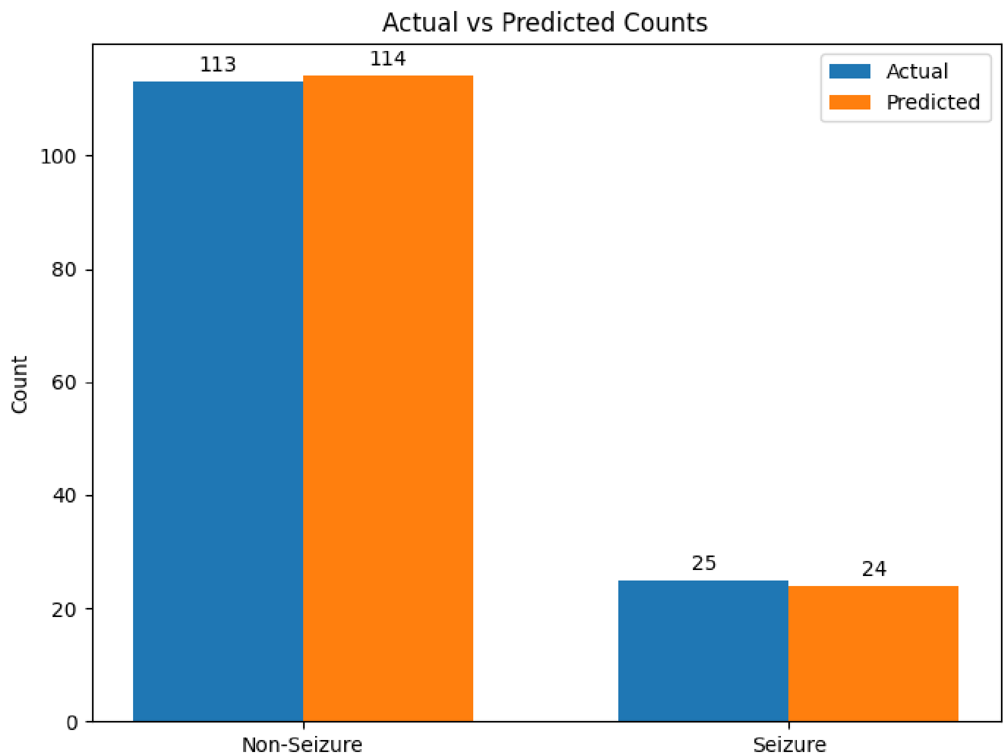
Our code implements a Convolutional Neural Network (CNN) using the Keras library for a binary classification task. Standardization is applied to the training and testing sets. A sequential model is created using Keras. The model comprises Conv1D layers with ReLU activation, MaxPooling1D layers for down sampling, a Flatten layer, and fully connected Dense layers. A binary classification output layer with a sigmoid activation function is added. The model is compiled with binary cross-entropy loss and the Adam optimizer. The training history, including accuracy and loss, is plotted using Matplotlib. These plots help visualize how well the model is learning over epochs, showing accuracy and loss on both the training and validation sets.





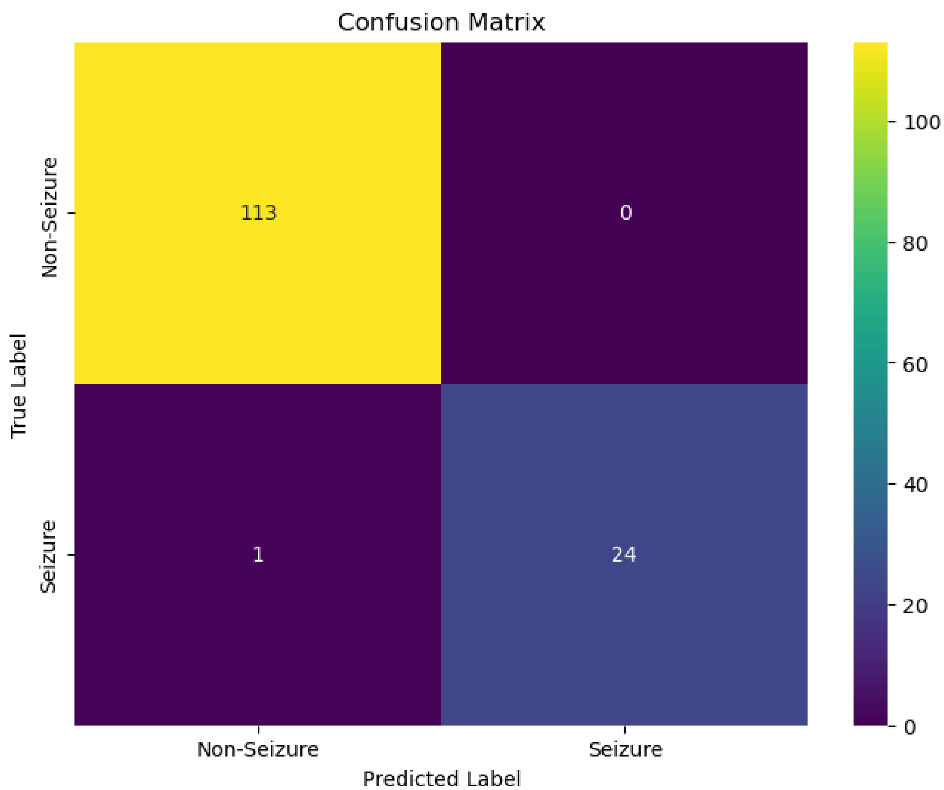
Evaluation Results and Discussion.

Our first model is a machine learning model using a Logistic Regression method. The test model consisted of 20% of the total data and contained 138 instances broken down by 113 non-seizures and 25 seizures. The logistic regression method returned a result with 99% accuracy meaning that it correctly predicted the observation at a great rate. When broken down further one can see that the model is very good at predicting both seizures and non-seizures. The below bar plot shows the breakdown of actual and predicted events, showing that there were 113 actual non-seizures with 114 non-seizures predicted as well as 25 actual seizures with 24 seizures predicted. The test set only contained one instance of a false negative prediction meaning there was a seizure that was incorrectly predicted as a non-seizure.

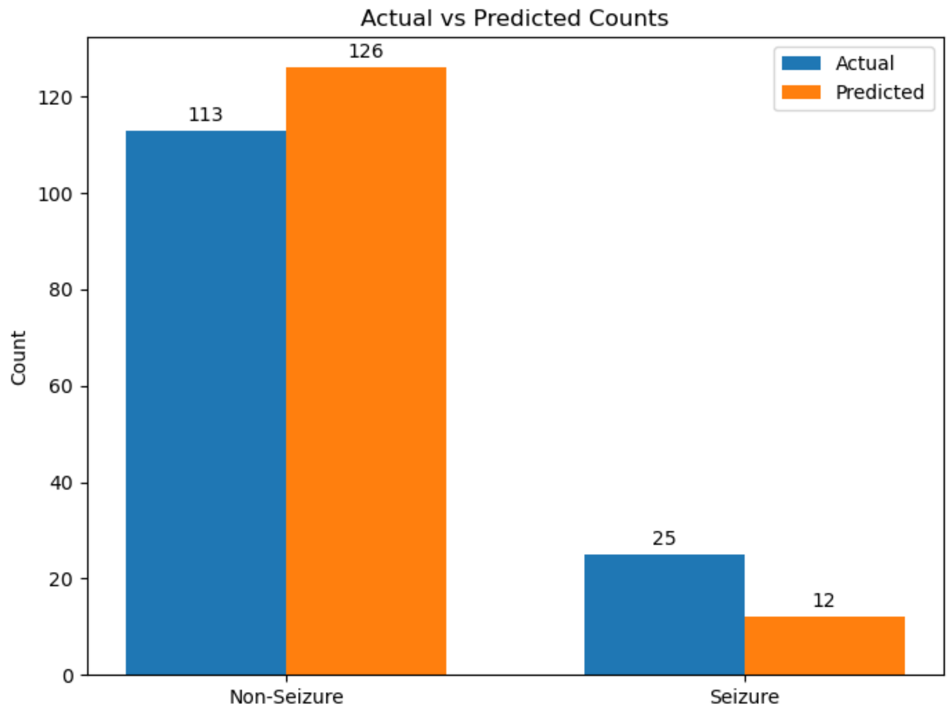


We can see that when determining a non-seizure event, the model has 0.99 precision and a recall of 1.0 and the model is 1.00 precise with a recall of 0.96 for seizure events. This means that the model was precise with all of the predicted seizures and most of the predicted non-seizures. Of the 113 non-seizures 113 were correctly predicted with zero false positives predicted (non-seizure incorrectly predicted as a seizure). Of the 25 seizures only 24 were correctly predicted as a seizure with only 1 predicted as false-negative (actual seizure incorrectly predicted as a non-seizure). The Classification Report and Confusion Matrix below show the result of the test model.

```
Classification Report:
              precision    recall  f1-score   support

 non-seizure       0.99      1.00      1.00       113
     seizure       1.00      0.96      0.98        25

    accuracy                           0.99       138
   macro avg       1.00      0.98      0.99       138
weighted avg       0.99      0.99      0.99       138
```



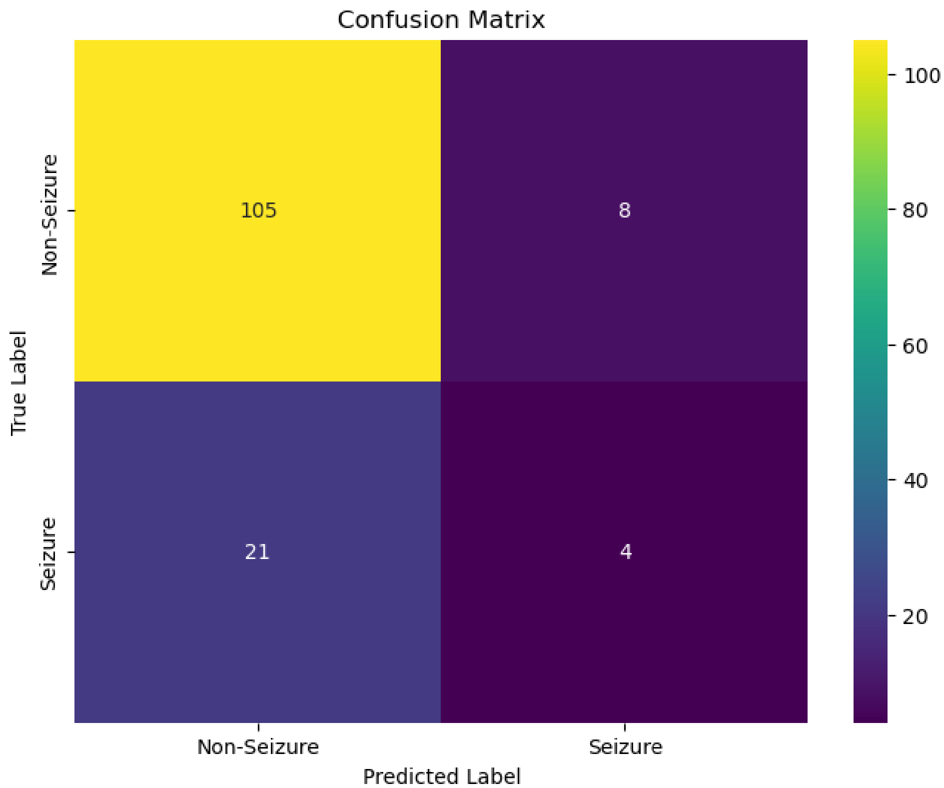
Our second model is a machine learning model using the Convolutional Neural Network method. Using the same test size of 138 instances broken down by 113 non-seizures and 25 seizures this model was determined to have 79% accuracy. The below bar plot shows the breakdown of actual and predicted events, showing that there were 113 actual non-seizures this time with 126 non-seizures predicted as well as 25 actual seizures with 12 seizures predicted. This model contains both false positives and false negatives which account for the incorrect predictions.



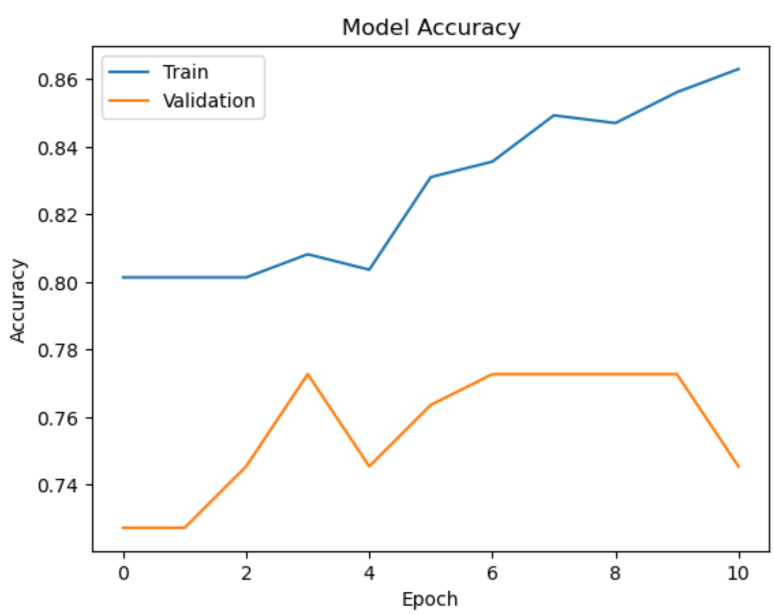
When broken down further we see that this model is precise 83% of the time when determining non-seizures with a recall of 0.93. For seizure events it is 0.33 precise with a recall of only 0.16. This shows that this model is much less accurate when predicting seizures than non-seizures. Of the 113 non-seizures 105 were correctly predicted with 8 predicted as false-positive (non-seizure incorrectly predicted as a seizure), and of the 25 seizures only 4 were correctly predicted as a seizure and 21 were predicted as false-negative (actual seizure incorrectly predicted as a non-seizure). The Classification Report and Confusion Matrix below show the result of the test model.

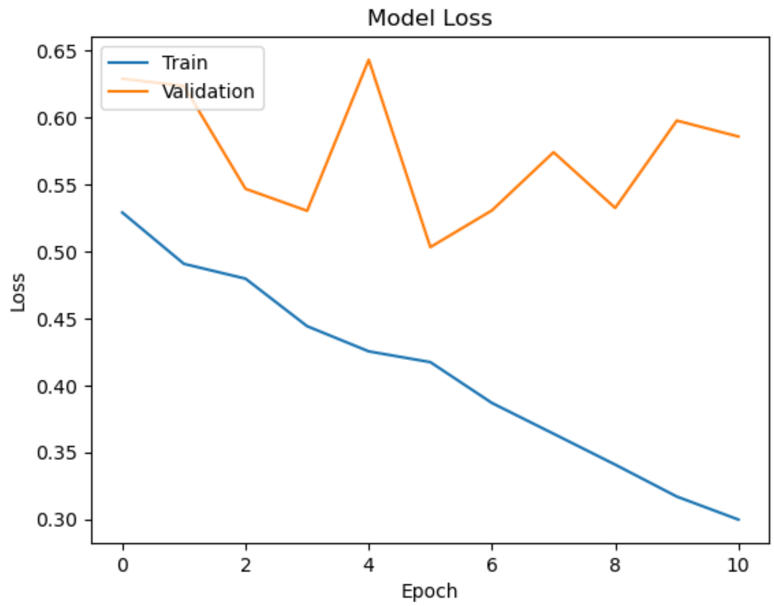
Classification Report:

	precision	recall	f1-score	support
0.0	0.83	0.93	0.88	113
1.0	0.33	0.16	0.22	25
accuracy			0.79	138
macro avg	0.58	0.54	0.55	138
weighted avg	0.74	0.79	0.76	138



The plots below show the model accuracy and model loss for both the Training and Validation iterations over the epochs. They show that for the convolution neural network method the model accuracy increased through each of its training epochs until it reached epoch 11. The model stopped at epoch 11 due to the early stopping function focusing on the model's value loss. The model loss plot shows that as the epochs increased the loss for the training iteration decreased however the loss for the validation iteration variable eventually causing the model to stop itself.





Overall, the two created models were functional at predicting seizures and non-seizures, however the Logistic Regression model was much better at correctly predicting each event.

Conclusion and future work

This research was all about using fancy computer techniques to study brain waves and figure out if someone is having a seizure. We looked at a bunch of different brain wave recordings from people with seizures and people without seizures. First, we had to clean up the data and make it easier to understand. Then, we looked for patterns in the brain waves that could help us tell if someone was having a seizure. We tried two different models to do this. The first model, called logistic regression, did a really good job. It was able to predict seizures with 99% accuracy! It hardly made any mistakes. This model is great because it's easy to understand and it works well for this kind of problem.

The second model, called a convolutional neural network (CNN), was designed for pictures but we tried using it for brain waves. It did decent, with 79% accuracy, but it wasn't as good as the logistic regression model. It had a hard time figuring out when someone was having a seizure. We think we can make it better with more work. We used a bunch of different measurements to see how well the models were doing. We looked at parameters like accuracy, precision, recall, and F1-score. This helped us understand what each model was good at and where we needed to improve. The logistic regression model was the winner in this study.

This study shows how combining data science, machine learning, and neuroscience can help us understand and detect neurological disorders, like epilepsy, a lot better. The logistic regression model is a really useful tool in hospitals because it's easy to understand and it's really accurate. If we make some improvements to the CNN model, we might be able to use it to understand even more complicated patterns in brain activity.

To sum it up, this research is a starting point for future studies on analyzing brain data and using machine learning in neuroscience. The results help us make better and faster diagnoses for neurological disorders, which means patients can get better treatment and we can learn more about how the brain works.

Future Work

1. Making the CNN Model Even Better:

We tried using a Convolutional Neural Network (CNN) model, and it showed some promise. But it didn't beat the logistic regression model. So, in the future, we should focus on tweaking the settings, trying different designs, and using fancy techniques like transfer learning to make it even more efficient.

2. Time is Important:

EEG data is all about time. To make our classifications more accurate, we should think about using something called recurrent neural networks (RNNs) or attention mechanisms. These can help us capture patterns in the EEG signals that change over time.

3. Teamwork Makes the Dream Work:

Combining the strengths of different models can make them even better. So, we could try combining the logistic regression model with the CNN model or even adding in other models that work well together. This could make our predictions more accurate and reliable.

4. More Data, More Knowledge:

If we include more diverse EEG datasets in our study, we can make our models even smarter. Different datasets might have unique challenges and patterns that can help us understand epilepsy and EEG signals even better.

5. Brainy Collaboration:

Working with experts in the field of neuroscience can be super helpful. They can give us their knowledge and insights, which we can use to make our models smarter and easier to understand. By teaming up with these experts, we can figure out which features are important and get a better understanding of how the brain works.