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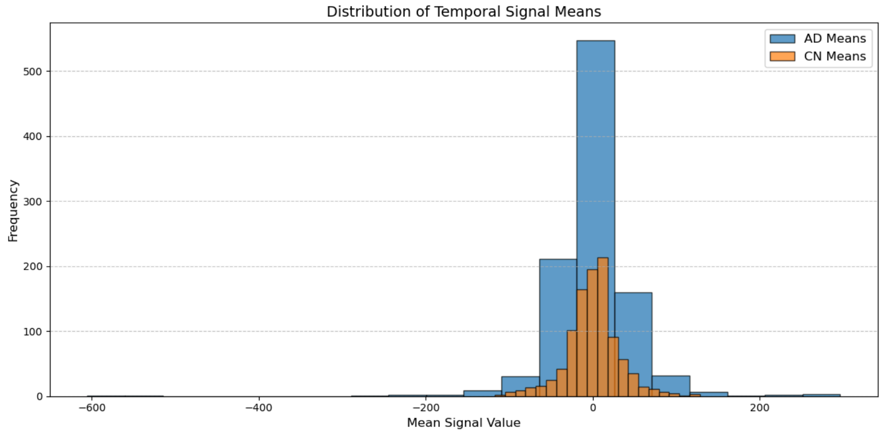
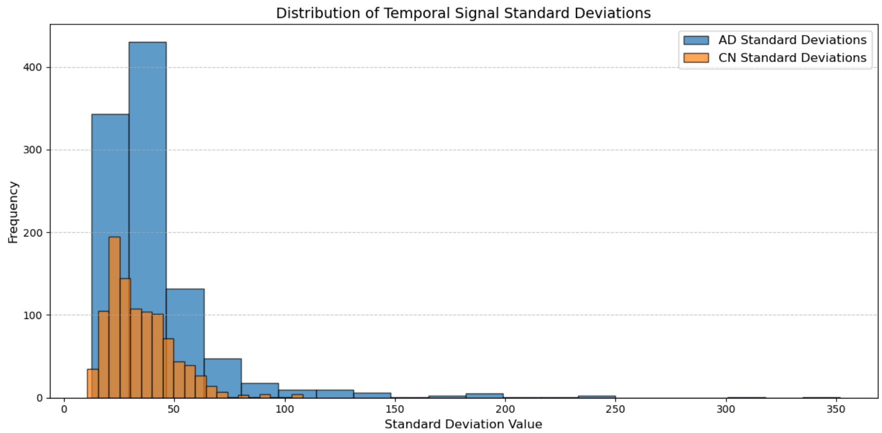
Project 3(CSE 6389-001)

Dataset:

- The dataset consists of 10 samples for AD and 10 samples for CN so the classes are balanced for training. Each sample has functional and structural connectivity along with temporal information in fmri_average_signal.
- We used StratifiedKFold which is a cross-validation technique provided by scikit-learn that ensures each fold of the cross-validation split maintains the same proportion of each class label as in the entire dataset.
- AD is encoded as 1 and CN is encoded as 0 here for this project.
- The mean and std deviation of fMRI signals:
    - 

    - 

    - The distribution here shows a significant overlap between the two classes.
    - So we did the experiment using the spatial data which was functional and structural connectivity.
- The correlation between FC vs SC for AD vs CN [5] is similar to the project2:

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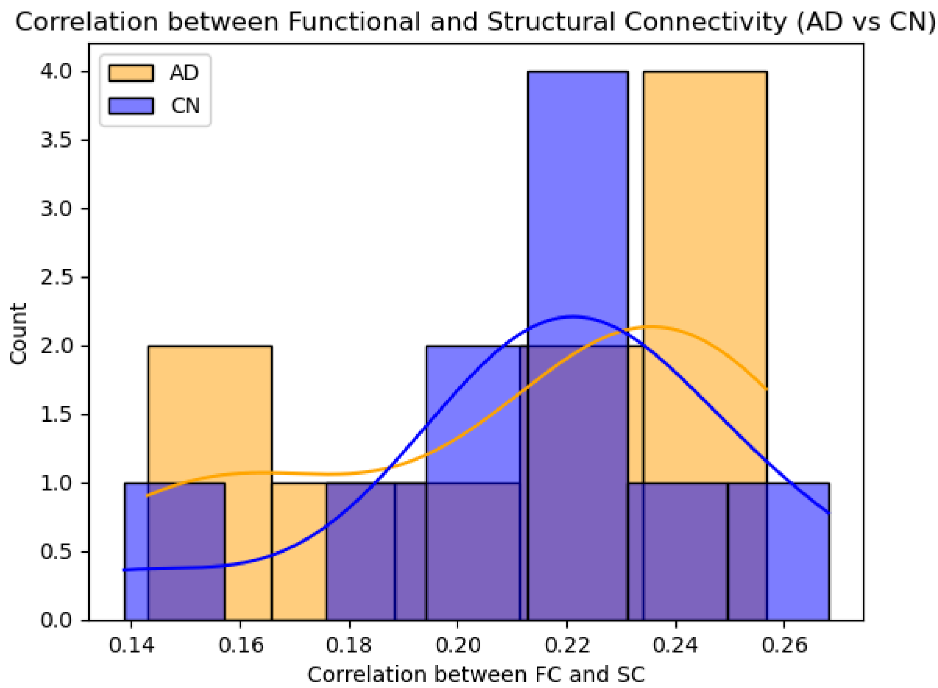

- There is a significant overlap in the correlation distributions for AD and CN groups, with both centered around similar values (approximately 0.22-0.24).

Model:

- GCN_RNN_Model(
- (gcn1): GCNLayer(
- (linear): Linear(in_features=150, out_features=128, bias=True)
-)
- (gcn2): GCNLayer(
- (linear): Linear(in_features=128, out_features=150, bias=True)
-)
- (rnn): LSTM(150, 16, batch_first=True)
- (fc): Linear(in_features=16, out_features=2, bias=True)
-)
-
- We used a combination of GCN and RNN(LSTM).
- The first two GCN layers extract the features using functional and structural connectivity.
- Two layers (150–128–150 dimensions) process adjacency matrices representing connectivity graphs.
- The Last layer is an LSTM layer which combines the connectivity and time series fMRI signals to give a binary output of AD/CN.
- Here our matrices for SC and FC are 150*150 in dimension.
- We have 100 signal feature matrices in each AD/CN folder.
- We used the **batch size of 4** for training and validation as we have a very small dataset.
- Summary:

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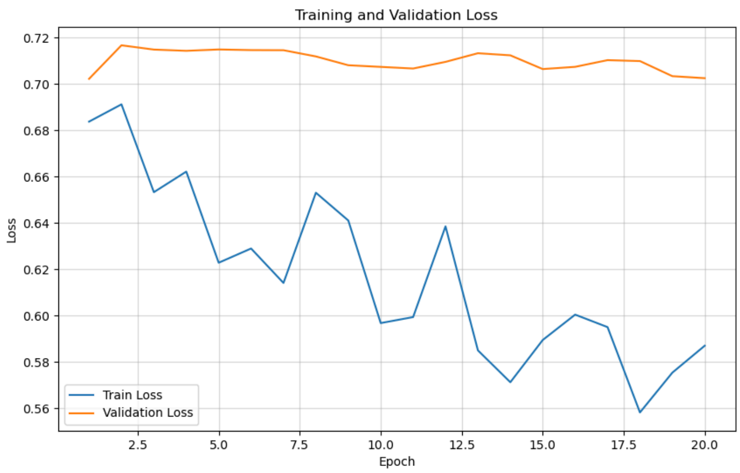
- The GCN leverages the adjacency matrix (which represents the connectivity structure) to aggregate information from neighboring nodes.
- The model is pretty small as it has just two layers for GCN and simple LSTM implementation at the end to capture temporal and spatial features.

Training:

- We used k-fold cross-validation in model training. The K value is 5 here which means the model is split into 5 folds with a random sampling of **12 training inputs and 4 validation inputs**.
- The k-fold cross-validation is used as the data set is small and we need to generalize the model to avoid overfitting.
- As the dataset was quite small and our model was simple we didn't have the problem of exploding gradients so didn't clip our gradient.
- We used an **ADAM optimizer** as it adjusts the learning rate dynamically and as our dataset is small we have to sure that the learning rate doesn't make the validation loss or training loss plateau at a certain point.
- The **learning rate** and **weight decay** [2] are set to **0.001 and 5e-8** respectively.
- We used **20 epochs** to train because the dataset is small and we can see the validation loss decreasing at a slow rate towards the end.
- Average train and validation loss across all the folds.



  - Here we can see the training and validation loss decreases with each epoch which signifies the model is learning well.
  - There is a bit of fluctuation in validation loss as the dataset is small, so Improving it sometimes can lead to unstable results but since we have used L2 regularization the model doesn't overfit.
- We also did experiments only using the temporal information(just the LSTM part) and our graph looks like this.

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- The variations here are quite high for validation loss and the training is smooth.
- Even though we trained it on 50 epochs we just obtained an accuracy of 56%.
- So combined with spatial features we can say that the model trains well even though it has higher variability.

Evaluation:

- We referred to the paper "*Longitudinal analysis for Alzheimer's disease diagnosis using RNN*" [4] for evaluation.
- We used the test dataset to evaluate our model which had 4 samples 2 from AD and 2 from CN.
- Evaluation metrics for test set:
  - **Accuracy**: 100.00%
  - **Precision**: 100.00%
  - **Recall (Sensitivity)**: 100.00%
    - Recall (sensitivity) shows that the model successfully identified all actual positive cases.
  - **F1-Score**: 1.00
    - indicates a perfect balance between precision and recall.
  - **AUC-ROC**: 1.00
    - The Area Under the Curve is 1, indicating perfect classification with no errors.

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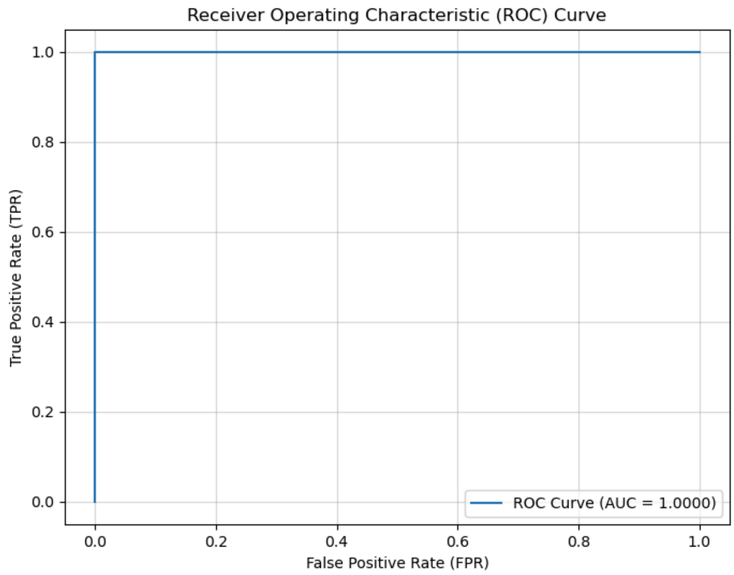

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Conclusion:

The implemented GCN-RNN model demonstrates the capability of integrating spatiotemporal features for binary classification tasks, effectively leveraging both functional and structural brain connectivity data along with temporal fMRI signals. The model achieved high evaluation metrics, including perfect test accuracy, precision, recall, F1-score, and AUC-ROC (1.0000). However, there is some amount of overfitting in the dataset as it is small and we use the test set from the same sample set.

Advantages of the Model:

1. **Integration of Spatiotemporal Data**: The combined GCN and RNN architecture efficiently processes spatial (connectivity matrices) and temporal (fMRI time-series) features, capturing complex relationships.
2. **Flexibility**: The modular design allows the model to adapt to diverse neuroimaging data types and binary classification tasks.

Despite its advantages, the model's fluctuating validation loss and accuracy across folds highlight the need for improvements in generalization, particularly on unseen data.

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