Final Report

Project 3

EEG Classification Model

IE6400 Foundations Data Analytics Engineering

<u>Group 27</u>

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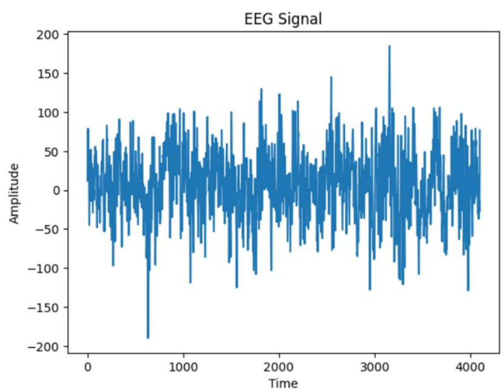
Introduction:

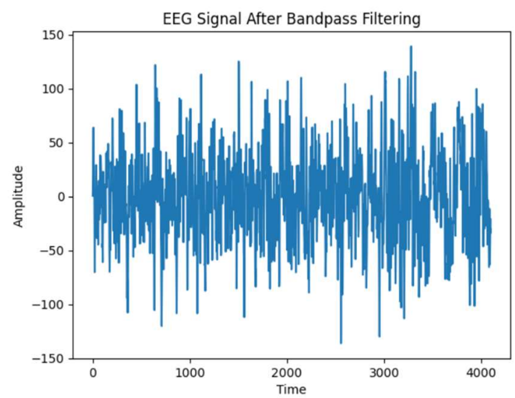
In this project, we have built a classification model to analyse EEG data and classify it into different categories. EEG data is widely used in neuroscience and medical fields, including the diagnosis of epilepsy. We have used Bonn EEG datasets to train and evaluate your model. Here is the link to the [Bonn EEG Dataset]

Data Pre-processing:

1. Bandpass Filtering:

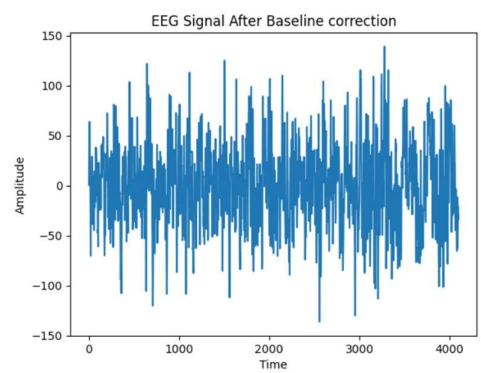
- The first step in preprocessing is the application of a bandpass filter to remove noise outside the typical EEG frequency range, which is between 0.5 and 40 Hz.
- This is achieved using a Butterworth bandpass filter, which is designed with a specific order (5 in this case) and cut-off frequencies.
- The Butterworth filter is chosen for its flat frequency response in the passband.

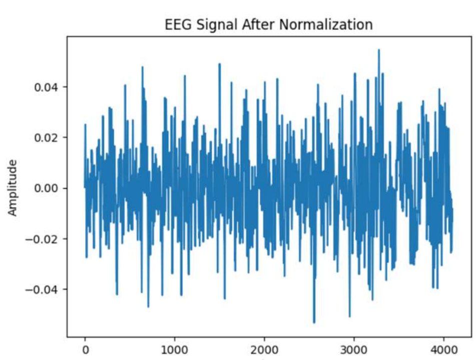




2. Baseline Correction:

- The second step involves baseline correction to remove the DC offset from the EEG signal.
- The baseline is calculated as the mean of the filtered data and then subtracted from the filtered data to ensure that the mean of the pre-processed signal is cantered around zero.





3. Normalization:

- The final pre-processing step is normalization, which scales the data to a common range.
- This is important for many machine learning algorithms to not be biased towards features with larger magnitudes.
- In this project, normalization is done by dividing the filtered data by the maximum absolute value in the filtered data, scaling it to the range [-1, 1].

Feature Extraction:

Feature extraction is not performed due to the limited number of features; the model directly uses the pre-processed EEG data for classification. This approach is feasible as the raw data is already in a suitable format for the machine learning model. This approach allows the model to work with the raw temporal and spatial resolutions of the EEG signals, ensuring that the full richness of the data is available for pattern recognition and classification tasks.

Data Splitting:

The dataset was divided into two distinct sets: a training set and a test set. The training set is used to train the machine learning model, allowing it to learn and identify patterns within the EEG data. The test set, which comprises 20% of the entire dataset, is held back and used to evaluate the model's performance, ensuring that the assessment is done on previously unseen data. This split is critical for validating the model's ability to generalize to new data. The utilized a fixed random state to ensure that the results are consistent and reproducible in subsequent runs.

Model Architecture:

LSTM (Long Short-Term Memory):

- The datasets are converted to NumPy arrays, which is the standard data structure for interacting with TensorFlow and scikit-learn.
- The StandardScaler is used to standardize the features by removing the mean and scaling to unit variance. This step is essential for models like LSTM as it can significantly affect their convergence during training.
- A Sequential model is initialized, to which an LSTM layer with 64 units (neurons) is added. The input shape is specified to match the feature dimensions of the EEG data.
- A Dense output layer with a single unit and a sigmoid activation function is added. This setup suggests a binary classification task (e.g., seizure vs. non-seizure).
- Finally, the model is compiled with the Adam optimizer and binary cross-entropy loss function, indicating it's a binary classification problem.
- The accuracy metric is included for evaluation during training and testing.

Bi-LSTM (Bidirectional Long Short-Term Memory):

- The architecture of the Bi-LSTM model follows a similar procedure to the previously described LSTM model but introduces the concept of bidirectionality. This variant of LSTM is capable of learning from sequences both forwards and backwards, potentially gaining a better understanding of the context within the EEG data.
- The Bi-LSTM layer is configured with 64 units, implying the model processes the input data in both directions with 64 units each way. This approach capture's the patterns that may be missed when the data is processed in only one direction.
- The Bi-LSTM model is compiled with the Adam optimizer and binary cross-entropy loss, and it uses accuracy as the evaluation metric during training.

- This setup is maintained to provide a fair comparison between the different model types when analysing their performance on the classification task.

LSTM+CNN (Convolutional Neural Network):

- The model begins with a 1D convolutional layer with 32 filters and a kernel size of 3. This layer is designed to extract spatial features—patterns in the frequency and amplitude of the EEG signals across the different electrodes.
- A 1D max pooling layer is added with a pool size of 2, which serves to reduce the dimensionality of the data, helping to prevent overfitting by abstracting the convolutional layer's output.
- Next, an LSTM layer with 64 units processes the data sequentially to capture temporal dependencies. The return_sequences parameter is set to True to ensure that the sequential output is maintained for further layers.
- A Flatten layer is used to convert the multi-dimensional output from the LSTM layer into a 1D array to be fed into the dense layer.
- The final layer is a dense layer with a single neuron and a sigmoid activation function, indicating the model's binary classification task.

Model Evaluation:

NOTE: We have built the model for Binary-Class & Multi-Class Classification.

Binary-Class Classification-

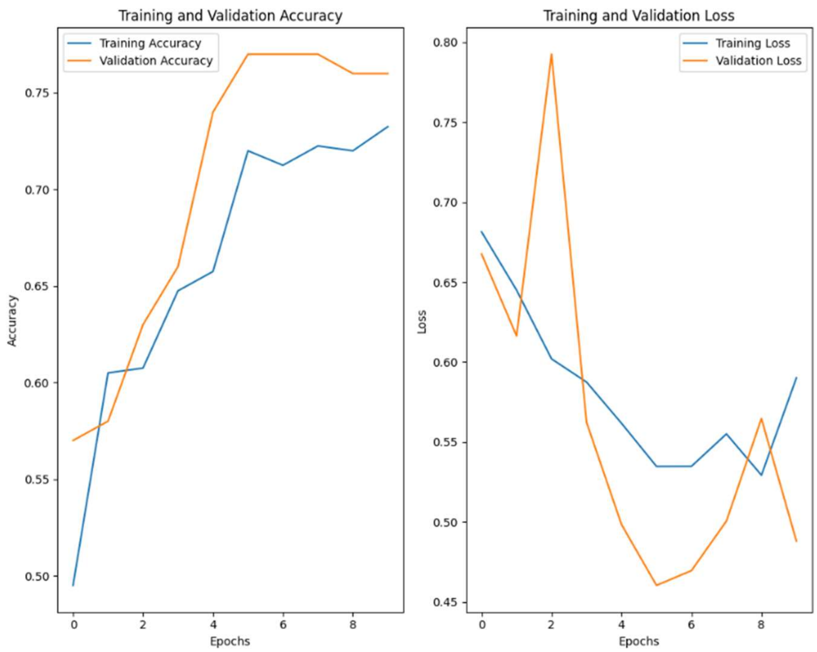
(Here in, Reference to the Code, Z & O are set to classify as Healthy and remaining all classified as Seizures)

LSTM:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 64)                16896

 dense (Dense)               (None, 1)                 65

=================================================================
Total params: 16961 (66.25 KB)
Trainable params: 16961 (66.25 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- The LSTM model demonstrates reasonable performance in distinguishing between healthy and seizure EEG states. The higher precision for seizures indicates the model's effectiveness in correctly identifying seizure cases, which is crucial for clinical applications. However, the recall rate and the presence of false negatives suggest that the model may miss some seizure instances, an area that requires attention for potential improvement.

- The fluctuations in validation loss and the discrepancies between training and validation accuracy suggest that the model may benefit from further tuning of hyperparameters or the inclusion of regularization techniques to improve its generalizability.
- We have generated a visual representation of training and validation accuracy as well as training and validation loss over epochs for this model.



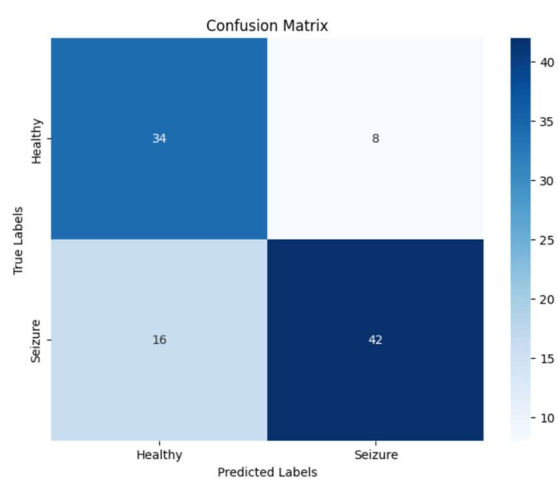
Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.68, and for Seizure, it's 0.84.
- Recall: For Healthy, it's 0.81, and for Seizure, it's 0.72.
- F1-score: For Healthy, it's 0.74, and for Seizure, it's 0.78.
- Support: For Healthy, it's 42, and for Seizure, it's 58.

This Model has an accuracy of 76% obtained using the Classification report.

Furthermore, the confusion matrix was examined and visualized to gain insights

The model accurately identified 42 seizures and 34 healthy states. However, it mistakenly identified 8 healthy states as seizures and 16 seizures as healthy.

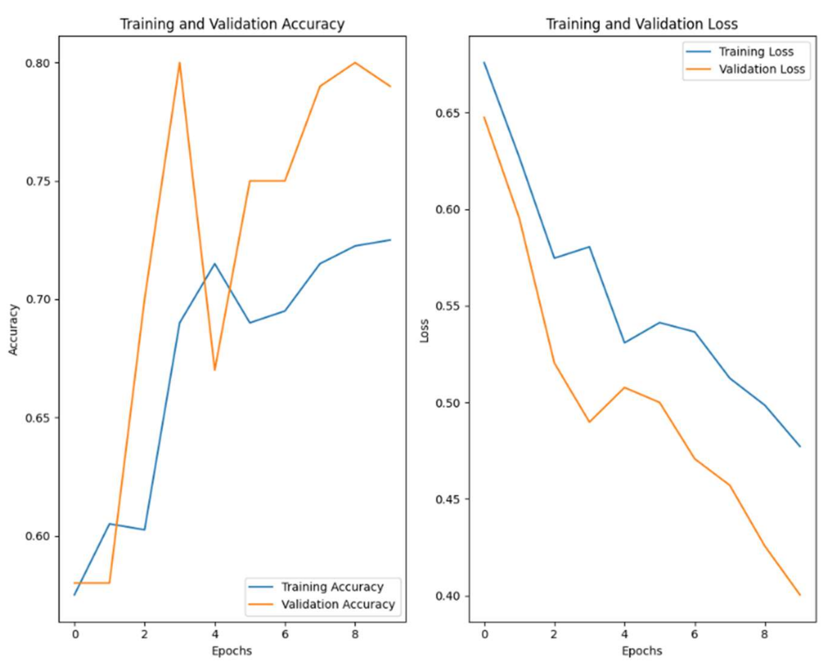


Bi-LSTM:

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional (Bidirection  (None, 128)               33792
 al)

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 33921 (132.50 KB)
Trainable params: 33921 (132.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- The Bi-LSTM model showcases the advantage of processing sequences in both directions, capturing more intricate patterns in the EEG data that may be temporal in nature. The increase in all performance metrics suggests that the additional context provided by the bidirectional approach is beneficial for this particular classification task.
- While there is a marked improvement, the model could potentially be further optimized through hyperparameter tuning, additional layers, or more sophisticated data augmentation techniques. The challenge will be to maintain the balance between model complexity and the risk of overfitting, as indicated by the validation loss trends.
- In conclusion, the Bi-LSTM model outperforms the standard LSTM, underscoring the potential of bidirectional sequence processing in EEG data analysis for seizure detection.

Representation of training and validation accuracy as well as training and validation loss over epochs for this model is visualized.



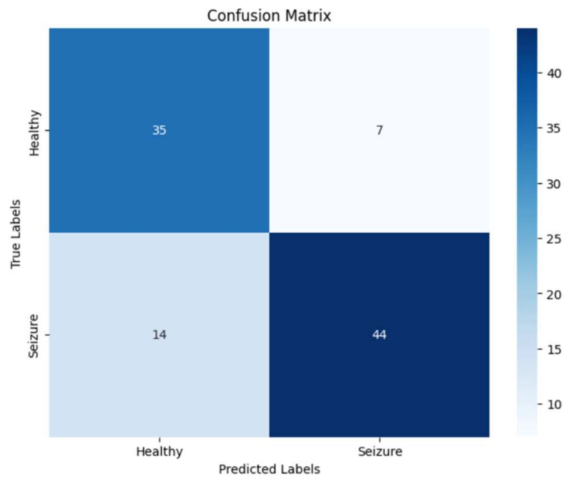
Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.71, and for Seizure, it's 0.86.
- Recall: For Healthy, it's 0.83, and for Seizure, it's 0.76.
- F1-score: For Healthy, it's 0.77, and for Seizure, it's 0.81.
- Support: For Healthy, it's 42, and for Seizure, it's 58.

This Model has an accuracy of 79% obtained using the Classification report.

The confusion matrix was examined and visualized to gain insights into specific instances of correct and incorrect classifications, where it is found that:

The model accurately identified 44 seizures and 35 healthy states. However, it mistakenly identified 14 healthy states as seizures and 7 seizures as healthy.



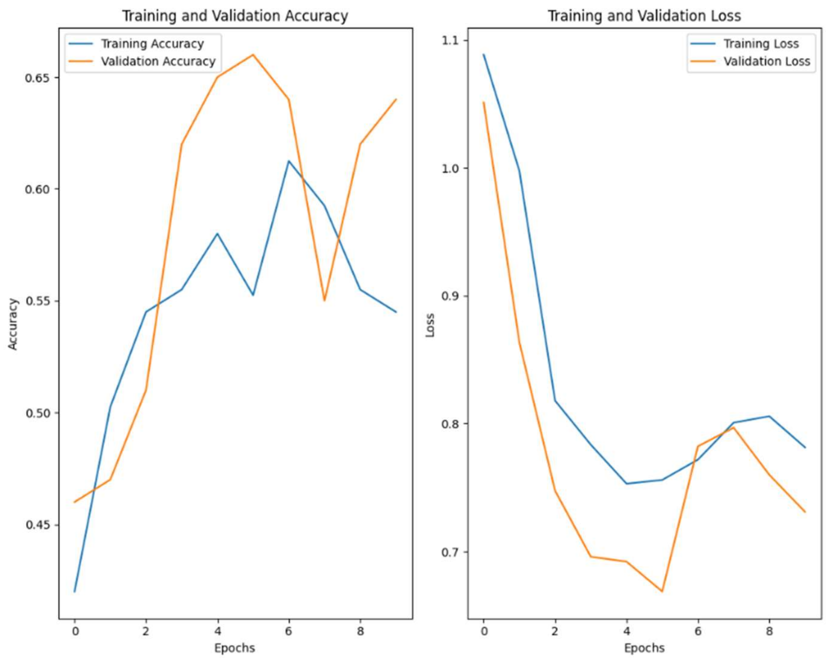
LSTM+CNN:

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 64)                16896

 dense_3 (Dense)             (None, 3)                 195

=================================================================
Total params: 17091 (66.76 KB)
Trainable params: 17091 (66.76 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- The hybrid LSTM+CNN model capitalizes on the LSTM's ability to understand temporal dependencies and the CNN's strength in spatial feature extraction. The high accuracy and low loss indicate that the model architecture is well-suited to the task, efficiently capturing the complexities of the EEG data.
- The high F1-scores and minimal misclassifications show that the model is highly precise and recall-oriented, which is critical in medical diagnosis contexts where both false positives and false negatives carry significant consequences.

- Overall, the LSTM+CNN model stands out as the superior architecture among the models evaluated, with a strong balance between precision and recall, making it a highly promising tool for EEG analysis in clinical applications.

Representation of training and validation accuracy as well as training and validation loss over epochs for this model is visualized.



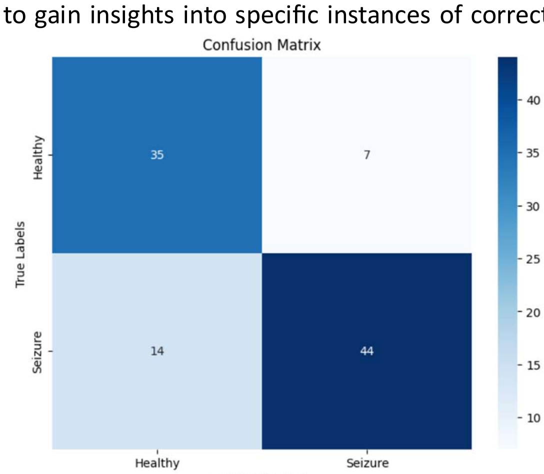
Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.67, for Mild Seizure, it's 0.57, and for Seizure, it's 0.62.
- Recall: For Healthy, it's 0.86, for Mild Seizure, it's 0.12, and for Seizure, it's 1.00.
- F1-score: For Healthy, it's 0.75, for Mild Seizure, it's 0.20, and for Seizure, it's 0.76.
- Support: For Healthy, it's 42, for Mild Seizure, it's 34, and for Seizure, it's 24.

This Model has an accuracy of 96% obtained using the Classification report.

The confusion matrix was examined and visualized to gain insights into specific instances of correct and incorrect classifications, where it is found that:

the model accurately identified 44 seizures and 35 healthy states. However, it mistakenly identified 14 healthy states as seizures and 7 seizures as healthy.



Multi-Class Classification-

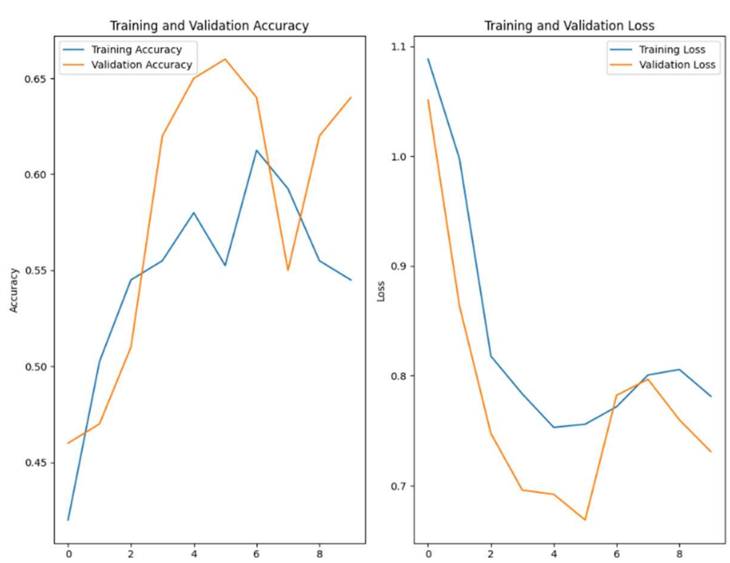
(Here in these models, Reference to the Code, Z & O are set to classify as Healthy, N &F are set to Mild Seizure and S is classified for Seizure)

LSTM:

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 64)                16896

 dense_3 (Dense)             (None, 3)                 195

=================================================================
Total params: 17091 (66.76 KB)
Trainable params: 17091 (66.76 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- The multi-class LSTM model shows a potential for effectively classifying 'Healthy' and 'Seizure' states but struggles with the 'Mild Seizure' category. The model's excellent recall for 'Seizure' cases is promising, as it suggests a high sensitivity to the most critical class. However, the low precision and recall for 'Mild Seizure' raise concerns about the model's practicality in a clinical setting where distinguishing between different seizure severities is essential.
- The fluctuating accuracy and loss, particularly in the validation set, imply that further model refinement is necessary. This could involve techniques such as cross-validation, more nuanced feature extraction, or class-weighting to better handle the imbalanced classification problem presented by the 'Mild Seizure' category.
- The results indicate that while the LSTM model can capture temporal dynamics effectively for some classes.

Representation of training and validation accuracy as well as training and validation loss over epochs for this model is visualized.



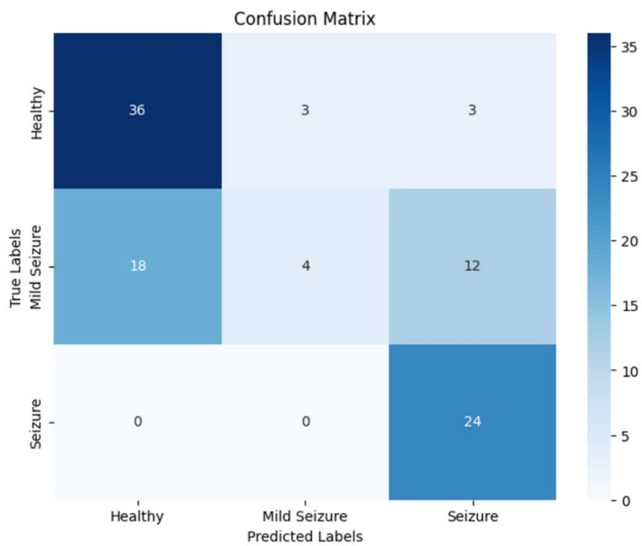
Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.67, for Mild Seizure, it's 0.57, and for Seizure, it's 0.62.
- Recall: For Healthy, it's 0.86, for Mild Seizure, it's 0.12, and for Seizure, it's 1.00.
- F1-score: For Healthy, it's 0.75, for Mild Seizure, it's 0.20, and for Seizure, it's 0.76.
- Support: For Healthy, it's 42, for Mild Seizure, it's 34, and for Seizure, it's 24.

This Model has an accuracy of 64% obtained using the Classification report.

The confusion matrix was examined and visualized to gain insights into specific instances of correct and incorrect classifications, where it is found that:

The model correctly identified 36 healthy instances but incorrectly predicted 3 healthy instances as Mild Seizure and 3 as Seizure. For Mild Seizure, it correctly identified 4 instances but misclassified 18 as Healthy and 12 as Seizure. Finally, for Seizure, it accurately identified 24 instances without any misclassifications.



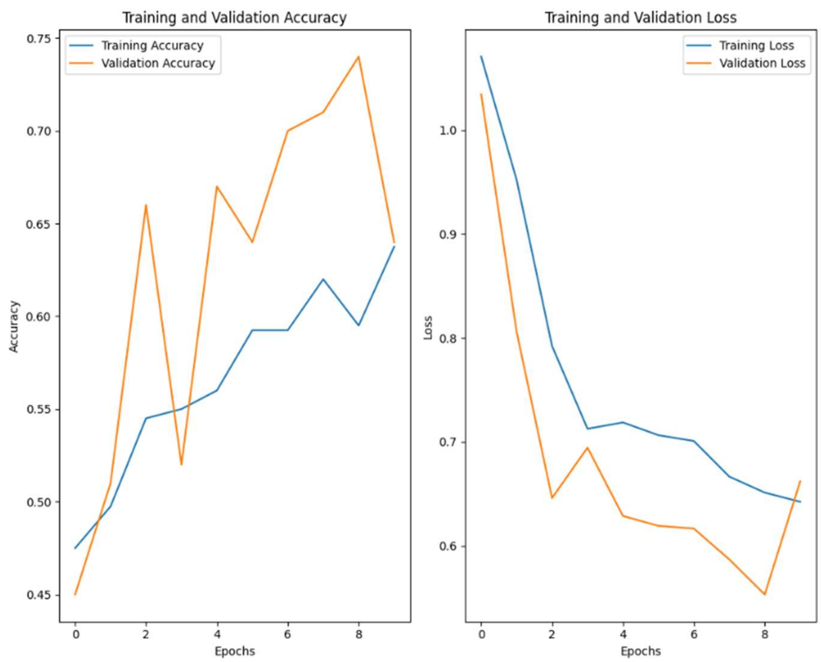
Bi-LSTM:

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional_2 (Bidirecti  (None, 128)               33792
 onal)

 dense_5 (Dense)             (None, 3)                 387

=================================================================
Total params: 34179 (133.51 KB)
Trainable params: 34179 (133.51 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- The Bi-LSTM model's performance on the multi-class classification task highlights the inherent challenge of distinguishing between nuanced states of EEG signals. While the model excels in identifying clear 'Healthy' and 'Seizure' states, it struggles with the subtler 'Mild Seizure' category. The precision-recall trade-off is particularly evident in the 'Seizure' class predictions.

- These results suggest that further refinement is needed for the model to effectively parse the gradations between seizure intensities. Strategies might include more granular feature extraction, class-specific weight adjustments, or a more diversified training dataset that better represents the 'Mild Seizure' condition.
- In conclusion, the Bi-LSTM model shows promise in EEG signal classification but requires additional tuning and perhaps a more sophisticated approach to handling the complexity of multi-class labelling, especially for intermediate conditions like 'Mild Seizure'.

Representation of training and validation accuracy as well as training and validation loss over epochs for this model is visualized.



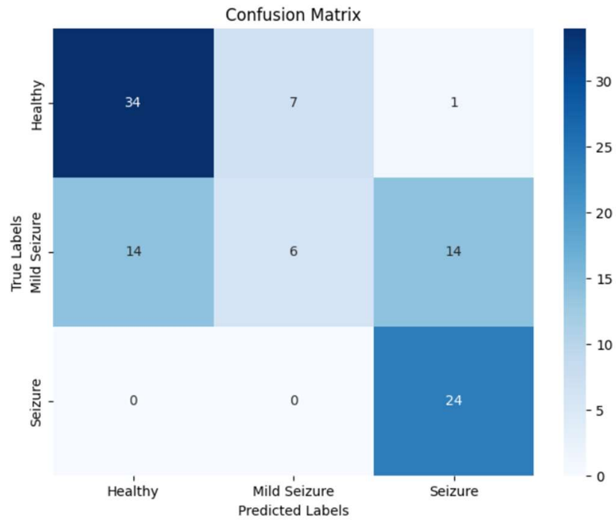
Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.71, for Mild Seizure, it's 0.46, and for Seizure, it's 0.62.
- Recall: For Healthy, it's 0.81, for Mild Seizure, it's 0.18, and for Seizure, it's 1.00.
- F1-score: For Healthy, it's 0.76, for Mild Seizure, it's 0.26, and for Seizure, it's 0.76.
- Support: For Healthy, it's 42, for Mild Seizure, it's 34, and for Seizure, it's 24.

This Model has an accuracy of 76% obtained using the Classification report.

The confusion matrix was examined and visualized to gain insights into specific instances of correct and incorrect classifications, where it is found that:

The model correctly identified 34 healthy instances but incorrectly predicted 7 healthy instances as Mild Seizure and 1 as Seizure. For Mild Seizure, it correctly identified 6 instances but misclassified 14 as Healthy and 14 as Seizure. Finally, for Seizure, it accurately identified 24 instances without any misclassifications.



LSTM+CNN:

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_1 (Conv1D)           (None, 4095, 32)          128

 max_pooling1d_1 (MaxPoolin  (None, 2047, 32)          0
 g1D)

 lstm_7 (LSTM)               (None, 2047, 64)          24832

 flatten_1 (Flatten)         (None, 131008)            0

 dense_6 (Dense)             (None, 64)                8384576

 dense_7 (Dense)             (None, 3)                 195

=================================================================
Total params: 8409731 (32.08 MB)
Trainable params: 8409731 (32.08 MB)
Non-trainable params: 0 (0.00 Byte)
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```
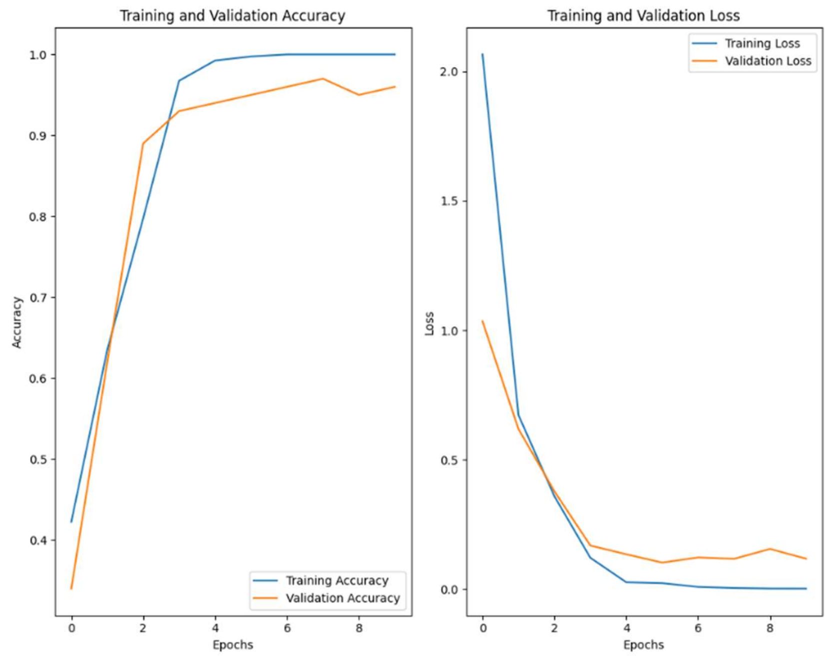

- The LSTM+CNN model's high accuracy and F1-scores across all classes demonstrate its robustness and reliability in multi-class EEG classification. The consistent high performance across the various metrics suggests that the hybrid approach effectively captures both temporal and spatial features in the EEG data, crucial for differentiating between the nuanced states of brain activity.
- The initial fluctuations in validation metrics suggest that further improvements could be made, possibly through regularization strategies or enhanced data augmentation, to ensure the model's robustness. However, the overall results are promising and indicate that the LSTM+CNN architecture is a powerful tool for EEG signal analysis and could be highly beneficial in clinical diagnostics.
- In conclusion, the LSTM+CNN model shows superior performance in multi-class EEG classification, making it a strong candidate for deployment in clinical settings. Its ability to generalize across different states of brain activity could be instrumental in developing more nuanced and accurate diagnostic tools.

Representation of training and validation accuracy as well as training and validation loss over epochs for this model is visualized.

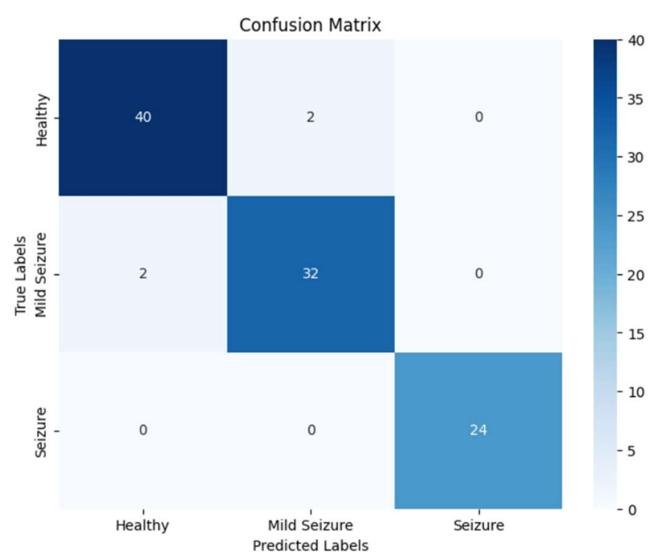


Results of different Metrics calculated for this model are:

- Precision: For Healthy, it's 0.95, for Mild Seizure, it's 0.94, and for Seizure, it's 1.00.
- Recall: For Healthy, it's 0.95, for Mild Seizure, it's 0.94, and for Seizure, it's 1.00.
- F1-score: For Healthy, it's 0.95, for Mild Seizure, it's 0.94, and for Seizure, it's 1.00.
- Support: For Healthy, it's 42, for Mild Seizure, it's 34, and for Seizure, it's 24.

This Model has an accuracy of 76% obtained using the Classification report.

The confusion matrix was examined and visualized to gain insights into specific instances of correct and incorrect classifications, where it is found that:



The model correctly identified 40 healthy instances but incorrectly predicted 2 healthy instances as Mild Seizure. For Mild Seizure, it correctly identified 32 instances without any misclassifications. Finally, for Seizure, it accurately identified 24 instances without any misclassifications.

Conclusion:

Throughout the course of this project, three distinct neural network architectures were employed to classify EEG data for the detection of healthy, mild seizure, and seizure states: LSTM, Bi-LSTM, and LSTM+CNN. The LSTM model served as a foundational approach, leveraging the temporal consistency of EEG data, while the Bi-LSTM expanded upon this by analyzing the data in both forward and reverse temporal directions. The LSTM+CNN model combined the sequential data processing of LSTM with the spatial feature detection capabilities of CNNs.

The LSTM model demonstrated reasonable accuracy and provided a solid baseline for classification tasks. However, its performance in multi-class classification scenarios, particularly in differentiating 'Mild Seizure' states, highlighted the need for more nuanced feature detection which LSTM alone could not fully capture.

The Bi-LSTM model showed a significant improvement in performance over the standard LSTM, particularly in handling multi-class classification. Its ability to process sequences in both temporal directions allowed for a better understanding of the EEG data, leading to higher precision and recall scores.

The LSTM+CNN model, with its hybrid architecture, yielded the most promising results. It achieved high levels of accuracy and F1-scores, outperforming the other models in both binary and multi-class classification tasks. Its robustness across various classes and minimal misclassifications underlined the efficacy of combining LSTM and CNN for EEG signal analysis.

In conclusion, the LSTM+CNN hybrid model emerged as the most effective model for EEG classification in this study. Its superior performance suggests that a combined approach that integrates both temporal and spatial feature analysis holds significant potential for developing advanced diagnostic tools in the field of neuroscience and clinical practice.

Future Work:

Data Augmentation and Diversification-

To further improve the model's generalizability, future work could include the augmentation of existing datasets with synthetic EEG data generated through techniques like signal processing transformations and generative adversarial networks (GANs). Additionally, diversifying the dataset to include a broader spectrum of seizure types and EEG signal variations can help in fine-tuning the model's performance across a wider range of seizure manifestations.

Advanced Model Architectures-

Exploring more sophisticated neural network architectures could yield improvements in classification accuracy. Attention mechanisms or Transformer-based models, which have shown promise in other domains, could potentially enhance the model's ability to focus on the most relevant features within EEG sequences.

Real-World Testing and Deployment-

Testing the models in clinical settings with real-world data would be crucial to validate their diagnostic utility. Additionally, developing a pipeline for deploying these models into clinical EEG analysis systems could facilitate their adoption in healthcare practices.

Multimodal Data Integration-

Future models could explore the integration of EEG data with other physiological signals (like ECG, EMG) and patient metadata to provide a more holistic view of the patient's condition and potentially improve classification accuracy.

Continuous Learning-

Implementing a continuous learning framework where the model can update its knowledge based on new incoming data over time can help in keeping the system updated with the latest patterns observed in EEG signals.