Project :

Motor Imagery EEG Signal Analysis for Finger Movement: An Approach to Brain-Computer Interfaces

Presented to :

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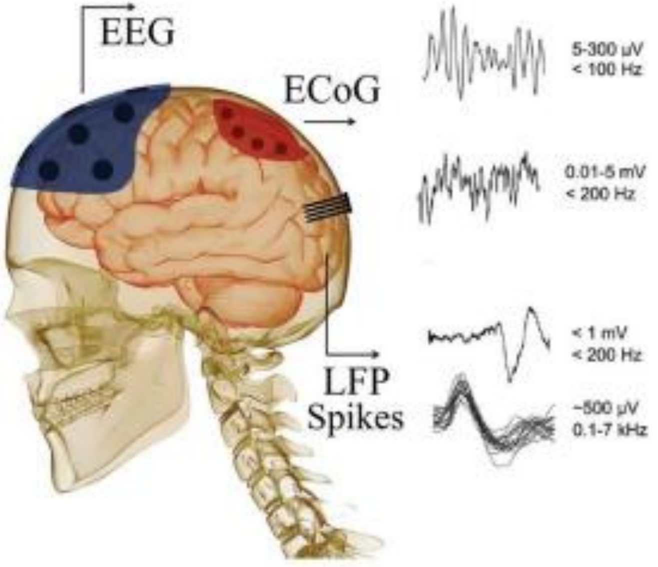
Contents :

Introduction

- Brain-Computer Interfaces (BCIs) are systems that enable direct communication between the brain and external devices.
- Electroencephalography (EEG) is a non-invasive method used to measure electrical activity in the brain.
- In 19 century after the success of Richard Caton in recording electroencephalogram (EEG) from cortical surfaces of animals.
- Motor imagery involves imagining a specific movement, which generates measurable EEG signals.

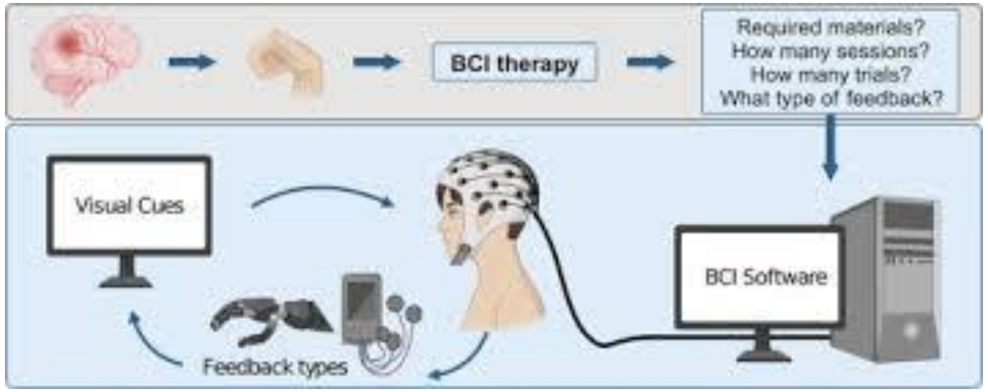


Introduction

Motor and sensory motor: They come from motor actions as a result for moving any kind of lamps. They are in frequency band **(8: 30)** HZ produced from motor cortex in brain

- **Prosthetics Control:** Accurate finger movement classification can enhance the functionality of prosthetic limbs, offering users more natural and intuitive control.

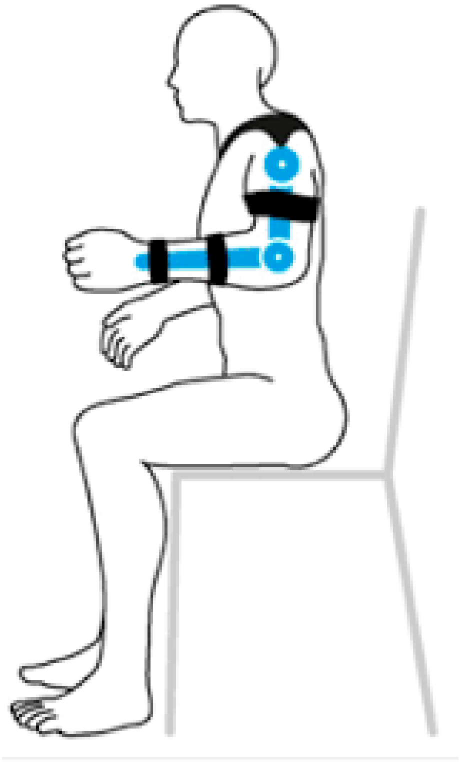
- **Rehabilitation:** Effective BCIs can aid in the rehabilitation of patients with motor impairments by providing a non-invasive means to control assistive devices.



Motivation

Every year, millions of people suffer strokes, and about half of the survivors end up with difficulty moving their upper limbs. This highlights the need for better rehabilitation options.

EEG technology could be a great solution because it's non-invasive, allows patients to control therapy with their brains, and provides real-time feedback, making therapy more engaging and possibly speeding up recovery.



https://www.stroke.org/en/about-stroke/effects-of-stroke

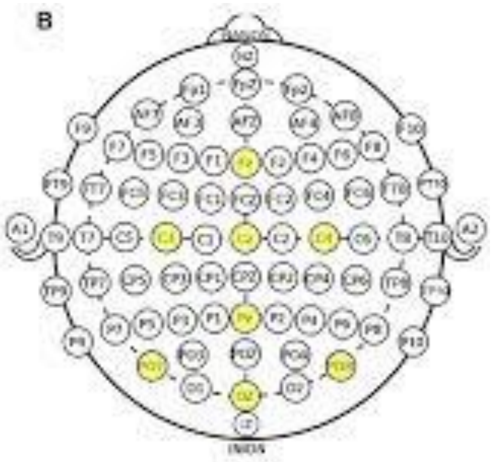
Motivation

Using the full 64-electrode sensor array in Brain-Computer Interface (BCI) systems presents several limitations:

- ❑ **Increased Complexity**: Processing data from 64 electrodes requires more computational resources
- ❑ **Higher Cost**: The 64-electrode kits are significantly more expensive, making them less accessible for widespread use.
- ❑ **Challenging Setup**: Precise placement of each electrode is time-consuming and often uncomfortable for users.

Motivation

<u>**Focusing on fewer channels**</u> can make real-time application feasible by reducing number of EEG channels from 64 to 8 (Cheaper kit) while maintaining high accuracy.



❑ **Simpler Setup:**

Easier and faster to set up, enhancing user convenience.

❑ **Real-Time Application:**

Full sensor setups are complex and impractical for real-time scenarios.

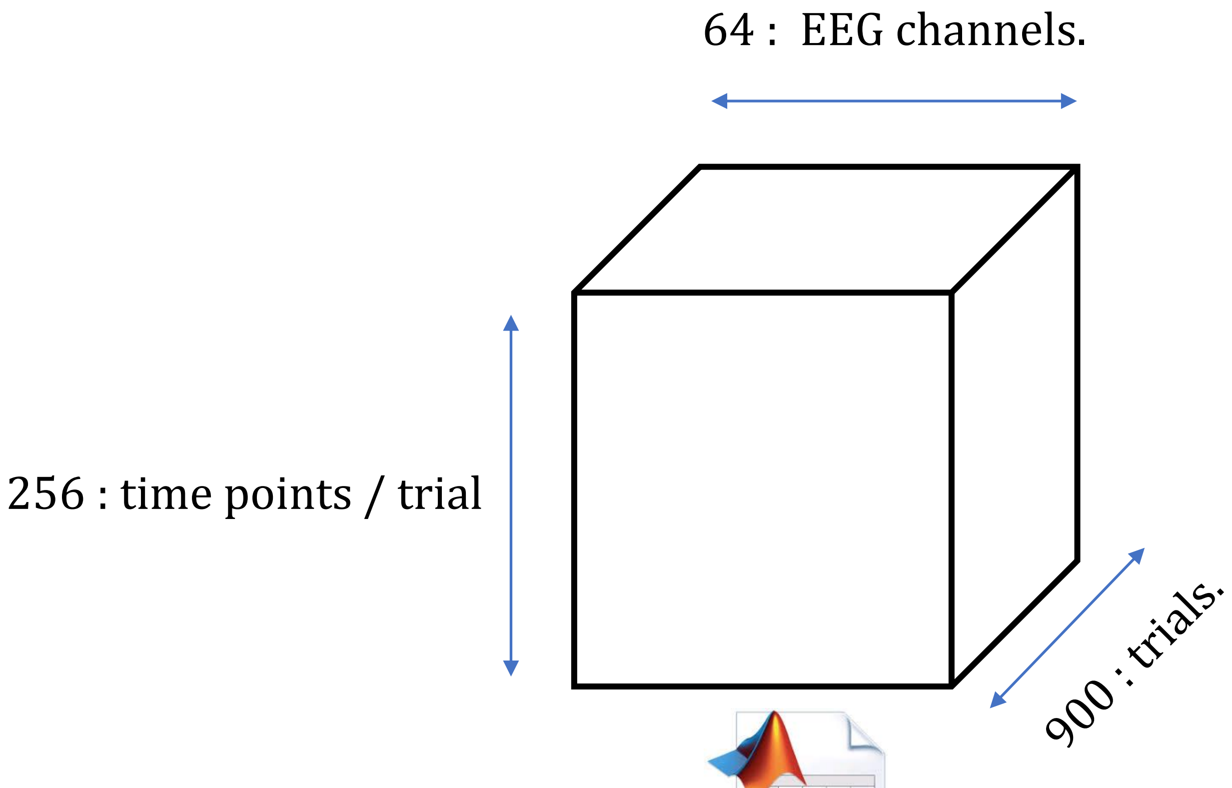
Dataset Statistics

- The dataset used in this study, related to finger movements, was collected from five male volunteers aged 21 to 23 years.

- The data were recorded using 64 electrodes placed according to the international 10–20 system.

- The experiments involved subjects performing individual finger movements with their right hands 5 classes :

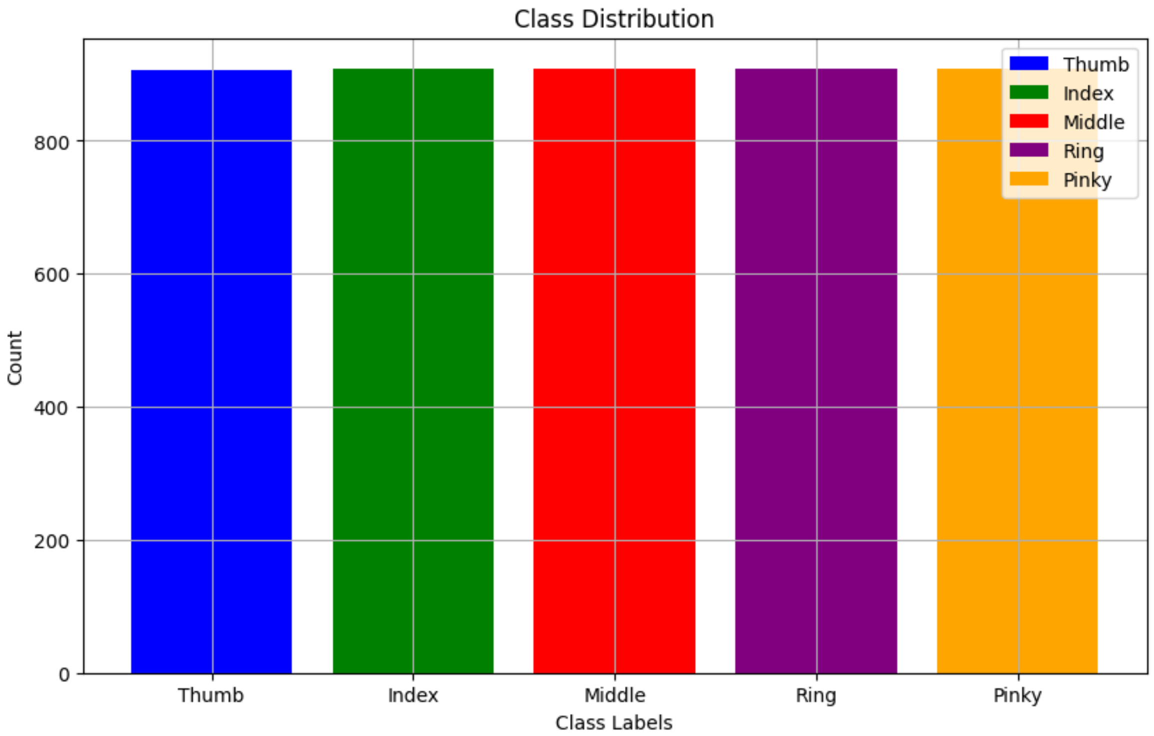
  (Thumb, Index, Middle , Ring, Pinky).



Dataset Statistics

After concatenating the EEG data from all five files, we observed that the dataset is balanced across all finger movement classes.

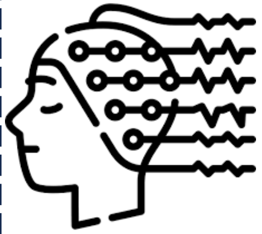
This balance, including the first class, ensures that the dataset is evenly distributed, which will be beneficial for training machine learning models without class bias.



Thumb: 906 samples, **Index**: 909 samples, **Middle**: 909 samples, **Ring**: 909 samples , **Pinky**: 909 samples

Methodology (1st Approach)

Raw Dataset



Preprocessing

Band-Pass Filtering (8 : 30)

Normalization (Robust Scaler)

Common Average Referencing (CAR)

Channel Selection : **8**
['T7', 'TP7', 'TP9','POz', 'Oz', 'O1', 'PO3', 'PO7']

Feature Extraction

Time domain

14 Features

Median
Kurtosis
.
.
Signal Energy

Frequency domain

3 Features

PSD
Peak Frequency
Spectral Entropy

Train set 80 %

Test set 20 %

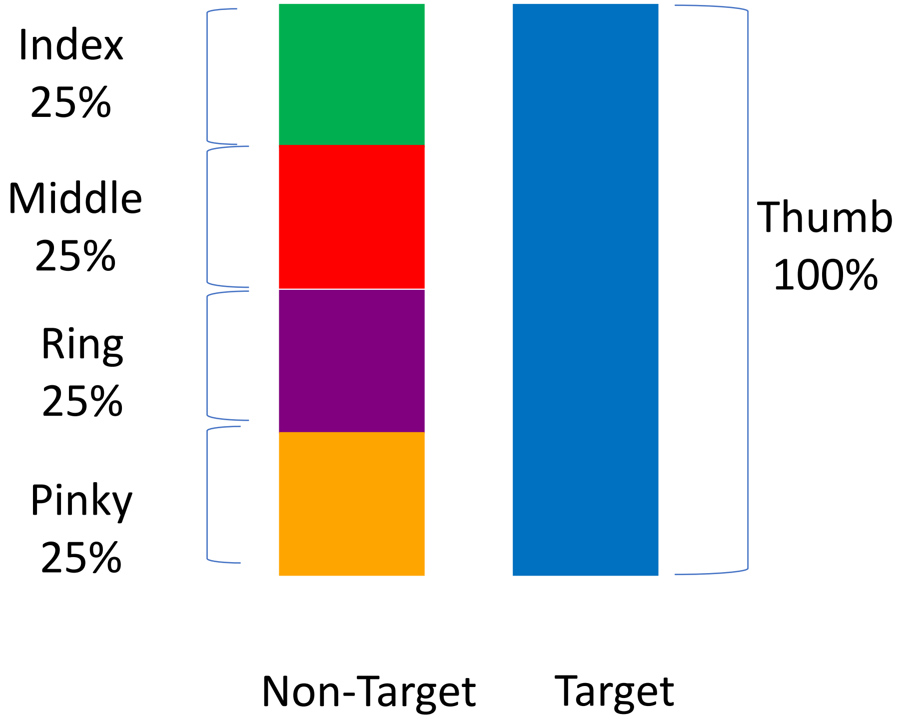
Train Model & evaluate performance

Methodology (Data preparation)

- We tried to feed dataset into ML model as multi classes problem and unfortunately model was struggle to distinguish patterns of each class

- This approach converts the problem into a binary classification task, helping the classifier distinguish between target and non-target trials more effectively. To balance the dataset, a percentage (25%) of trials from each non-target class.

- This approach will also enhance real-time performance, enabling the system to handle multiple simultaneous actions effectively.



Methodology (Preprocessing)

Band-pass Filtering:

Applies a Butterworth band-pass filter to retain frequencies between 8.0 and 30.0 Hz. This step removes noise and focus on the frequency range most relevant for EEG signal analysis.

Common Average Referencing (CAR):

Subtracts the mean signal across all channels from each channel. This method reduces noise and artifacts common to all channels, enhancing the signal-to-noise ratio.

Reducing the number of channels

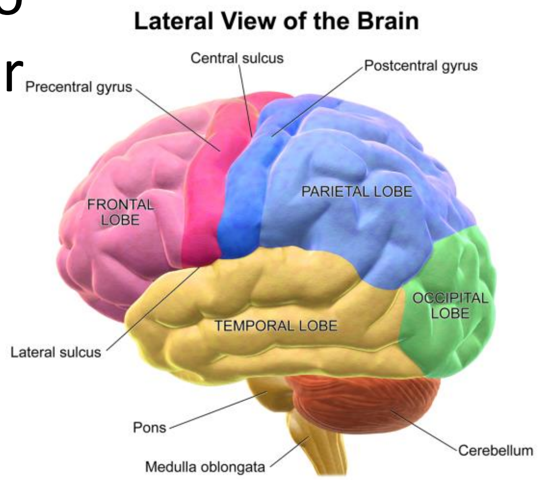
simplifies the analysis and focuses on the most informative signals, improving computational efficiency and potentially the accuracy of downstream tasks.

Robust Scaling:

Uses to normalize the data, reducing the influence of outliers. Ensures that the features have similar scales, which is crucial for many machine learning algorithms to function correctly.

Methodology (Channels selection)

We divided the 64 channels according to brain as the to determine the significant part that responsible for finger movement :



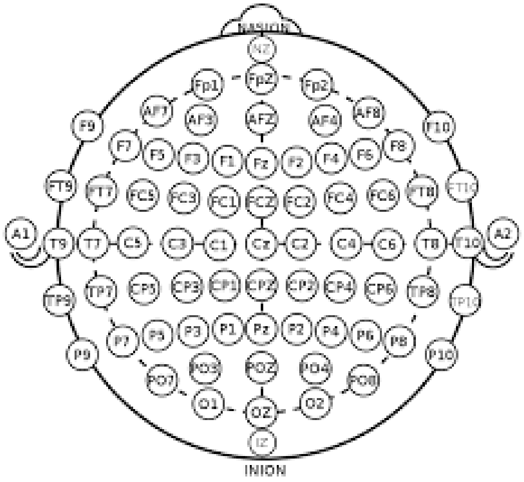
Frontal Region: : **16** electrodes [Fpz, Fp2, AF7, AF3, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8]

Central Region: **14** electrodes: [FC5, FC3, FC1, FCz, FC2, FC4, FC6, Cz, C5, C3, C1, C2, C4, C6]

Temporal Region: **10** electrodes [FT7, FT8, T7, T8, TP7, TP8, TP9, TP10, FT9, FT10]

Parietal Region: **16** electrodes [CP5, CP3, CP1, CPz, CP2, CP4, CP6, P7, P5, P3, P1, Pz, P2, P4, P6, P8]

Occipital Region: **8** electrodes [PO7, PO3, POz, PO4, PO8, O1, Oz, O2]



Methodology (Features extraction)

Time Domain Features : 14 features

- Standard Deviation
- Median
- Kurtosis.
- Root Mean Square
- Skewness
- Mean Absolute Deviation
- Zero Crossing Rate
- Hjorth Activity
- Hjorth Mobility
- Hjorth Complexity
- Mean Squared Value
- Signal Energy
- Log Root Sum Square
- Tsallis Entropy

Frequency Domain Features : 3 features

- Power Spectral Density
- Peak Frequency
- Spectral Entropy

Methodology (ML Models)

Classical ML Algorithms

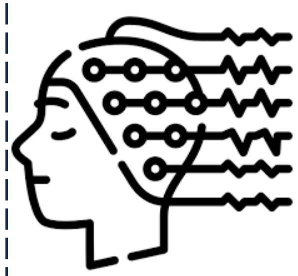
- Linear Discriminant Analysis
- Logistic Regression
- K-Nearest Neighbors
- Random Forest
- Decision Tree

Boosting Algorithms

- Gradient Boosting
- AdaBoost
- XGBoost

Methodology (2^{nd} Approach)

Raw Dataset



Preprocessing

- Band-Pass Filtering (8 : 30)
- Normalization (Robust Scaler)
- Common Average Referencing (CAR)
- Channel Selection : 4
  ['T7', 'TP7','PO3','POz']

Feature Extraction

Time Frequency domain
CWT
Scale : **100**
Mother wavelet : **Morlet**

Train set
80 %

Test set
20 %

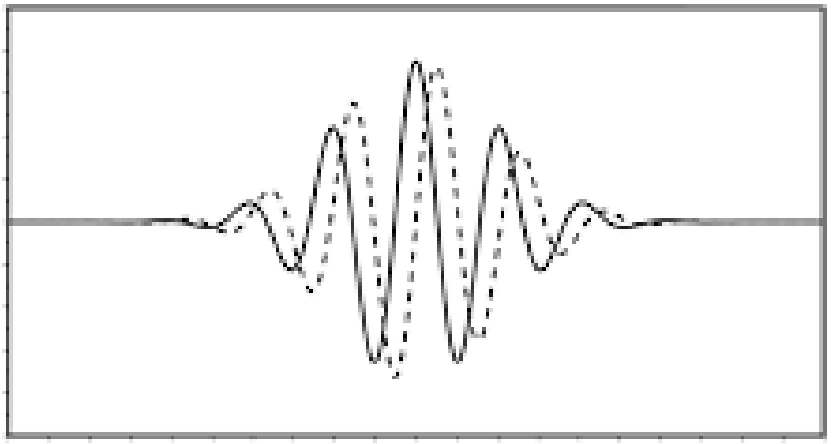
Train Model
&
evaluate
performance

Methodology (Features extraction)

Continuous Wavelet Transform (CWT)

- It is a method for analyzing time-series data as EEG signals by breaking it down into different wavelets over time. It shows how frequencies change over time, helping to see how different frequencies evolve.

- This method is best technique for signals that have varying frequencies and amplitudes over time, offering better insights into their changing patterns compared to standard methods.



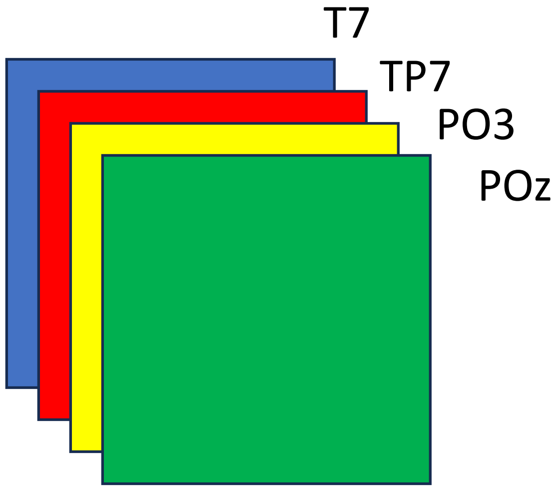
Morlet Mather wavelet

Methodology (Neural network Models)

Input Shape for CNN

(100, 256, 4)

- **100**: Number of scales (CWT)
- **256**: Number of time points/trial
- **4**: Number of channels 'T7', 'TP7','PO3','POz



Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 96, 252, 64)	6464
batch_normalization_8 (BatchNormalization)	(None, 96, 252, 64)	256
max_pooling2d_8 (MaxPooling2D)	(None, 48, 126, 64)	0
conv2d_9 (Conv2D)	(None, 46, 124, 128)	73856
batch_normalization_9 (BatchNormalization)	(None, 46, 124, 128)	512
max_pooling2d_9 (MaxPooling2D)	(None, 23, 62, 128)	0
flatten_4 (Flatten)	(None, 182528)	0
dense_8 (Dense)	(None, 256)	46727424
dense_9 (Dense)	(None, 1)	257

Total params: 46808769 (178.56 MB)
Trainable params: 46808385 (178.56 MB)
Non-trainable params: 384 (1.50 KB)

- ❑ The input data consists of four grayscale scalogram images, each representing a different channel of EEG data.
- ❑ Convolutional layers scan through the data, identifying patterns and relationships within and across the four channels.

"This approach leverages the CNN's ability to handle complex, multi-channel data, making it particularly effective for analyzing EEG signals."

Methodology (Neural network Models)

Input Shape for RNN

(100, 256*4)

•**1024**: Concatenated time points of 4 channels (256*4)

•**100**: 100 CWT coefficients

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 100, 128)          590336

lstm_5 (LSTM)                (None, 64)                49408

dense_4 (Dense)              (None, 64)                4160

dense_5 (Dense)              (None, 1)                 65

=================================================================
Total params: 643969 (2.46 MB)
Trainable params: 643969 (2.46 MB)
Non-trainable params: 0 (0.00 Byte)
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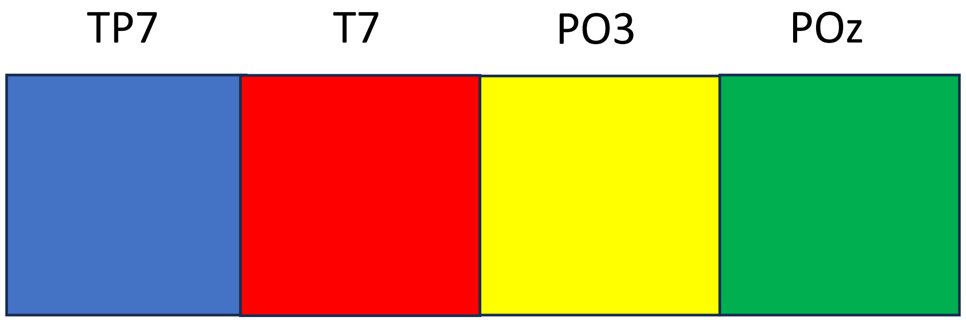
- The input data consists of continuous wavelet transform (CWT) coefficients concatenated across four EEG channels.

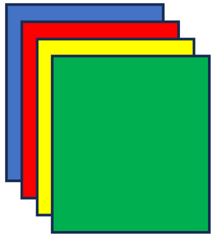
- LSTM layers can capture long-term dependencies in the temporal data, making them suitable for sequential data like EEG signals.



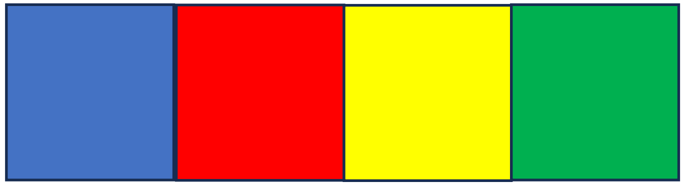
Methodology (Neural network Models)

CNN + Transformer Model

Input Data for CNN Branch : Four grayscale scalogram images of shape **(100, 256, 4)**



Input Data for Transformer Branch : Concatenated CWT coefficients across channels of shape **(100, 1024).**



Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	[(None, 100, 256, 4)]	0	[]
conv2d_2 (Conv2D)	(None, 98, 254, 32)	1184	['input_3[0][0]']
max_pooling2d_2 (MaxPooling2D)	(None, 49, 127, 32)	0	['conv2d_2[0][0]']
conv2d_3 (Conv2D)	(None, 47, 125, 64)	18496	['max_pooling2d_2[0][0]']
input_4 (InputLayer)	[(None, 100, 1024)]	0	[]
max_pooling2d_3 (MaxPooling2D)	(None, 23, 62, 64)	0	['conv2d_3[0][0]']
transformer_block_1 (TransformerBlock)	(None, 100, 1024)	8663168	['input_4[0][0]']
flatten_2 (Flatten)	(None, 91264)	0	['max_pooling2d_3[0][0]']
flatten_3 (Flatten)	(None, 102400)	0	['transformer_block_1[0][0]']
dense_5 (Dense)	(None, 128)	11681920	['flatten_2[0][0]']
dense_8 (Dense)	(None, 128)	13107328	['flatten_3[0][0]']
concatenate_1 (Concatenate)	(None, 256)	0	['dense_5[0][0]', 'dense_8[0][0]']
dense_9 (Dense)	(None, 1)	257	['concatenate_1[0][0]']

Total params: 33472353 (127.69 MB)
Trainable params: 33472353 (127.69 MB)

This hybrid approach combines the CNN's ability to handle complex, multi-channel spatial data and the Transformer's capability to capture temporal dependencies, making it particularly effective for analyzing EEG signals.

Results & Discussion

Brain Area	Number of electrodes	Electrodes Channels	Accuracy
Full Placement	64		82.68 %
Occipital Region	8	PO7, PO3, POz, PO4, PO8, O1, Oz, O2	77.23 %
Temporal Region	10	FT7, FT8, T7, T8, TP7, TP8, TP9, TP10, FT9, FT10	77.67 %
Frontal Region	16	Fpz, Fp2, AF7, AF3, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8	76.73 %
Parietal Region	16	CP5, CP3, CP1, CPz, CP2, CP4, CP6, P7, P5, P3, P1, Pz, P2, P4, P6, P8	73.156 %
Central Region	14	FC5, FC3, FC1, FCz, FC2, FC4, FC6, Cz, C5, C3, C1, C2, C4, C6	66.52 %

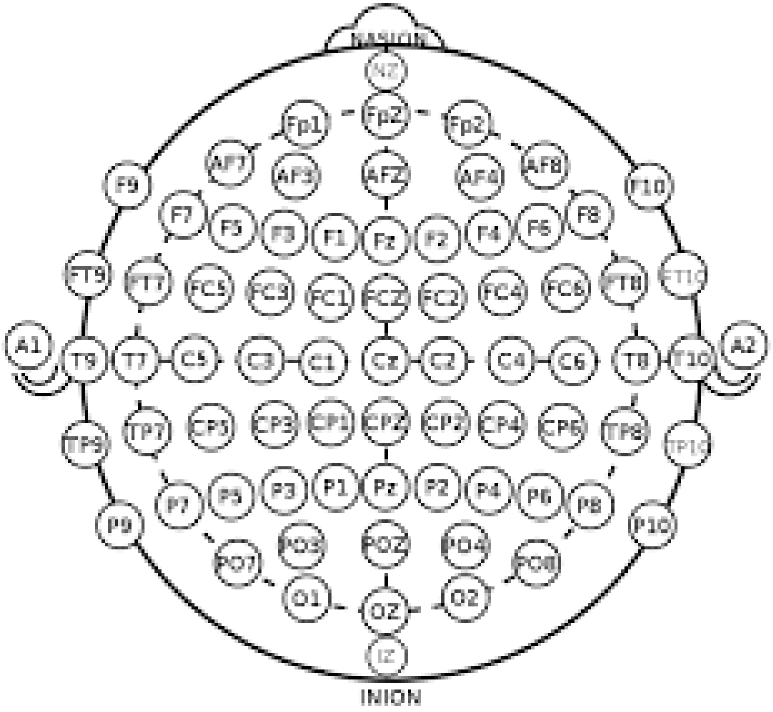
Results & Discussion

- We focused on both occipital and temporal regions, using a total of 18 channels: [PO7, PO3, POz, PO4, PO8, O1, Oz, O2, FT7, FT8, T7, T8, TP7, TP8, TP9, TP10, FT9, FT10].

- Since the dataset was recorded for **right-handed individuals**, we extract channels with odd numbers, which correspond to the left hemisphere responsible for the right side of the body.

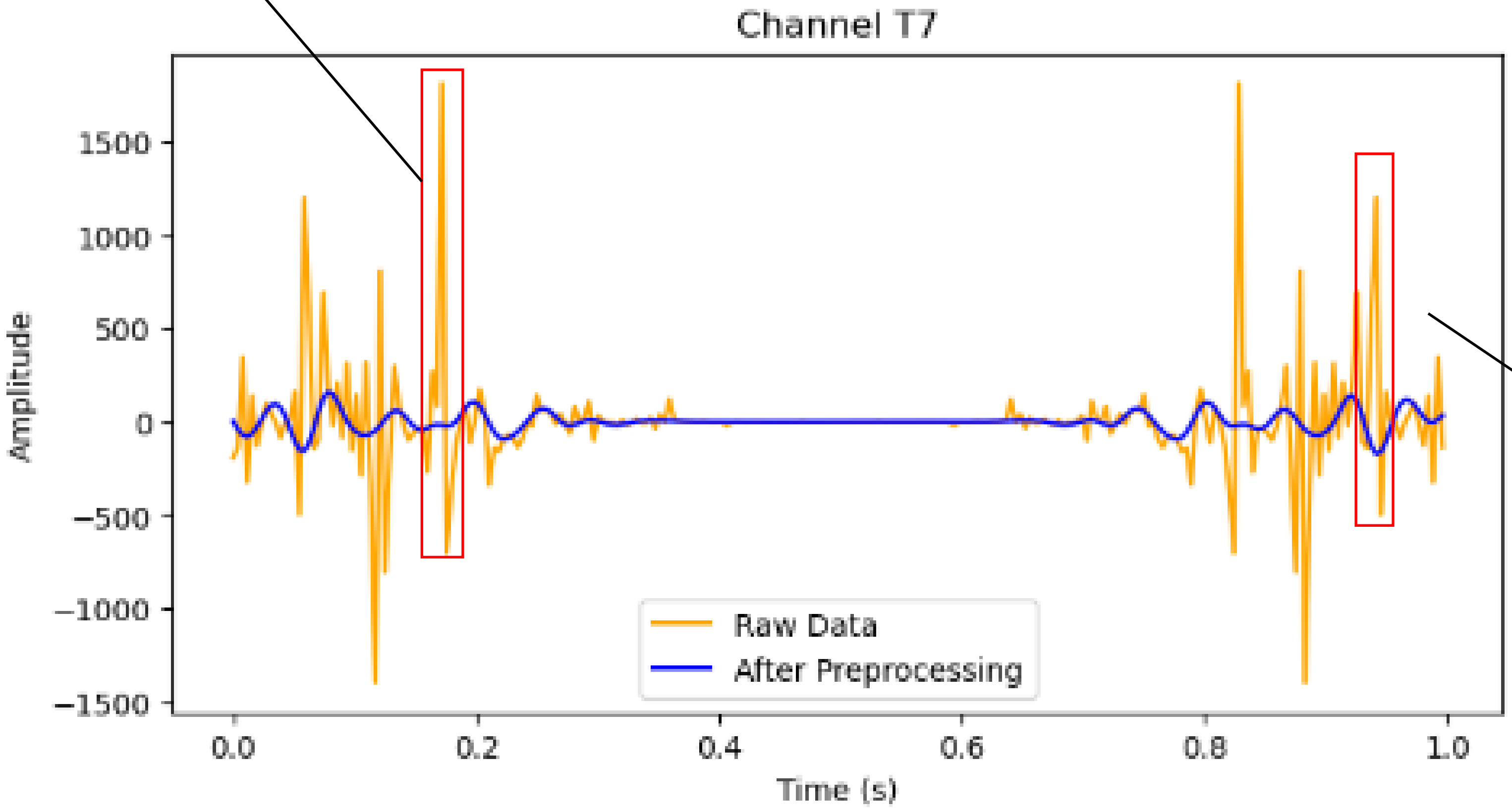
- After that , we applied correlation analysis to select the top 8 channels:

['T7', 'TP7', 'TP9', 'POz', 'Oz', 'O1', 'PO3', 'PO7’].



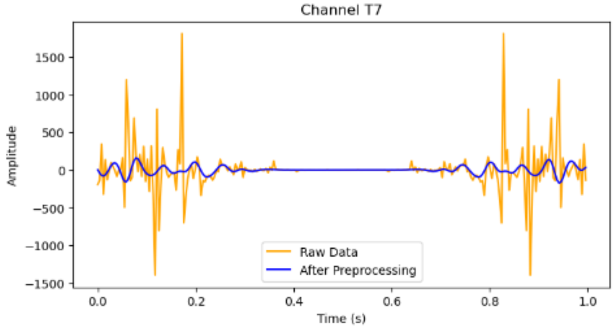
Results & Discussion

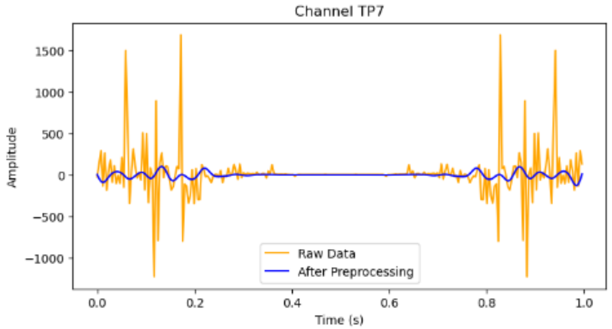
Spik of noise

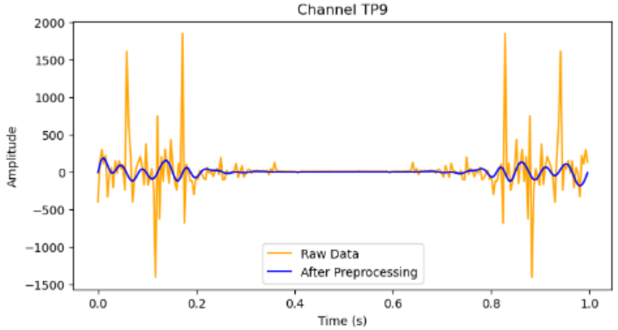


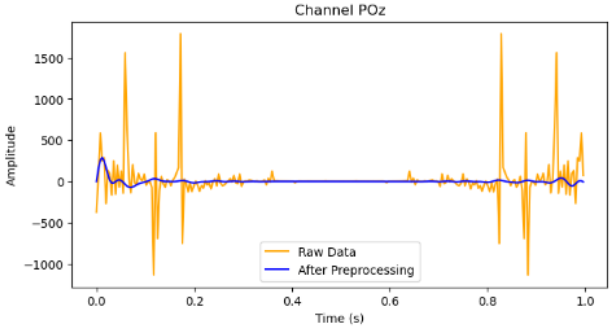
Spik of noise

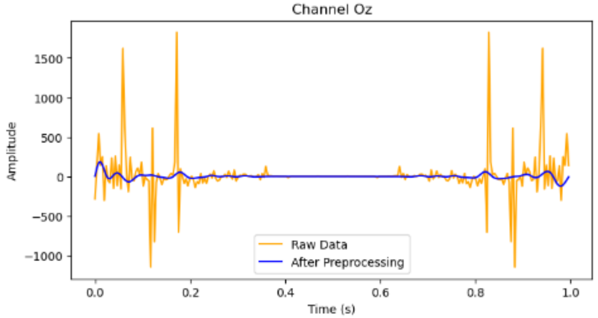
Results & Discussion

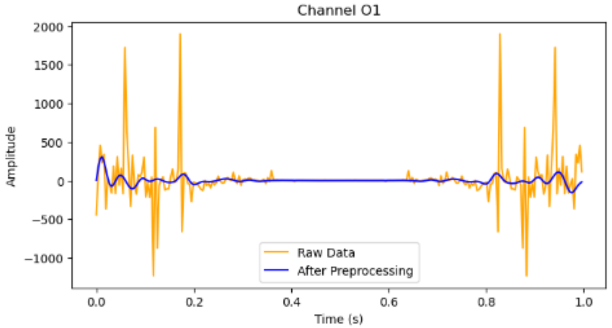


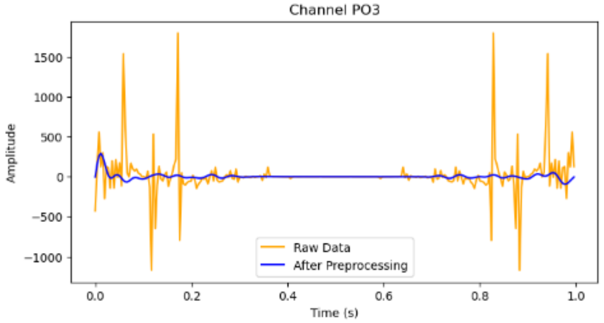


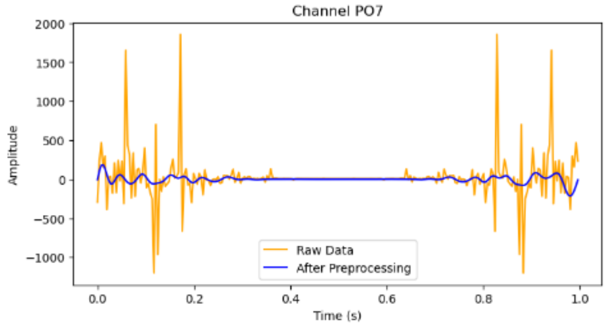






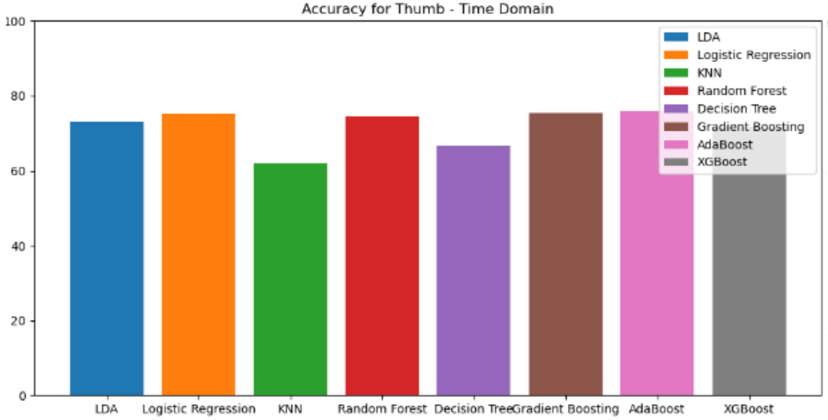


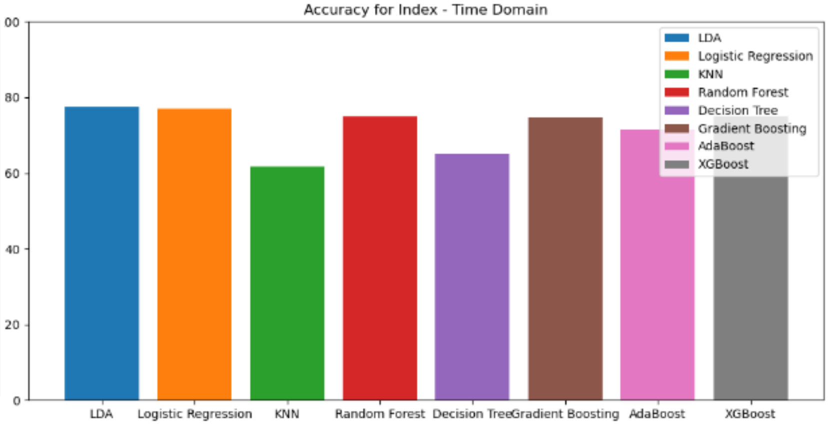


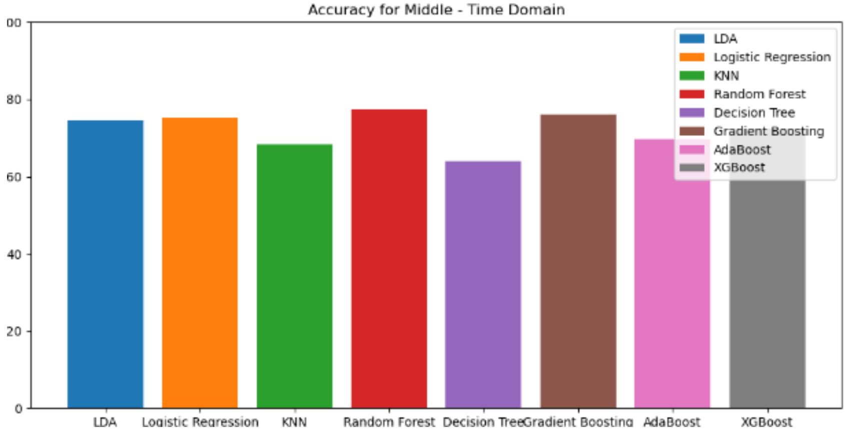


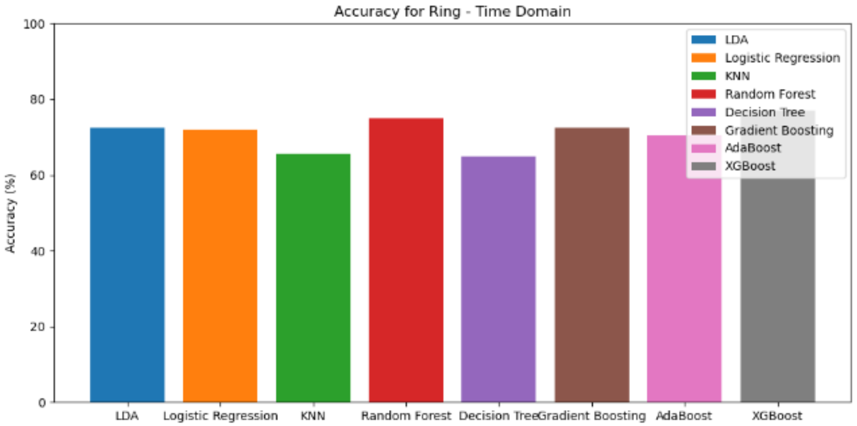
Results & Discussion

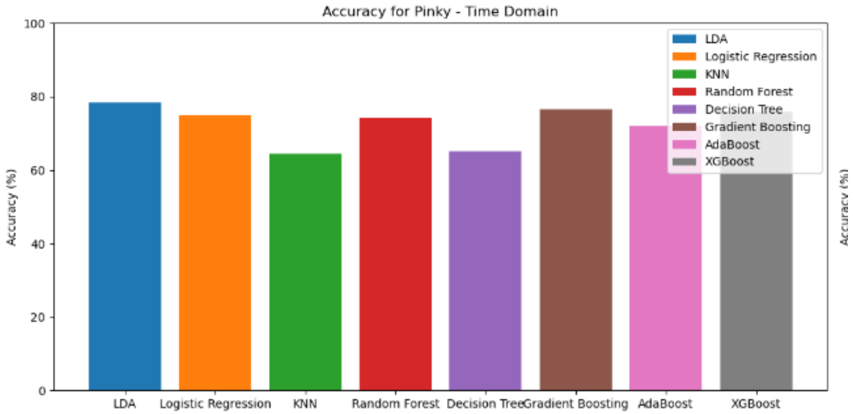
Time Domain : 14 Features





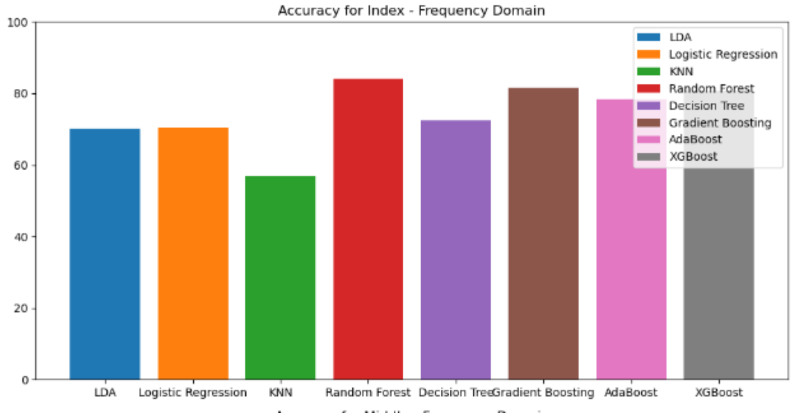


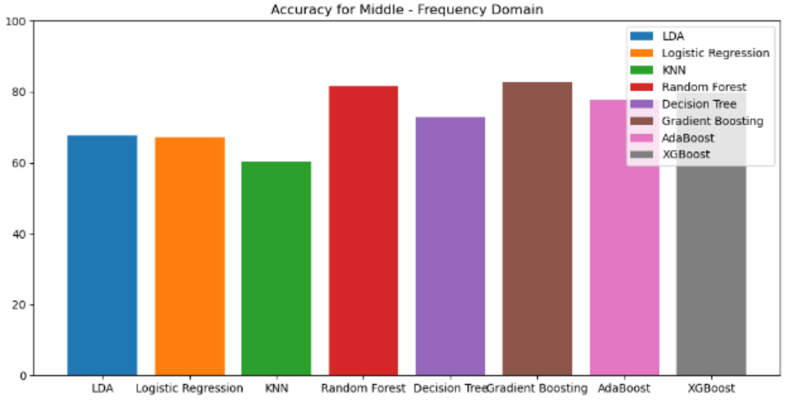


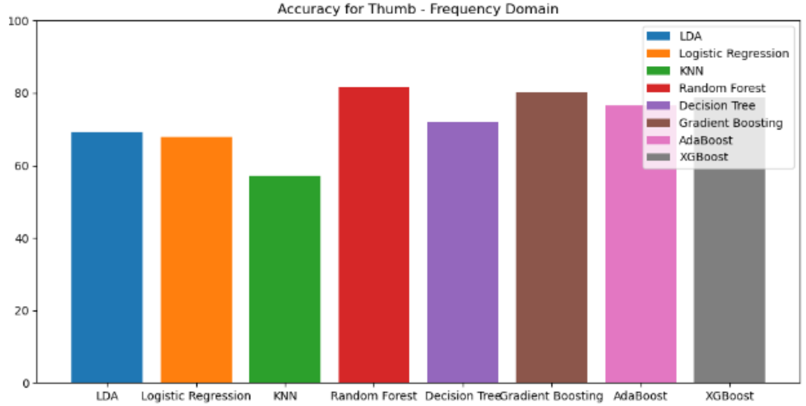


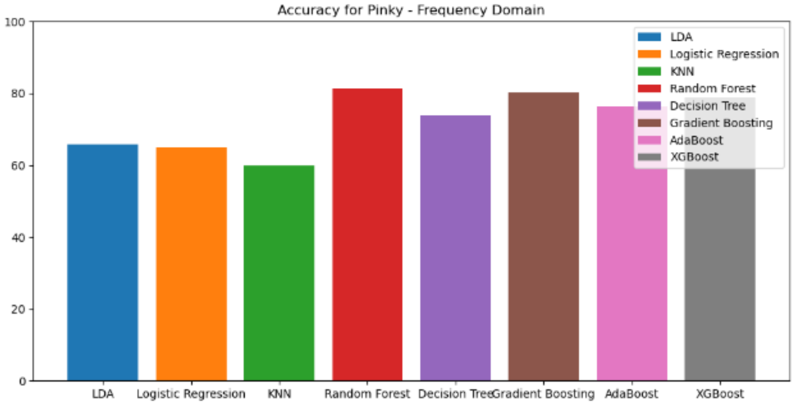
Results & Discussion

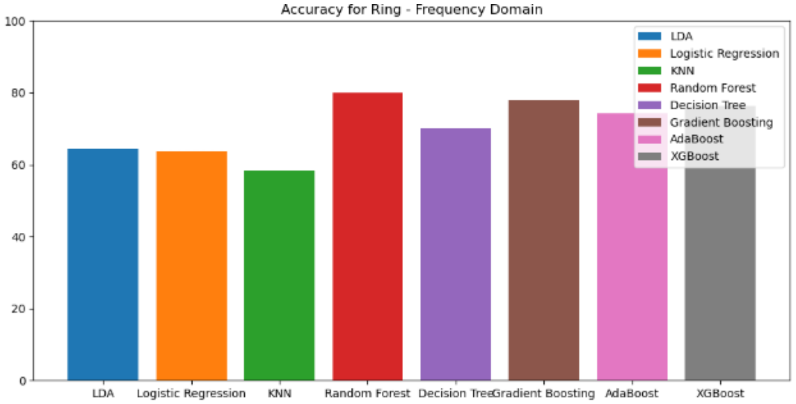
Frequency Domain : 3 Features





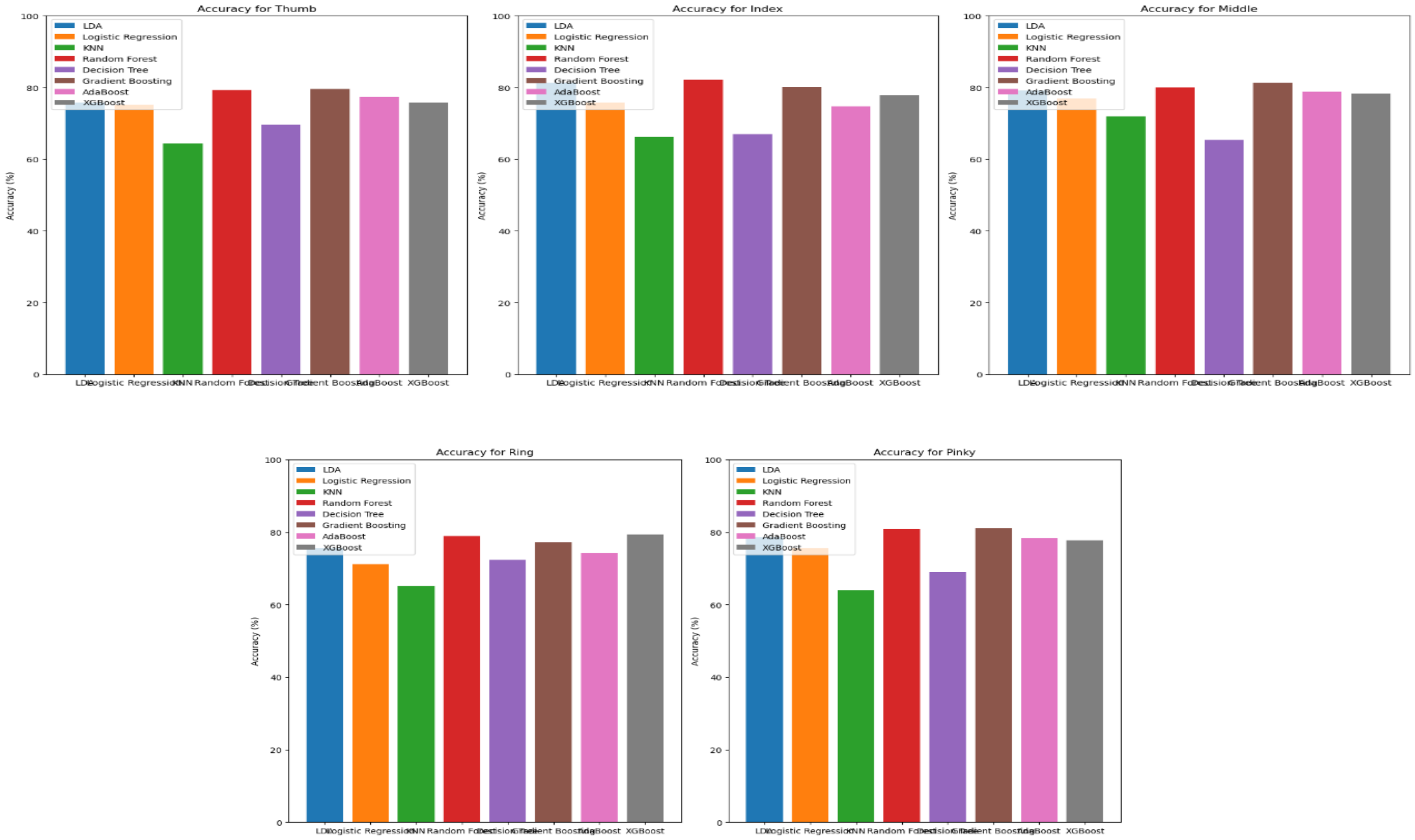






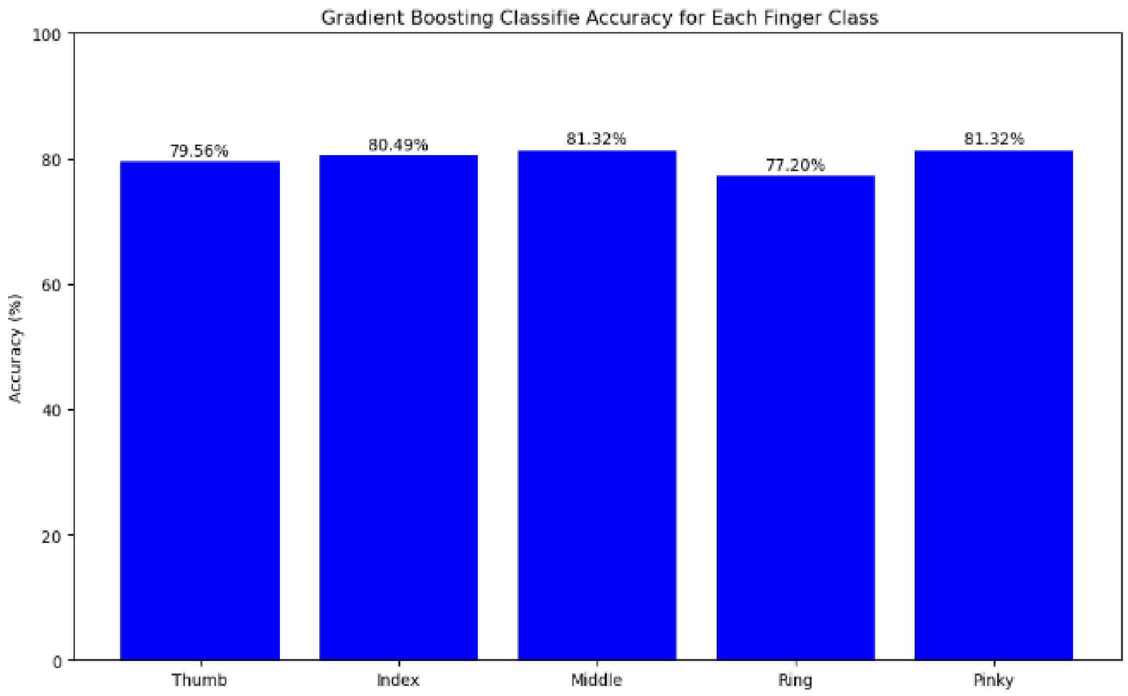
Results & Discussion

Time + Frequency Domain : 17 Features

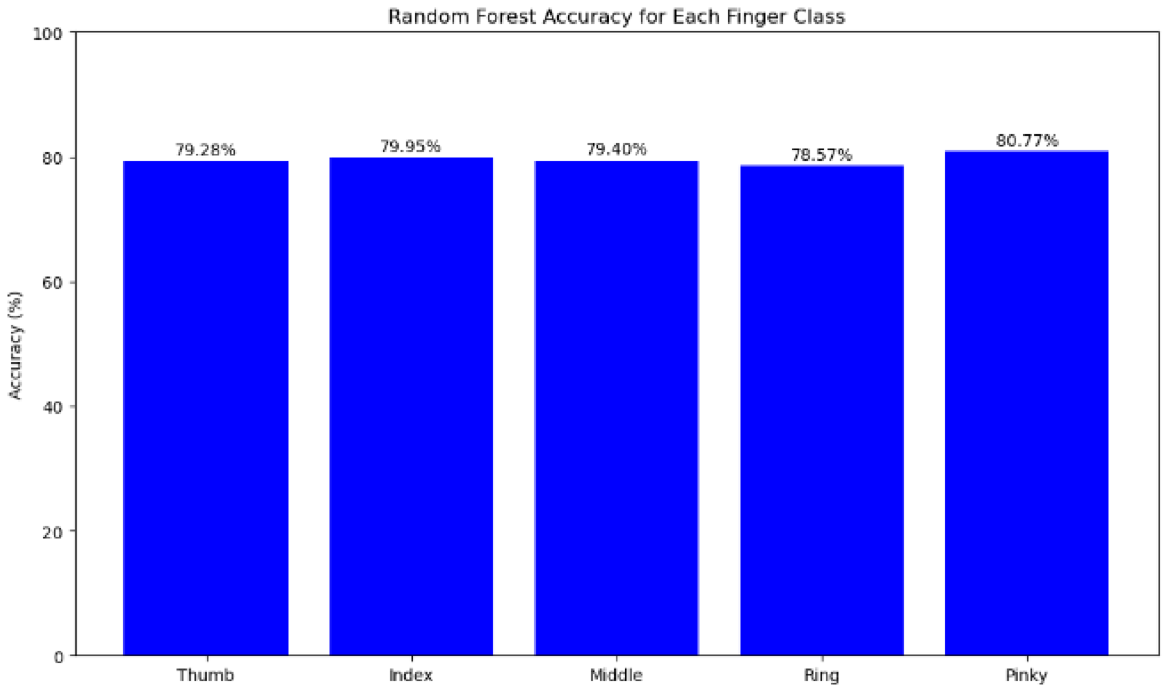


Results & Discussion

Accuracy of best models (Both Features)



Average accuracy **79.79 %**



Average accuracy **79.59 %**

Results & Discussion

Gradient Boosting Classification Report

Finger Class: Thumb
Accuracy: 79.28%
Classification Report:

	precision	recall	f1-score	support
0	0.77	0.83	0.80	181
1	0.82	0.76	0.79	181
accuracy			0.79	362
macro avg	0.79	0.79	0.79	362
weighted avg	0.79	0.79	0.79	362

Finger Class: Index
Accuracy: 79.95%
Classification Report:

	precision	recall	f1-score	support
0	0.78	0.84	0.81	182
1	0.83	0.76	0.79	182
accuracy			0.80	364
macro avg	0.80	0.80	0.80	364
weighted avg	0.80	0.80	0.80	364

Finger Class: Middle
Accuracy: 79.40%
Classification Report:

	precision	recall	f1-score	support
0	0.76	0.86	0.81	182
1	0.84	0.73	0.78	182
accuracy			0.79	364
macro avg	0.80	0.79	0.79	364
weighted avg	0.80	0.79	0.79	364

Finger Class: Ring
Accuracy: 78.57%
Classification Report:

	precision	recall	f1-score	support
0	0.75	0.86	0.80	182
1	0.84	0.71	0.77	182
accuracy			0.79	364
macro avg	0.79	0.79	0.78	364
weighted avg	0.79	0.79	0.78	364

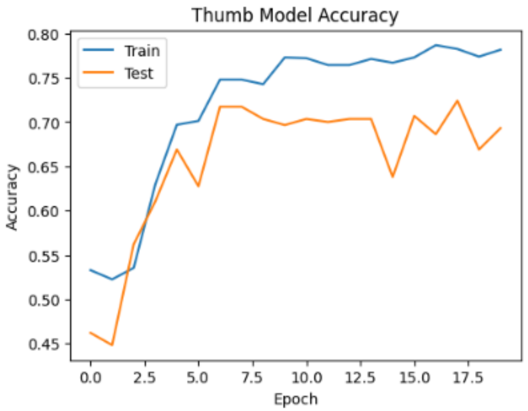
Finger Class: Pinky
Accuracy: 80.77%
Classification Report:

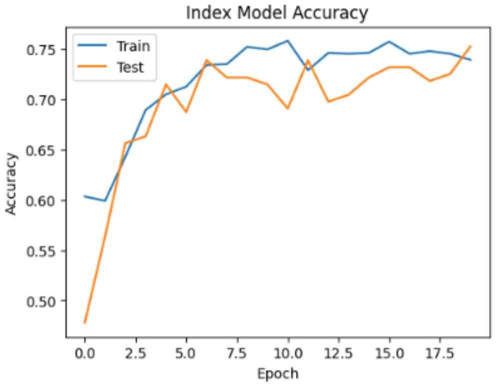
	precision	recall	f1-score	support
0	0.77	0.87	0.82	182
1	0.85	0.75	0.80	182
accuracy			0.81	364
macro avg	0.81	0.81	0.81	364
weighted avg	0.81	0.81	0.81	364

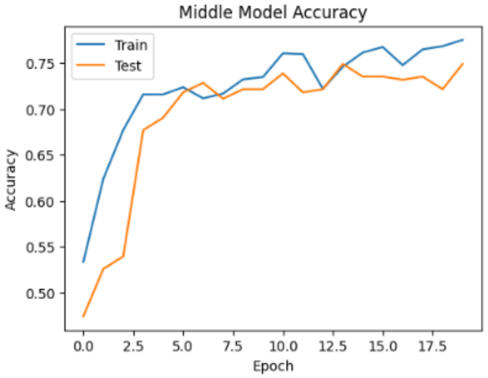
Results & Discussion

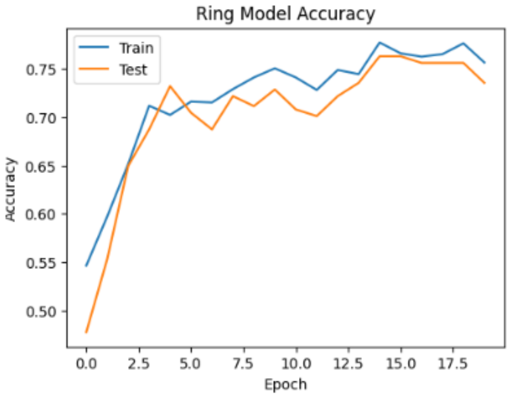
CNN Model – Average accuracy **: 78.16** % <u>(only 4 channels)</u>

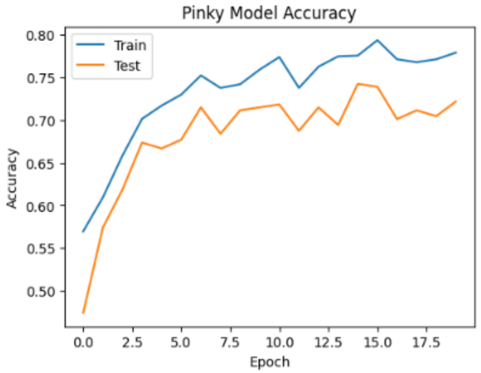
Thumb: 80.11% Index:77.47 % Middle:79.12% Ring:75.82 % Pinky:78.30 %

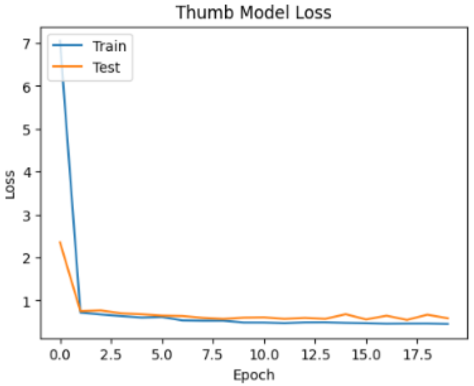


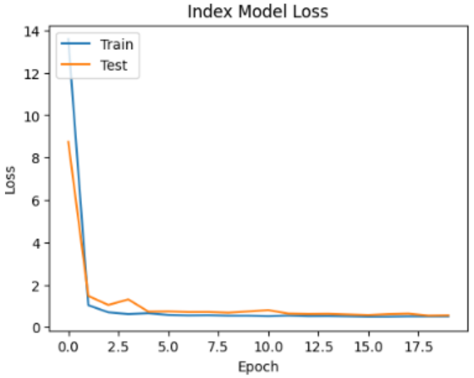


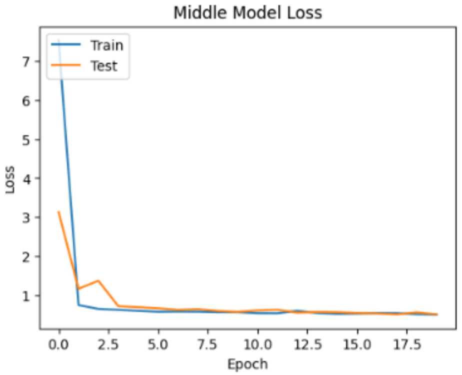


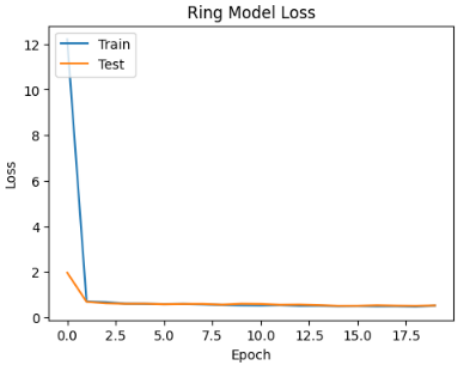


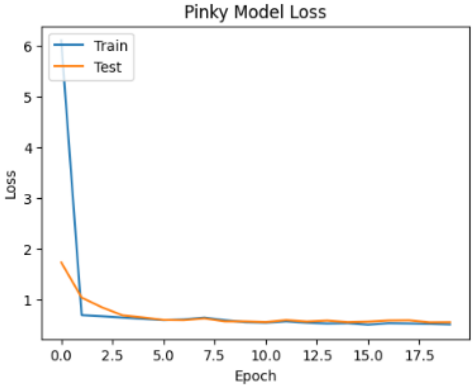








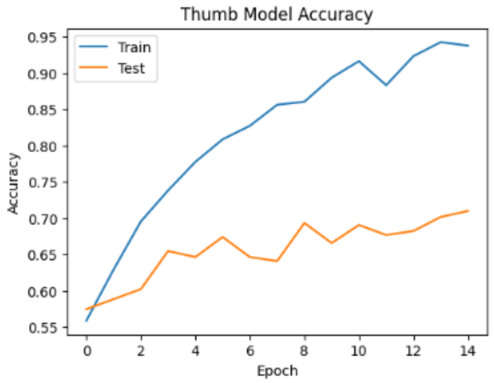


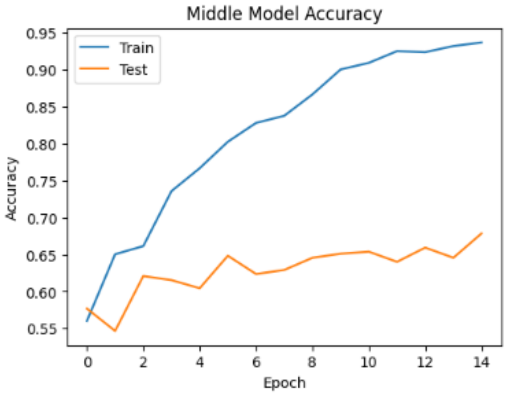


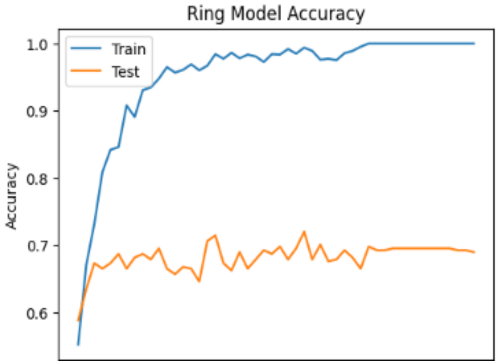
Results & Discussion

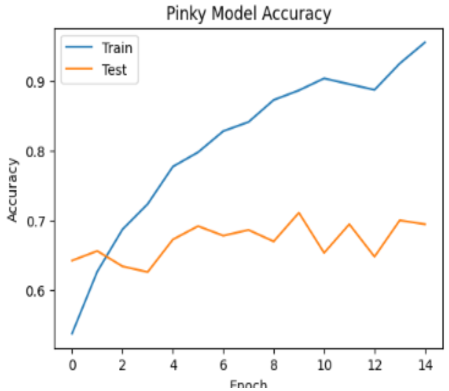
RNN Model - Average accuracy **: 68.26** % <u>(only 4 channels)</u>

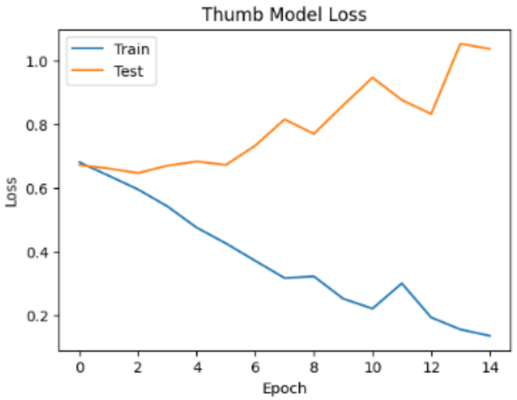
Thumb: 70.99% Index:64.01 % Middle:67.86% Ring:68.96 % Pinky:69.51 %

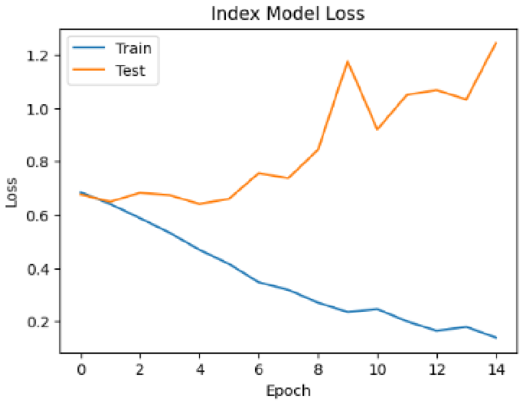


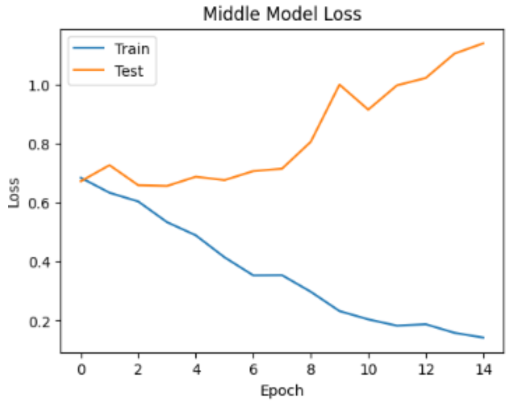


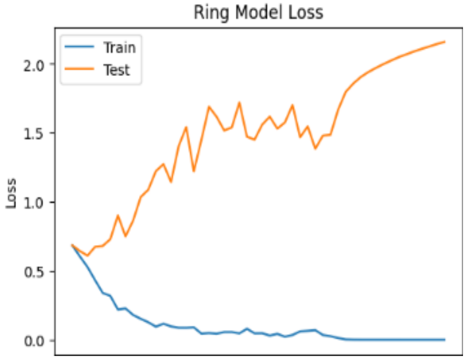


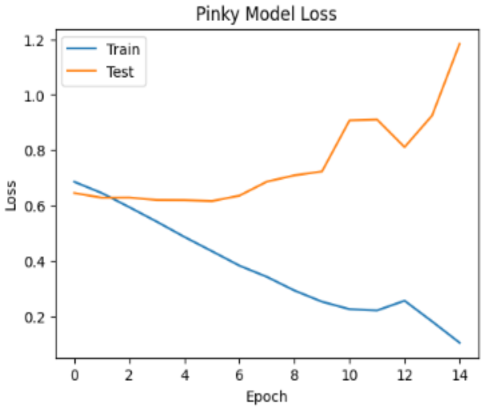








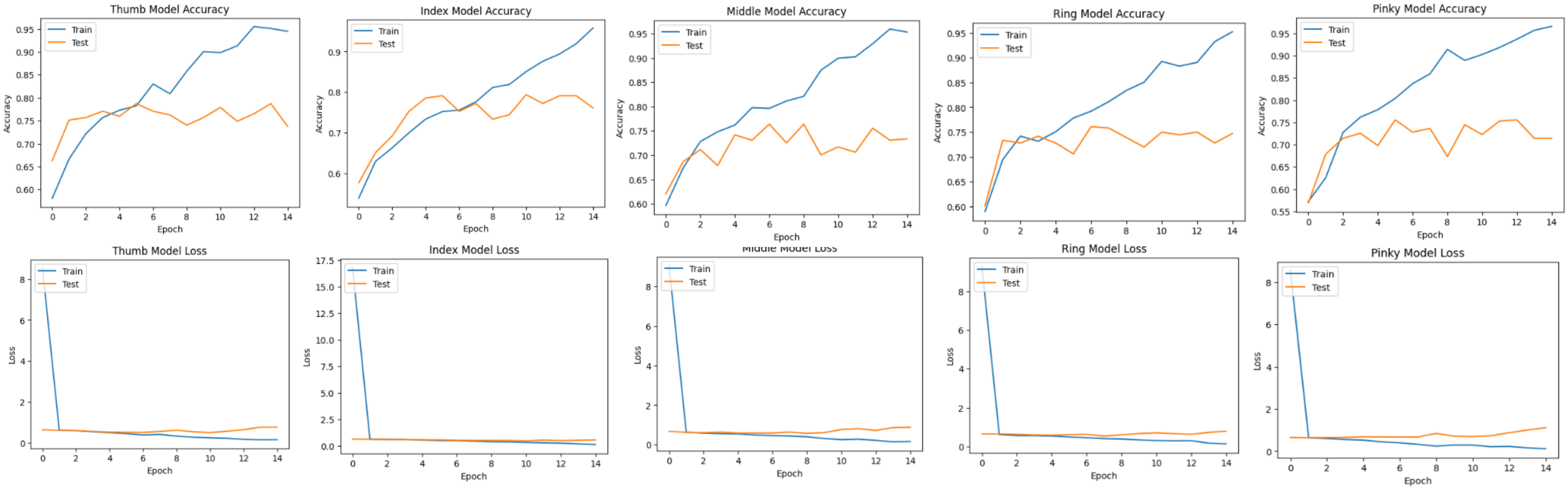




Results & Discussion

CNN + Transformer Model - Average accuracy **: 73.87** % <u>(only 4 channels)</u>

Thumb:73.76 % Index:76.10 % Middle:73.35 % Ring:74.73 % Pinky:71.43 %



Conclusion

Study	No. subjects	No. fingers	No. electrodes	Signal Processing Chain	Accuracy
[1]	18	4	64	CWD & 2LCF	43.5 %
[2]	4	5	19	RF & LDA & SVM & KNN	54 %
[3]	11	5	128	PCA & PSD & SVM	77 %
[4]	5	5	20	Band-pass filter (1:60) & CAR &CSP & LDA	80.82%
Proposed	5	5	64	Band-pass filter (8: 30) & CAR & Robust scaler &Combined features (time +frequency) & Gradian Boost	82.68 %
Proposed	5	5	8	Band-pass filter (8: 30) & CAR & Robust scaler &Combined features (time +frequency) & Gradian Boost	79.79%
Proposed	5	5	4	Band-pass filter (8: 30) & CAR & Robust scaler & CWT & CNN	78.16 %

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Q&A

Thanks for your attention