INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, KOTA

CSD405-PROJECT-II

Mentored by-
Dr.Amit Kumar

Submitted by-
Yogesh Meen(2020kucp1032)
Manish Kumawat(2020kucp1034)
Kummandas Meena(2020kucp1056)

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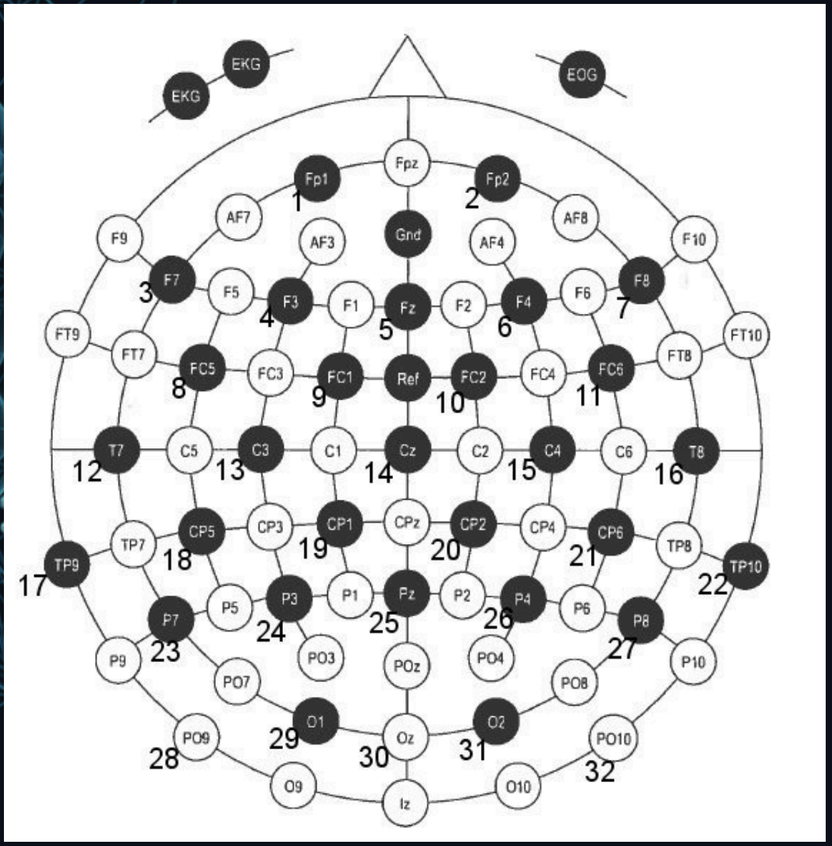
PROBLEM STATEMENT-

EEG SIGNAL-
GRASP AND LIFT
OF AN OBJECT BY
USING
ROBOTIC ARM

INTRODUCTION

Electroencephalography (EEG) signals-

- Electroencephalography is a non-invasive brain recording technique that records electric activites in cortex spontaneously
- Bandwidth:0.5-128Hz; amplitude:0.02-0.4mv
- During an EEG test,small electrodes like cup or disc type are placed on the scalp.



GRASP AND LIFT OPERATIONS-

- HAND START
- FIRST DIGIT TOUCH
- BOTH START LOAD PHASE
- LIFT OFF
- REPLACE
- BOTH-RELEASE

Dataset

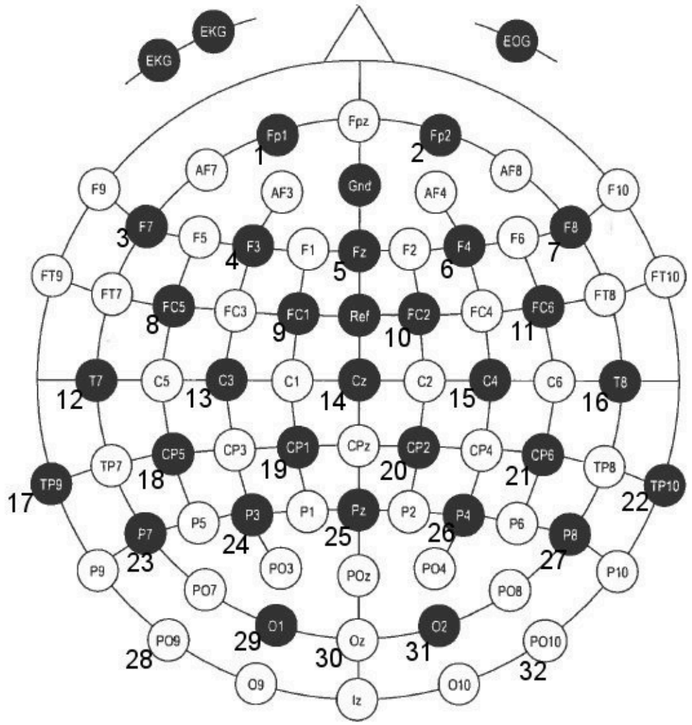
- 32 attributes(electrodes)
- 12 subjects
- 10 series
- 30 trails in each series

Traing dataset-

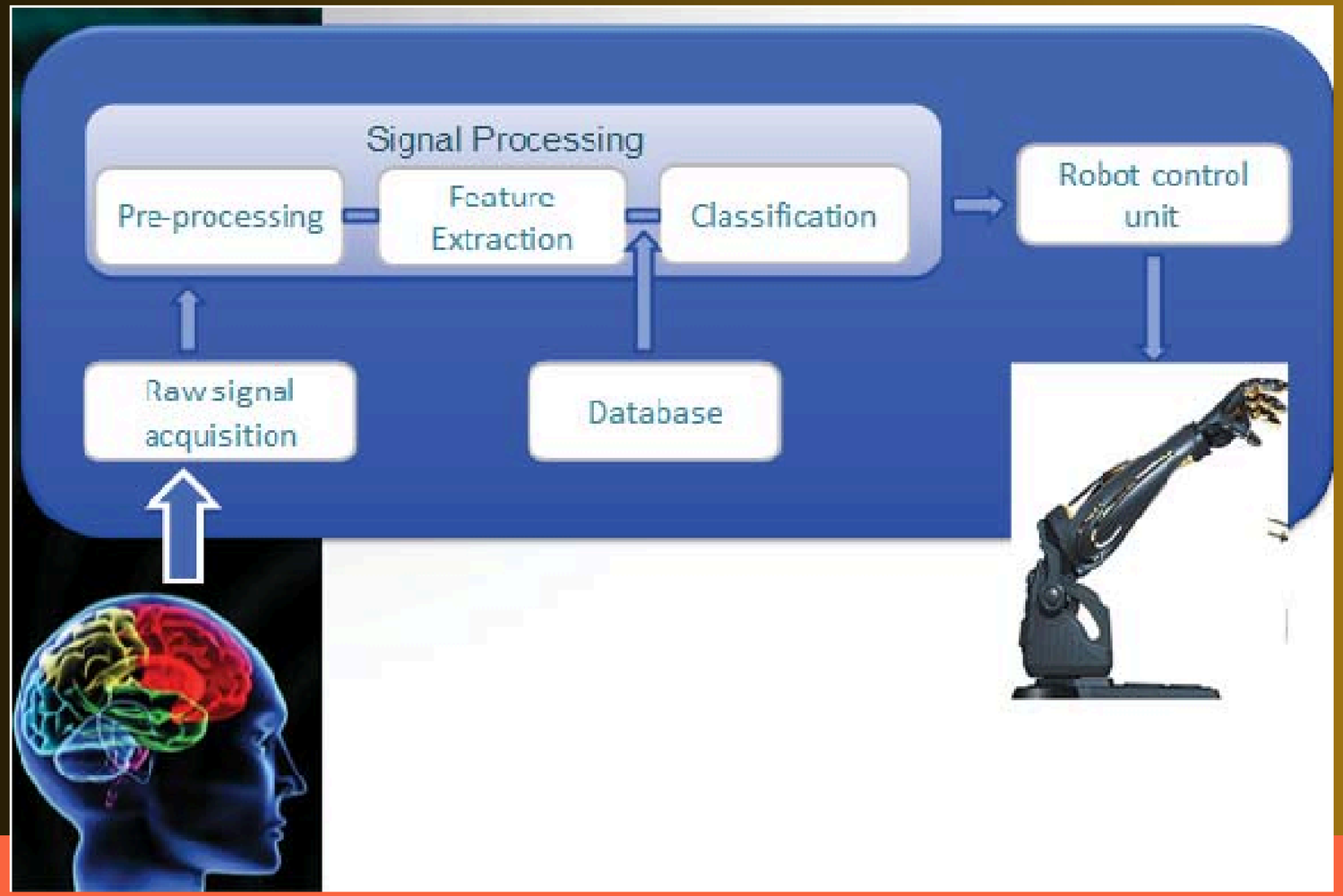
- First 8 series for each subject

Test dataset-

- 9th and 10th series

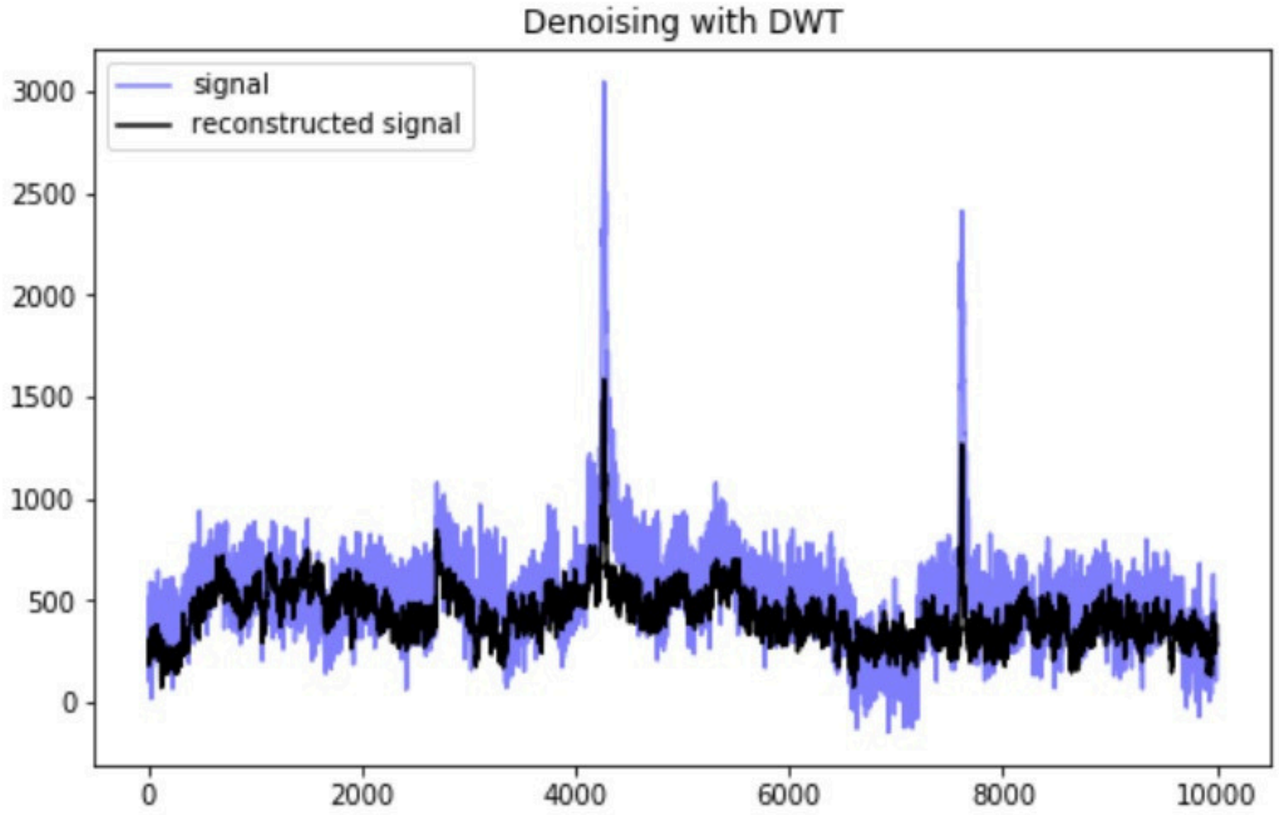


METHODOLOGY



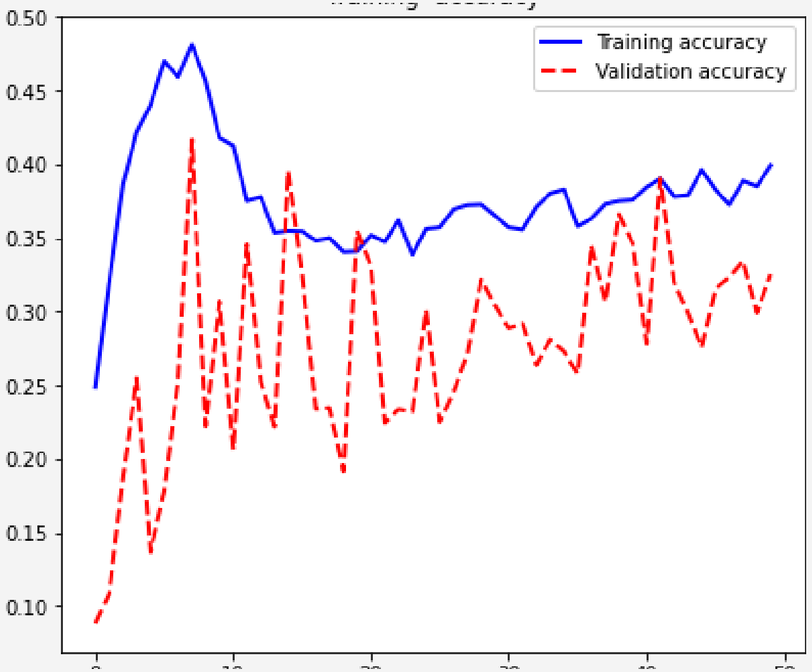
Wavelet Transformation

- Used for analyzing signals and extracting information
- Represent a signal in terms of localized wavelet
- Captures both time and frequency information

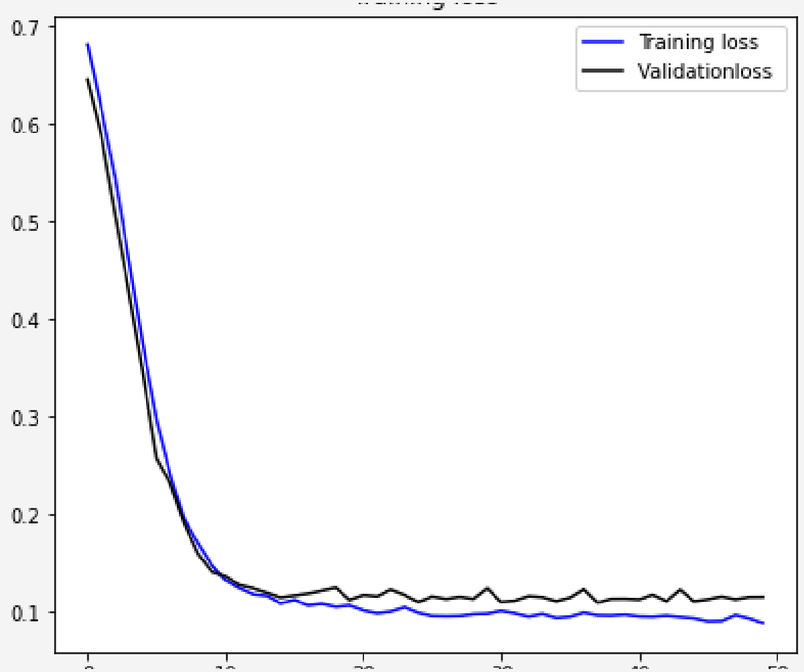


Convolutional Neural Network (CNN)

- Convolutional layer
- Polling layer
- Fully connected layer

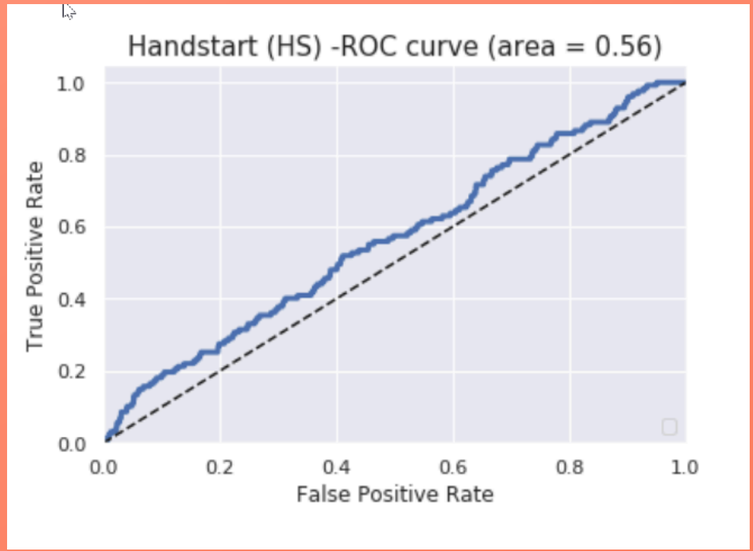


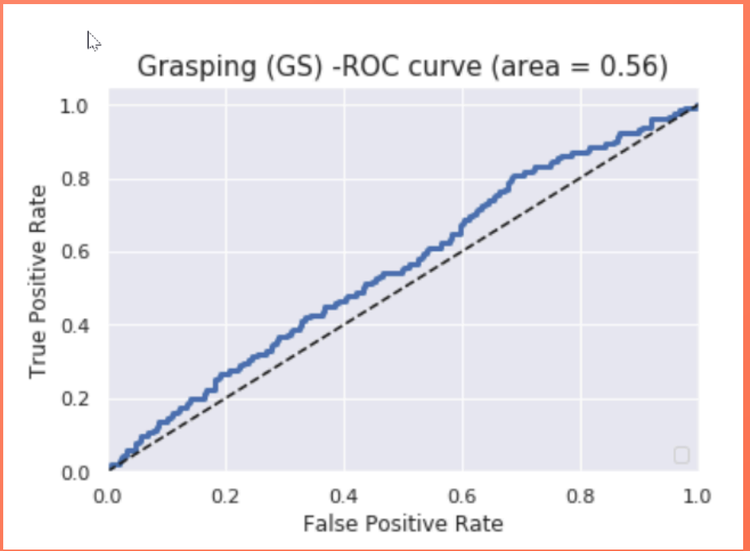
Training and Validation Accuracy



Loss

Results:


Handstart (HS) -ROC curve (area = 0.56)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Grasping (GS) -ROC curve (area = 0.56)
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0.2
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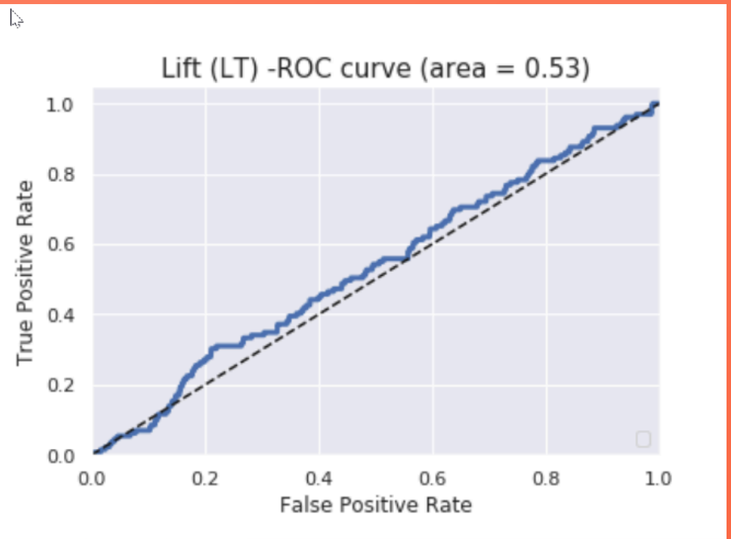
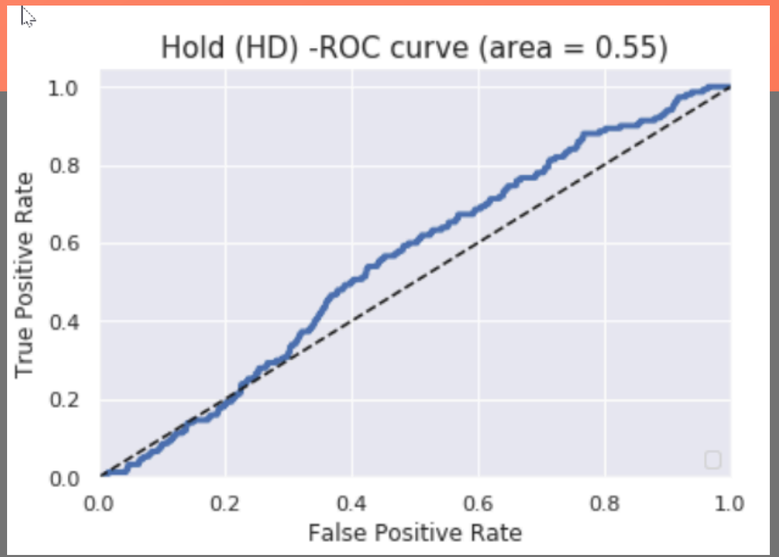
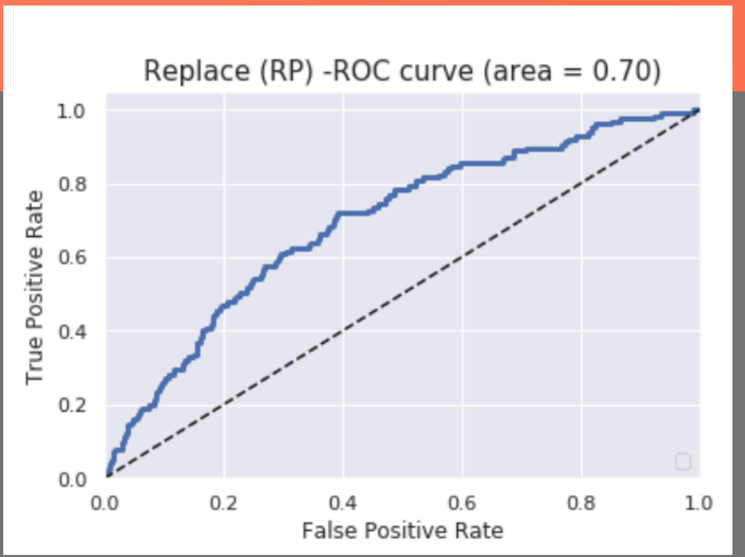
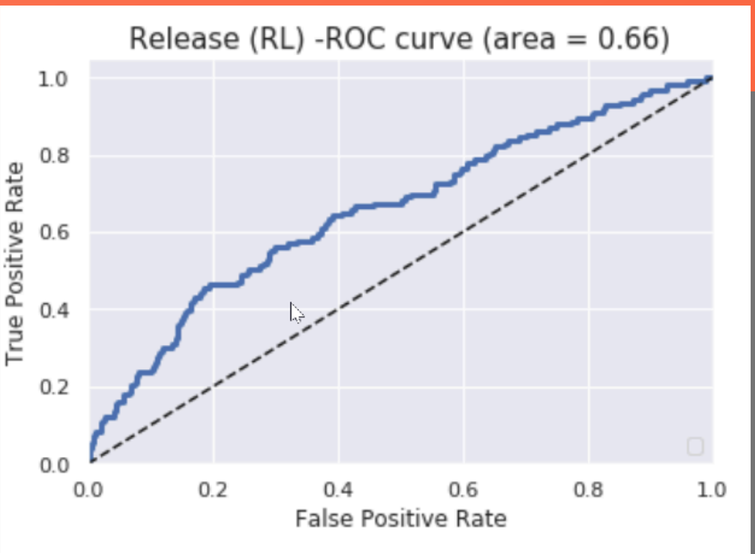
0.6
0.8
1.0


Lift (LT) -ROC curve (area = 0.53)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Hold (HD) -ROC curve (area = 0.55)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Replace (RP) -ROC curve (area = 0.70)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

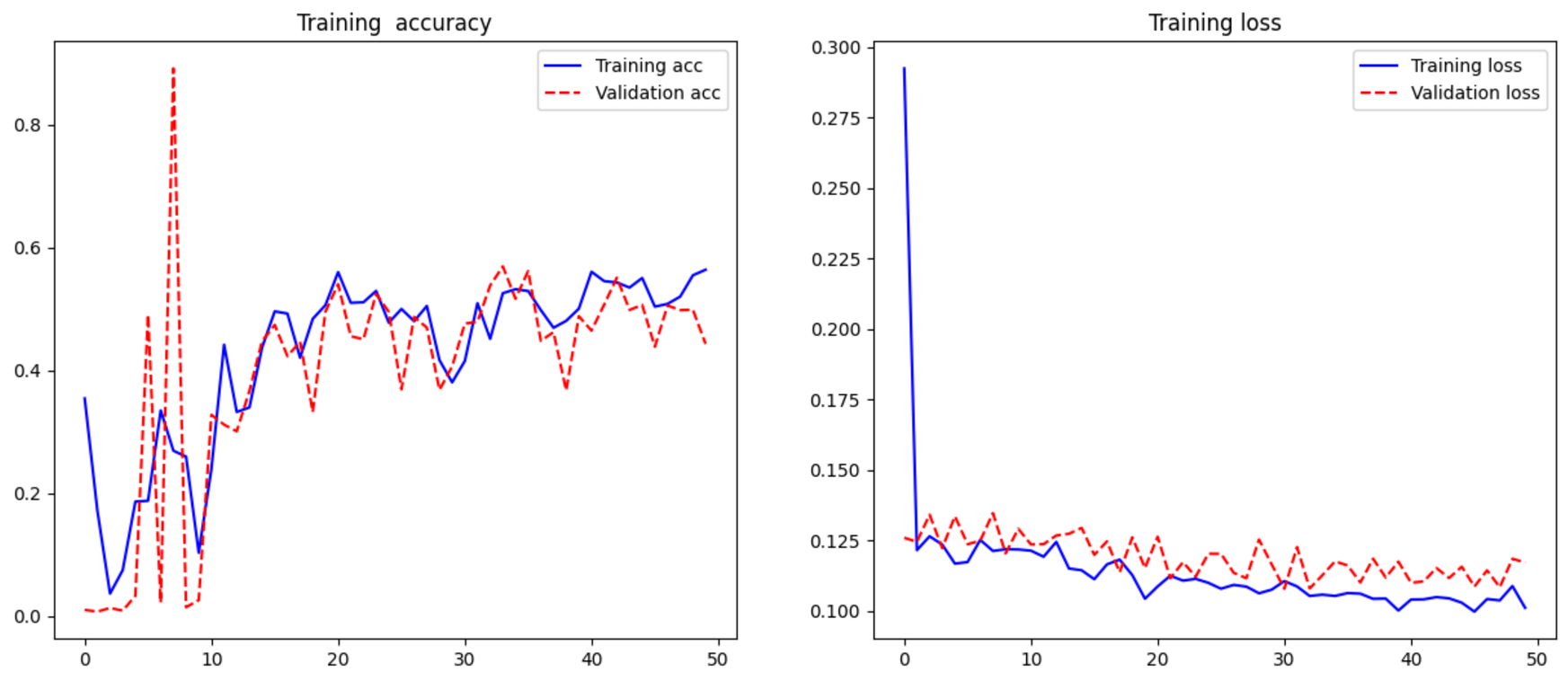

Release (RL) -ROC curve (area = 0.66)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

Long Short-Term Memory (LSTM) networks):-

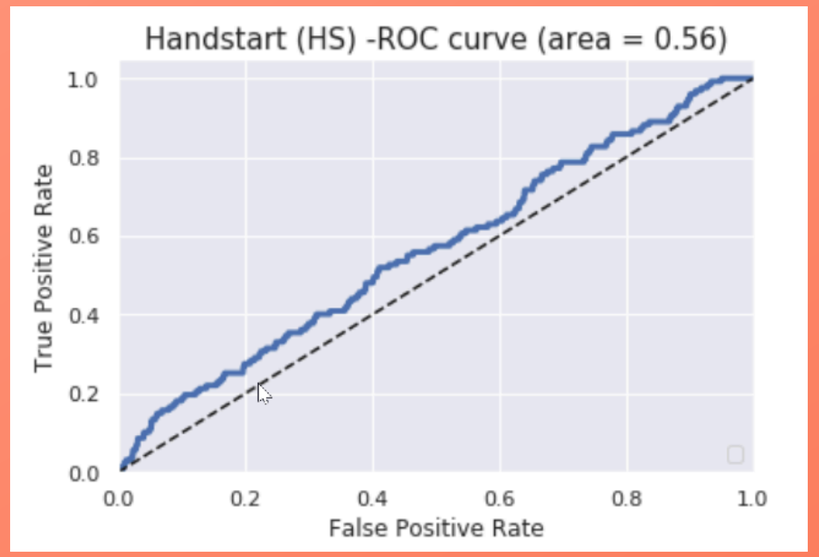
- Type of Recurrent neural network
- sequence input layer
- an LSTM layer,
- a fully connected layer
- classification output layer
- activation function :- sigmoid ,tanh

$$S(x) = \frac{1}{1 + e^{-x}}$$

LSTM



Training and Validation Accuracy and Loss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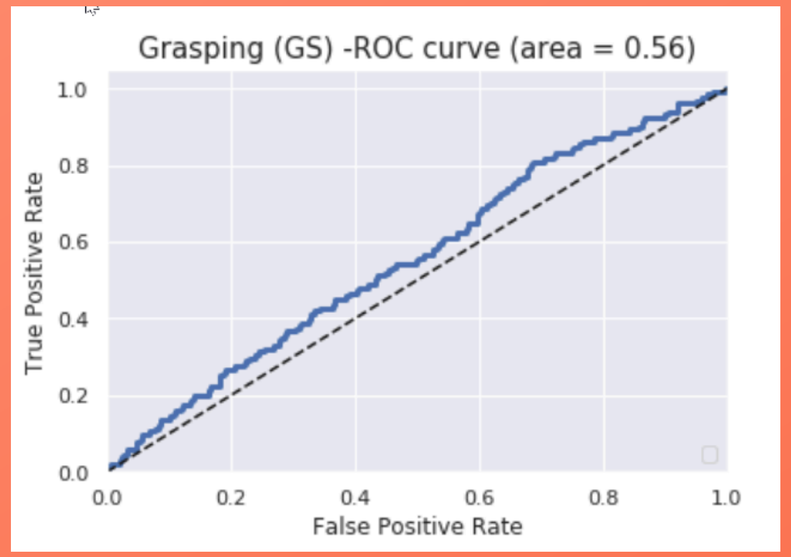
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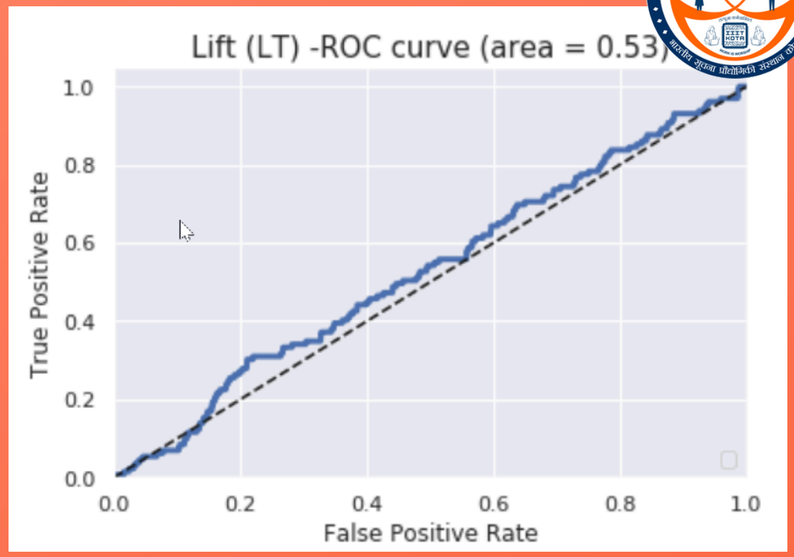
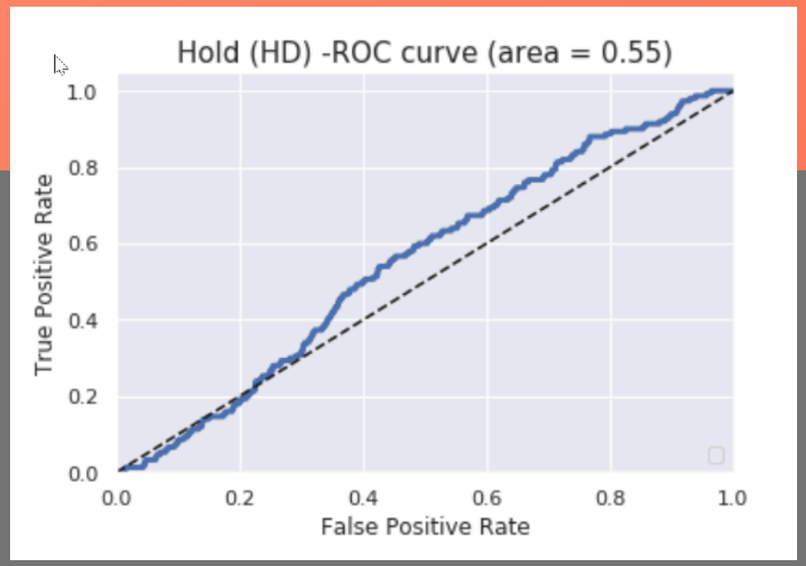

Lift (LT) -ROC curve (area = 0.53)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0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True Positive Rate
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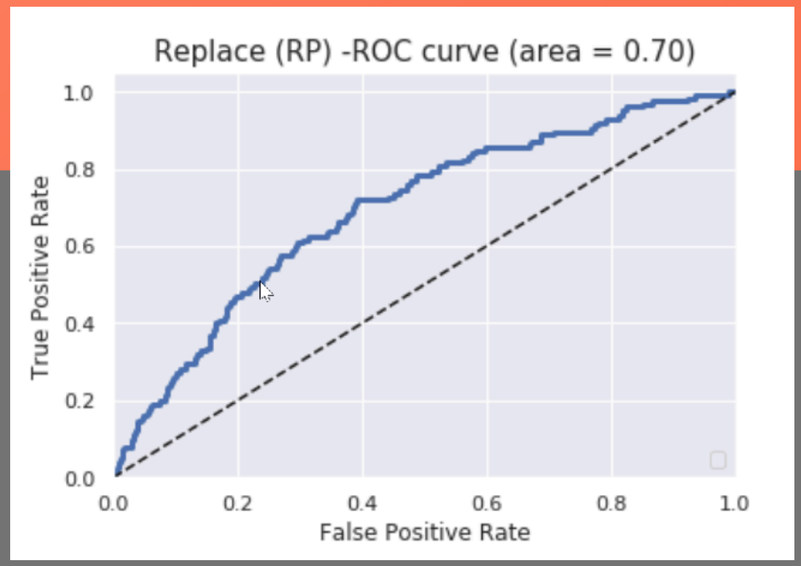
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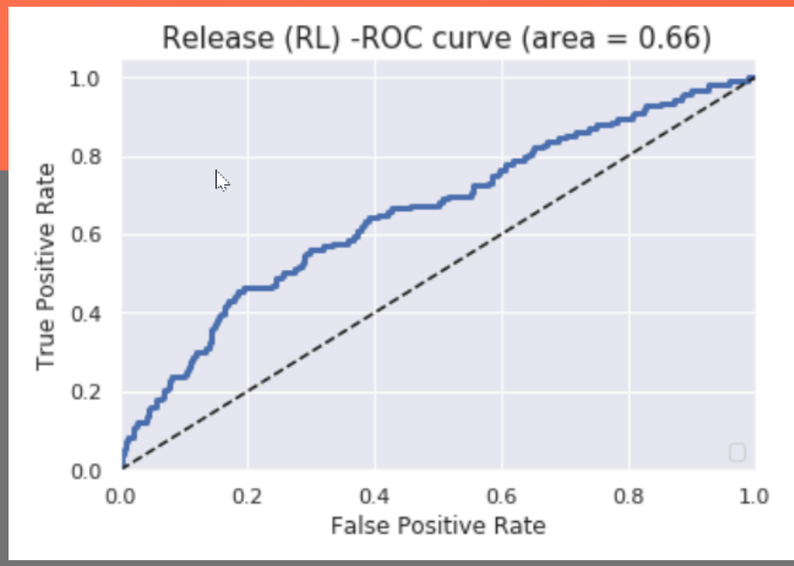
Release (RL) -ROC curve (area = 0.66)
True Positive Rate
False Positive Rate
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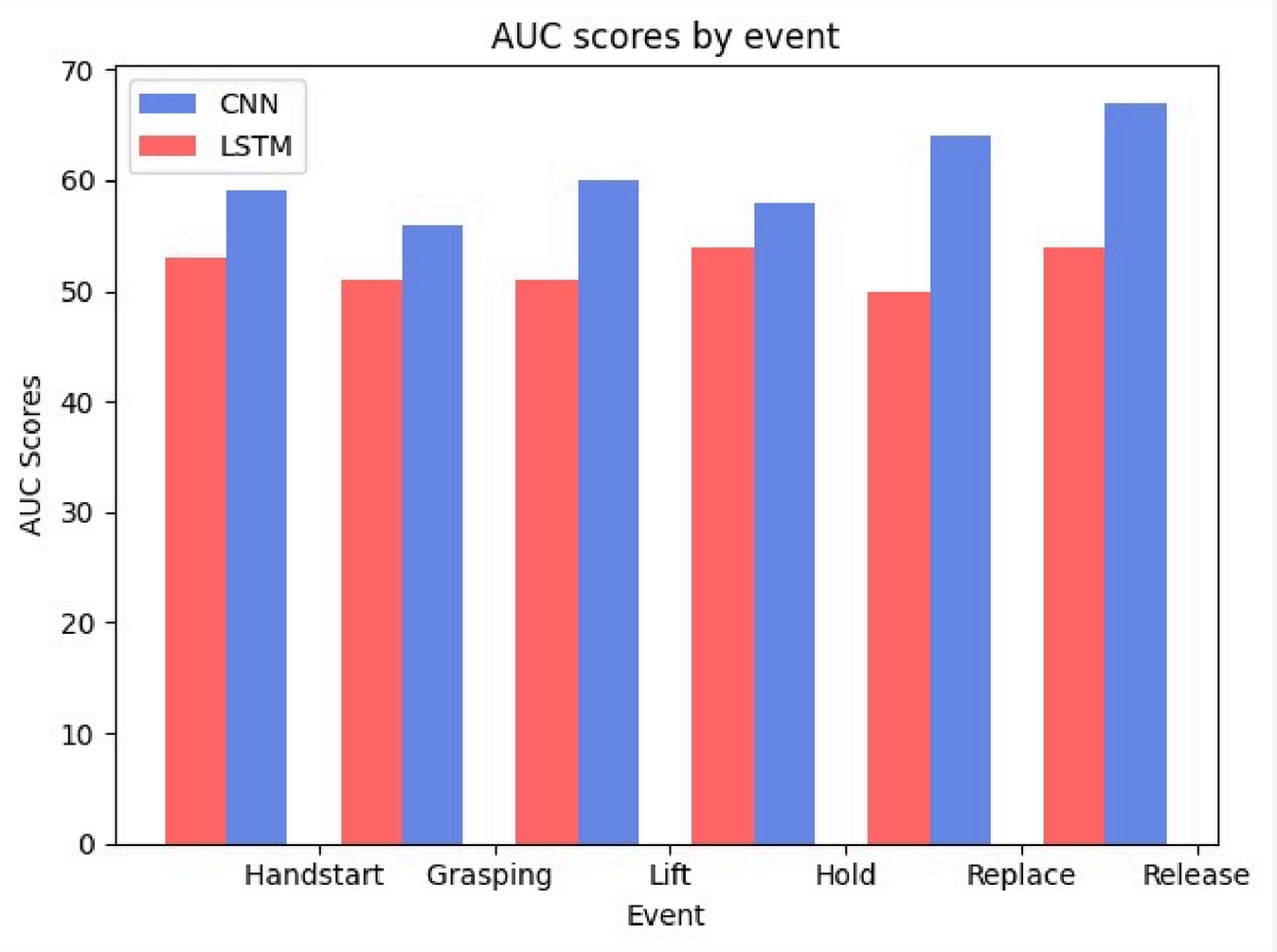
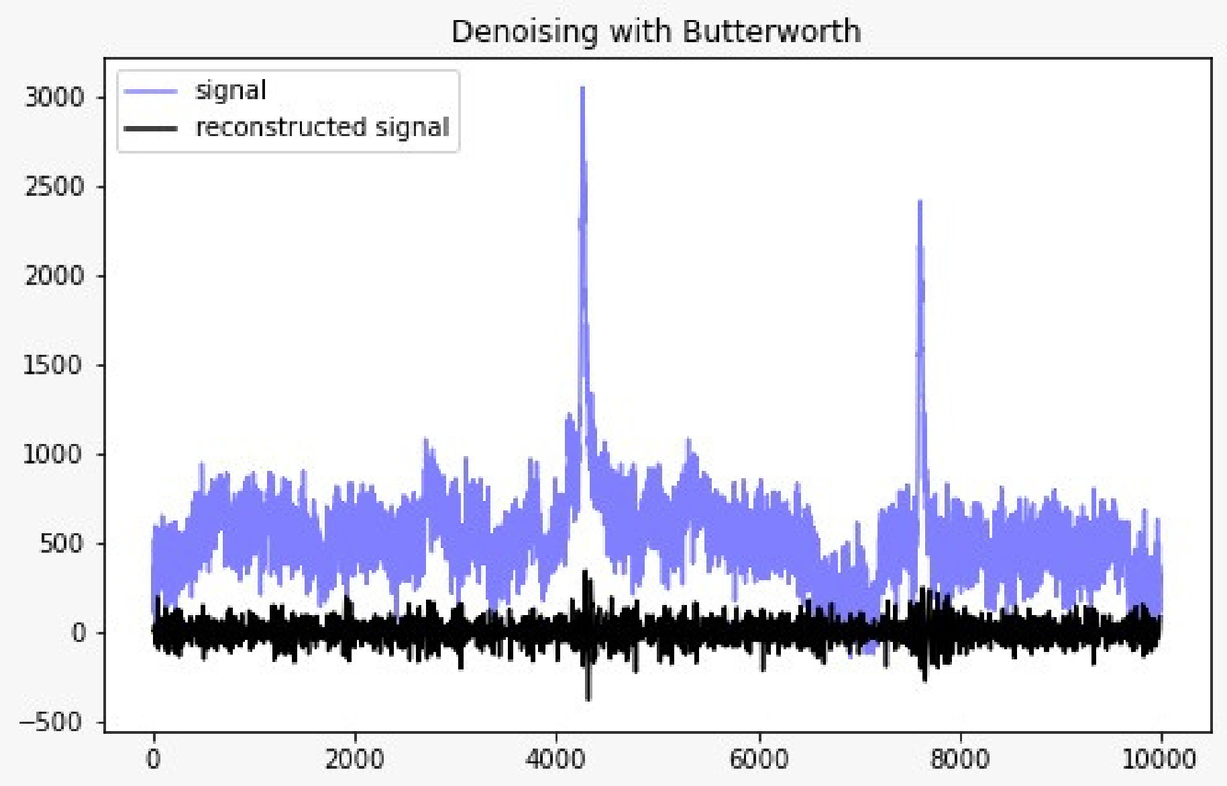
0.8
1.0

Comparison b/w CNN and LSTM



Butterworth

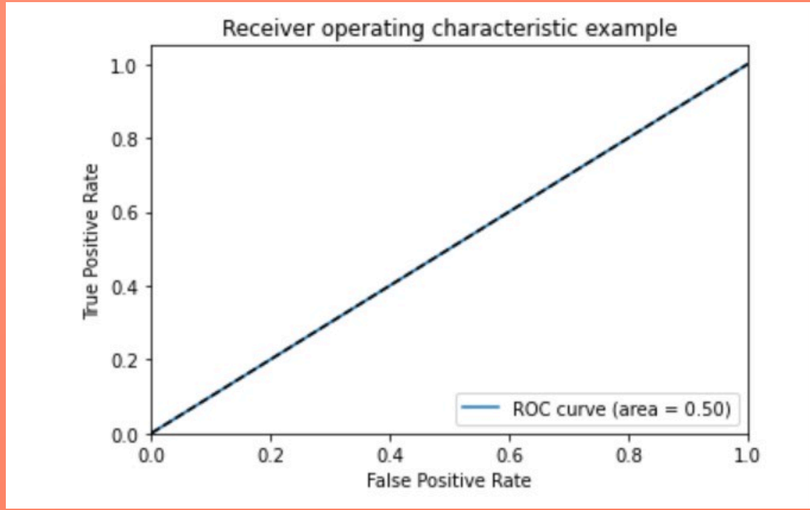
- Type of signal processing filter
- Butterworth Filter
- Cutoff Frequency
- Order

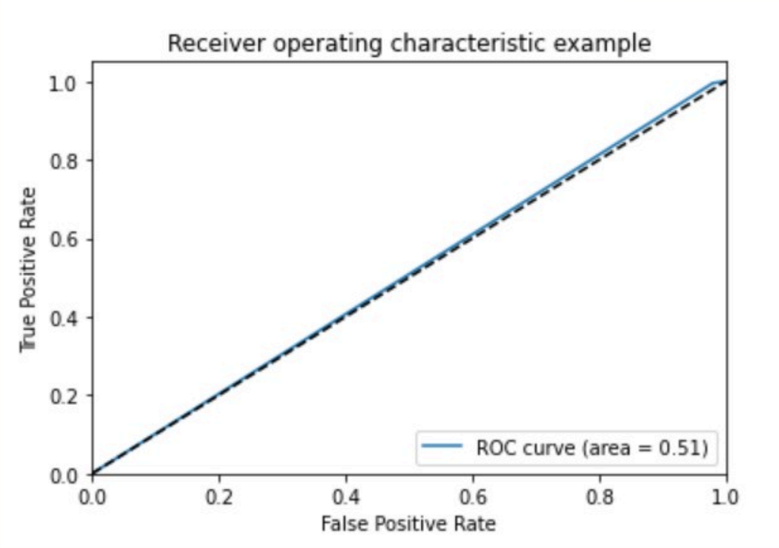


OneVsRestClassifier and SGDClassifier

- **One-vs-Rest (OvR):** Strategy for handling multi-class classification through binary classification tasks.
- **SGDClassifier:** Stochastic Gradient Descent-based linear classifier efficient for large datasets.
- OvR simplifies the multi-class problem, while SGDClassifier efficiently learns the decision boundaries.
- **Combined Approach:** OvR with SGDClassifier provides a versatile and efficient solution for multi-class classification

Results


Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.50)


Receiver operating characteristic example
True Positive Rate
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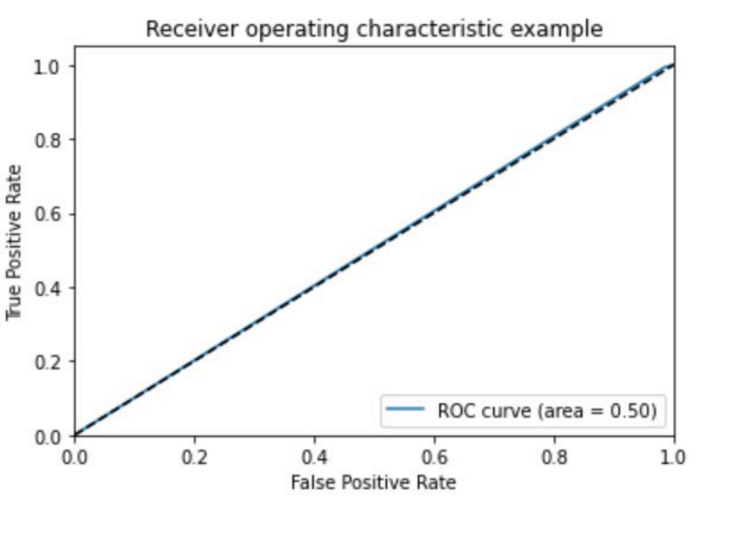
ROC curve (area = 0.51)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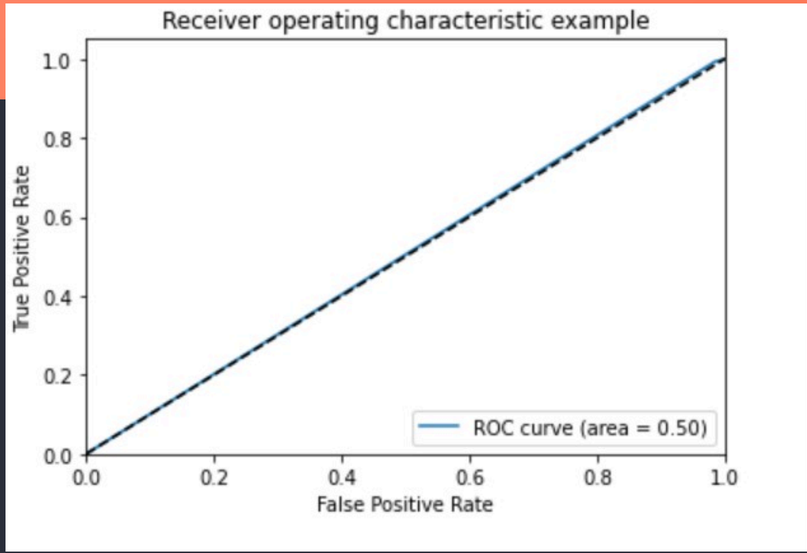
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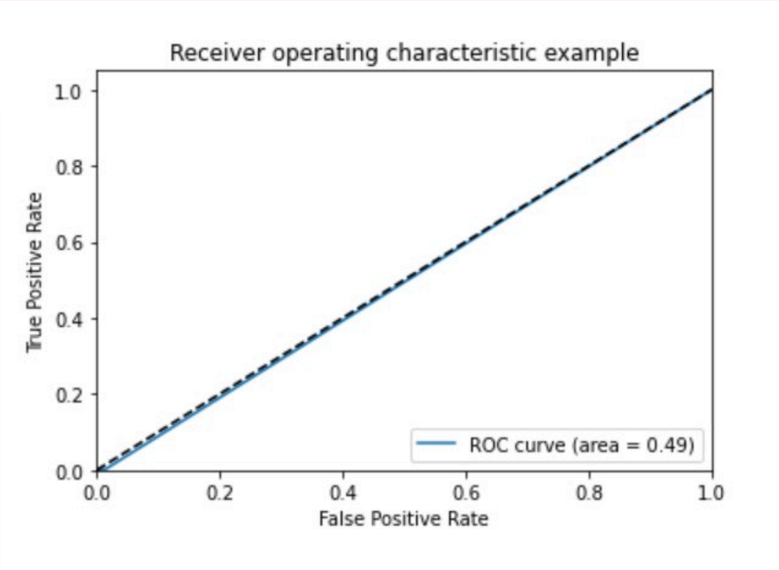
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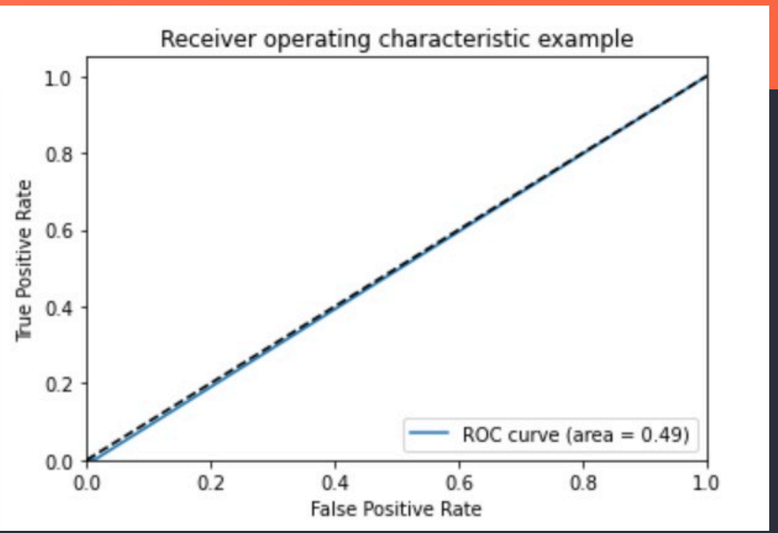

Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.49)

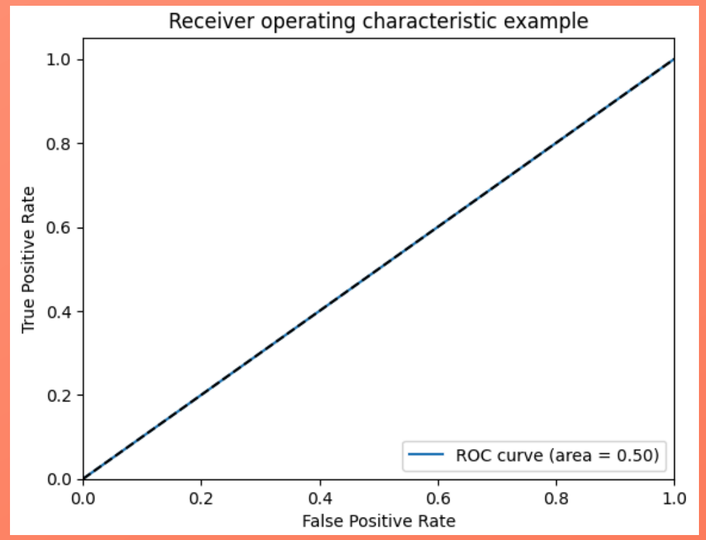
GaussianNB with ClassifierChain

- **Classifier Chain (CC):** Utilizes a sequence of binary classifiers to predict multiple labels, considering label dependencies in a chain-like fashion.

- **Gaussian Naive Bayes (GNB):** Employs a probabilistic classification approach based on Bayes' theorem

- **Combined Approach:** Offers an ensemble strategy to capture label dependencies and leverage the probabilistic nature of GNB, yielding a balanced prediction model.

Results: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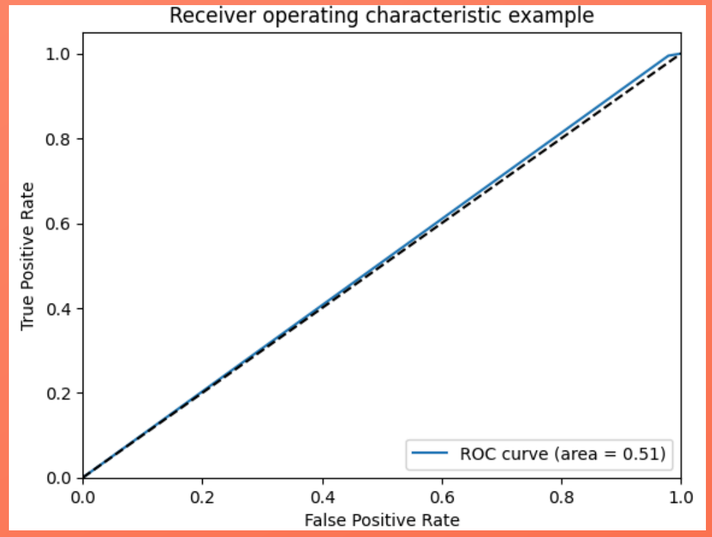
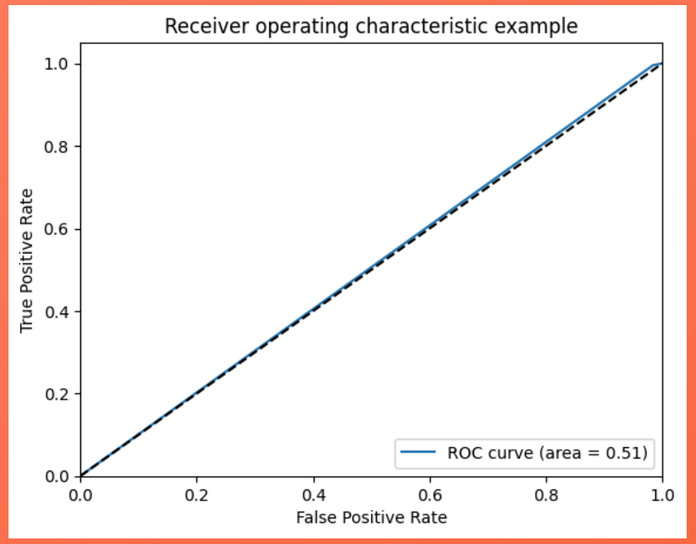

Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.51)


Receiver operating characteristic example
True Positive Rate
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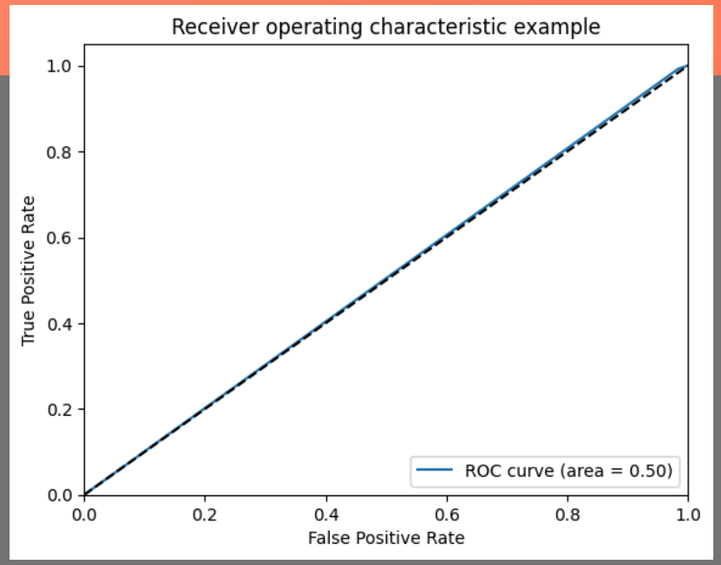
ROC curve (area = 0.51)


Receiver operating characteristic example
True Positive Rate
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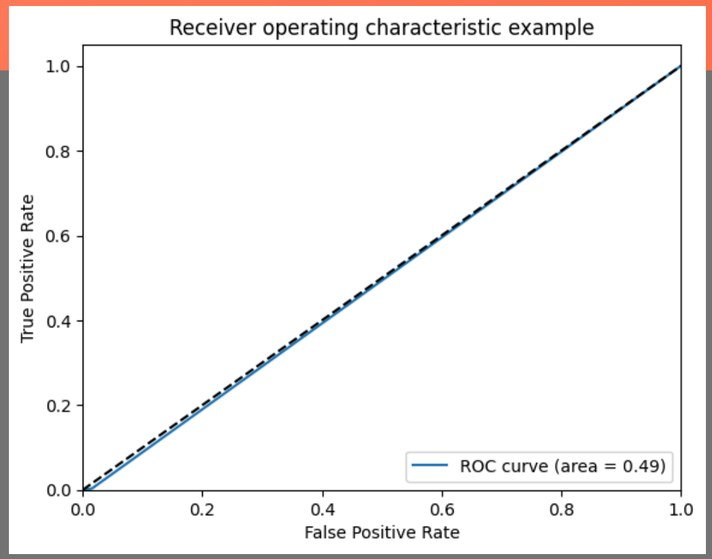
ROC curve (area = 0.50)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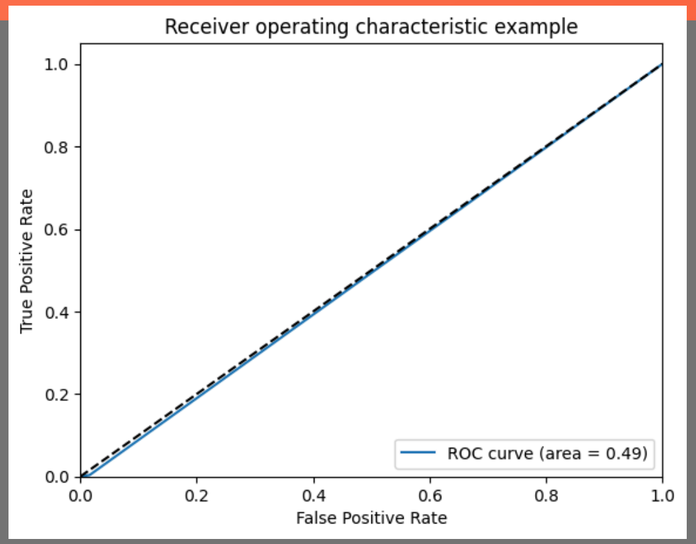
Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.49)

OneVsRest and SGD Vs GaussianNB with ClassifierChain

- OvR with SGDClassifier: **Accuracy:** 0.8748 , **Hamming Loss:** 0.0267
- CC with GNB : **Accuracy**: 0.0047 , **Hamming Loss**: 0.4965

- Accuracy: OvR with SGDClassifier significantly outperforms CC with GNB.
- Hamming Loss: OvR with SGDClassifier has a substantially lower Hamming Loss, indicating better precision in multi-label classification.
- OvR with SGDClassifier: Suitable for tasks prioritizing efficiency
- CC with GNB: Preferable when explicit handling of label dependencies is crucial

Conclusion

- Project explored diverse classification techniques :OvR with SGDClassifier, CC with GNB, CNN and LSTM.
- Butterworth filtering combined with Discrete Wavelet Transform (DWT), which outperformed Wavelet Transform (WT) alone.
- OvR with SGDClassifier demonstrated solid performance across various metrics,
- CC with GNB struggled with low accuracy and high loss.
- deep learning models like CNN and LSTM showcased robust performance,
- CNN exhibiting slightly superior results in our specific use case.

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Thank you!