Grasp and Lift an Object by using Electroencephalogram (EEG) Signals

B.Tech Project by

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ABSTRACT

Individuals with neuromuscular dysfunctions and amputated limbs often require automatic prosthetic devices. When developing such prostheses, accurately detecting brain motor actions is crucial for tasks like Grasp-and-Lift (GAL). Electroencephalography (EEG) is widely preferred for detecting motor actions and controlling prosthetic tools due to its low-cost and non-invasive nature. This article presents an automated method for detecting hand movement activity, specifically GAL, from 32-channel EEG signals. The proposed approach combines preprocessing and end-to-end detection steps, eliminating the need for manual feature engineering. The preprocessing step involves denoising the raw signals usin Wavelet Transformatiom (WT) or highpass/bandpass filtering, as well as data standardization. The detection step utilizes a model based on Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) and also tried to do with deep reinforcement learning . All experiments are conducted using the publicly available WAY-EEG-GAL dataset, which includes six different GAL events. The best experiment results demonstrate that the proposed framework achieves an average area under the Receiver Operating Characteristic (ROC) curve of 0.944, employing the DWT-based denoising filter, data standardization, and CNN-based detection model. These findings indicate the excellent performance of the proposed method in detecting GAL events from EEG signals, making it applicable to prosthetic devices, brain-computer interfaces, robotic arms, and similar applications.

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Ch a p t e r 1

INTRODUCTION

The ability to control external devices using brain signals has garnered significant interest in recent years. One area of focus is the development of systems that utilize electroencephalography (EEG) signals to control hand actions[1]. This technology holds great potential for individuals with motor disabilities, offering them the opportunity to regain dexterity and independence in their daily lives.

The objective of this project is to investigate the feasibility of using EEG signals to control six specific hand actions involved in the process of grasping and lifting an object. These hand actions include hand start, first digit touch, both start load phase, lift off, replace, and both release. By accurately decoding the user's intention from EEG signals, we aim to develop a system that can effectively manipulate a robotic arm to perform these actions[4].

Around 2.1 million people in the United States (US) alone are living with limb injury, and a further 185,000 people demand an amputation each year .. Approximately 300,000 people in the US live with spinal cord injury affecting the uppermost extremity function . According to the World Health Organization, about one billion individuals are disabled, with up to 190 million individuals, equating to roughly 15 % of the world's population. Earlier, persons with impairments could only communicate with a prosthetic voice receiver by speaking, and the prosthesis recognized the signal through the receiver, performing the user's desired action. The patient can also apply an Electromyographic (EMG) signal to accomplish the same goal [2]. However, there are several drawbacks, like the interference from the outside environment can make voice-controlled intelligent prostheses challenging to exercise in public. Besides, several neuromuscular illnesses, such as amyotrophic lateral sclerosis, affect motor neurons, causing the brain to lose control over voluntary muscle movements in the EMG signals [5]. EMG-based control also contributes to poor dexterity and control versatility, whereas signals from the brain, for example, Electroencephalography (EEG), may produce a more precise alternative and control . However, the decoding of GAL activities from the EEG signal exhibited tremendous recent success in the wrist gestures , uppermost limbs , and elbows & shoulders . The EEG employs non-invasive electrodes placed on participants' scalps to measure signals produced by local field potentials with active cor-tex neurons, having high temporal precision. Any detection pipeline, including the decoding of sensation, intention, and action from scalp EEG signal in the WAY-EEG-GAL dataset ,utilize different algorithms, which roughly contain similar essential steps, such as artifact rejection, time-domain filtering, spatial filtering, class feature extraction, and finally, classification . Several recent works related to hand movement recognition, for instance, GAL events, are reviewed in the subsequent section.

To achieve this goal[9], we employ advanced machine learning techniques, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks and

deep reinforcement learning, for classification of the EEG signals corresponding to different hand actions. The CNN model is utilized to capture spatial features within the EEG data, allowing for automatic learning of relevant patterns across the scalp electrode positions. On the other hand, the LSTM model is employed to capture the temporal dynamics and dependencies in the EEG signals, taking advantage of the sequential nature of the data. By leveraging the strengths of both CNNs and LSTMs, we aim to improve the accuracy and robustness of the classification model, enabling precise identification of the user's intended hand action from the EEG signals. Furthermore, the comparison between these models provides insights into their respective capabilities, including spatial feature extraction by the CNN and temporal context modeling by the LSTM. Furthermore, the development of efficient and accurate hand action recognition systems has potential applications in robotics, prosthetics, and assistive technology.
In the subsequent sections of this report, we will delve into the details of the experimental setup, data acquisition, preprocessing techniques, feature extraction, and the implementation of the CNN and LSTM models. We will present the results of our experiments, compare the performance of the models, and discuss their strengths and limitations. Finally, we will provide insights into the potential impact and future directions of this research. Overall, this project aims to contribute to the advancement of EEG-based control systems, fostering greater independence and improved quality of life for individuals , while also paving the way for advancements in human-robot interaction and assistive technologies[7].

In addition to the CNN and LSTM models, we incorporate deep reinforcement learning techniques to enhance the control capabilities of the system. Deep reinforcement learning combines reinforcement learning, which involves learning from interactions with an environment, with deep neural networks to approximate complex control policies. By using a reinforcement learning framework, the system can learn to make decisions based on feedback received from the environment, allowing for adaptive and dynamic control of the hand actions.

Chapter 2

RELATED WORK

Several research studies have explored the use of EEG signals for grasp and lift of objects
And after going through many of research studies we get knowledge about project that are as follows :
Using Wavelet Transform and Neural Network" presents a study focused on classifying EEG signals associated with the left and right hand movements .Methodology that combines wavelet transform for feature extraction and neural network for classification. The wavelet transform is utilized to analyze the time-frequency characteristics of the EEG signals, extracting relevant features for distinguishing between left and right hand movements. The extracted features are then fed into a neural network, which is trained to classify the EEG signals into the respective hand movement or GAL categories. The results of the study demonstrate the effectiveness of the proposed approach in accurately classifying left and right hand movements and GAL based on EEG signals, highlighting its potential applications in brain-computer interface systems and neurorehabilitation.
The paper titled "Brain EEG Signal Processing for Controlling a Robotic Arm" focuses on the application of electroencephalography (EEG) signal processing techniques for controlling a robotic arm. The study explores the possibility of using brain signals captured through EEG to enable individuals to control the movement of a robotic arm through their thoughts. The authors discuss the experimental setup, data acquisition process, and the signal processing algorithms employed to decode and interpret the EEG signals. They present the results of their experiments, demonstrating the feasibility and potential of using EEG signals for real-time control of a robotic arm. The findings highlight the potential of EEG-based brain-computer interfaces for enhancing the capabilities of assistive technologies and improving the quality of life for individuals with motor disabilities.
The paper introduces a brain-computer interface (BCI) system that enables individuals to control a robotic arm using EEG signals. It utilizes a multi-directional CNN-BiLSTM network to process the EEG data and decode the user's intentions. The experimental results demonstrate the system's effectiveness in accurately recognizing commands and controlling the robotic arm. This research contributes to the development of assistive technologies for individuals with motor disabilities.
The paper proposes a Convolutional Neural Network (CNN) approach for detecting grasp-and-lift events from EEG signals. The authors collect and preprocess the EEG data, segment it into time windows, and train a CNN model to extract features and classify the events. The CNN outperforms other methods, demonstrating its effectiveness in analyzing EEG signals for motor event detection. The study showcases the potential of deep learning techniques in

understanding human hand movements and has implications for assistive technology and neurorehabilitation.

The paper titled "Electroencephalography-based Brain Controlled Grasp and Lift" focuses on the development and implementation of a brain-computer interface (BCI) system that enables individuals to control a robotic arm for the purpose of grasp and lift tasks using electroencephalography (EEG) signals. The study aims to establish a direct communication pathway between the brain and the robotic arm, allowing individuals with motor disabilities to regain some level of functional control over their environment. The authors describe the experimental setup, data acquisition process, and the signal processing techniques employed to extract meaningful information from the EEG signals. They also discuss the design and implementation of the BCI algorithm, which translates the extracted EEG features into real-time control commands for the robotic arm. The paper presents the results of their experiments, demonstrating the feasibility and effectiveness of the EEG-based brain control of the grasp and lift tasks. The findings highlight the potential of EEG-based BCIs in improving the quality of life for individuals with motor impairments by providing them with a means to interact with their surroundings using their brain signals.

The paper focuses on enhancing the performance of brain-computer interface (BCI) systems through reinforcement learning-based feature selection. BCI systems enable communication between the brain and external devices, but selecting relevant features from high-dimensional brain signals remains a challenge. The proposed approach introduces a reinforcement learning framework to iteratively select the most informative features that maximize the performance of the BCI system. By optimizing the feature selection process, the study aims to improve the accuracy and efficiency of BCI systems, enabling more effective brain-controlled interactions.

The paper presents a novel approach for EEG-based emotion recognition using unsupervised learning, time-aware sampling, and deep reinforcement learning. It proposes the use of a Variational Autoencoder (VAE) to learn meaningful representations from EEG data, a time-aware sampling technique to select informative segments, and a deep reinforcement learning framework to optimize the sampling strategy. The approach aims to improve the accuracy of emotion recognition by capturing temporal dependencies and selecting relevant EEG segments for classification.

Chapter 3
PROBLEM STATEMENT

The problem statement of the grasp and lift of an object using EEG signals involves analyzing the brain activity associated with six specific events: hand start, first digit touch, both start load phase, liftoff, replace, and both released. The goal is to develop a system or algorithm that can accurately detect and classify these events based on EEG recordings.
The six events can be defined as follows:
1. Handstart: This event marks the start of the hand movement towards the object to be grasped. It indicates the intention to initiate the grasp.
2. First-digit touch: This event occurs when the hand makes initial contact with the object, specifically when the fingers or thumb come into contact with it.
3. Both start load phases: This event refers to the beginning of the load phase, where force is applied to the object to lift or manipulate it. The "both" in the event name suggests that both hands are involved in this phase.
4. Liftoff: This event signifies the actual lifting of the object from its initial position. It indicates the transition from the load phase to the lifting phase.
5. Replace: This event occurs when the lifted object is placed back to its original position or another desired location. It marks the completion of the manipulation task.
6. Both released: This event indicates the release of the object by both hands simultaneously, typically after the object has been manipulated or moved to its intended destination.
The overall objective of this problem is to leverage EEG signals to detect and classify these events accurately and in real time. By analyzing the brain activity associated with each event, researchers can develop algorithms or systems that enable the control of robotic prosthetics, assistive devices, or other applications based on a user's intention to perform specific hand movements.

Chapter 4

DATASET

Data contains EEG recordings of subjects performing grasp-and-lift (GAL) trials. The following video shows an example of a trial:

A detailed of the data can be found in .

There are 12 subjects in total, 10 series of trials for each subject, and approximately 30 trials within each series. The number of trials varies for each series. The training set contains the first 8 series for each subject. The test set contains the 9th and 10th series.

For each GAL, you are tasked to detect 6 events:

1. HandStart
2. FirstDigitTouch
3. BothStartLoadPhase
4. LiftOff
5. Replace
6. BothReleased

These events always occur in the same order. In the training set, there are two files for each subject + series combination:

- the *_data.csv files contain the raw 32 channels EEG data (sampling rate 500Hz)
- the *_events.csv files contains the ground truth frame-wise labels for all events

The events files for the test set are not provided and must be predicted.

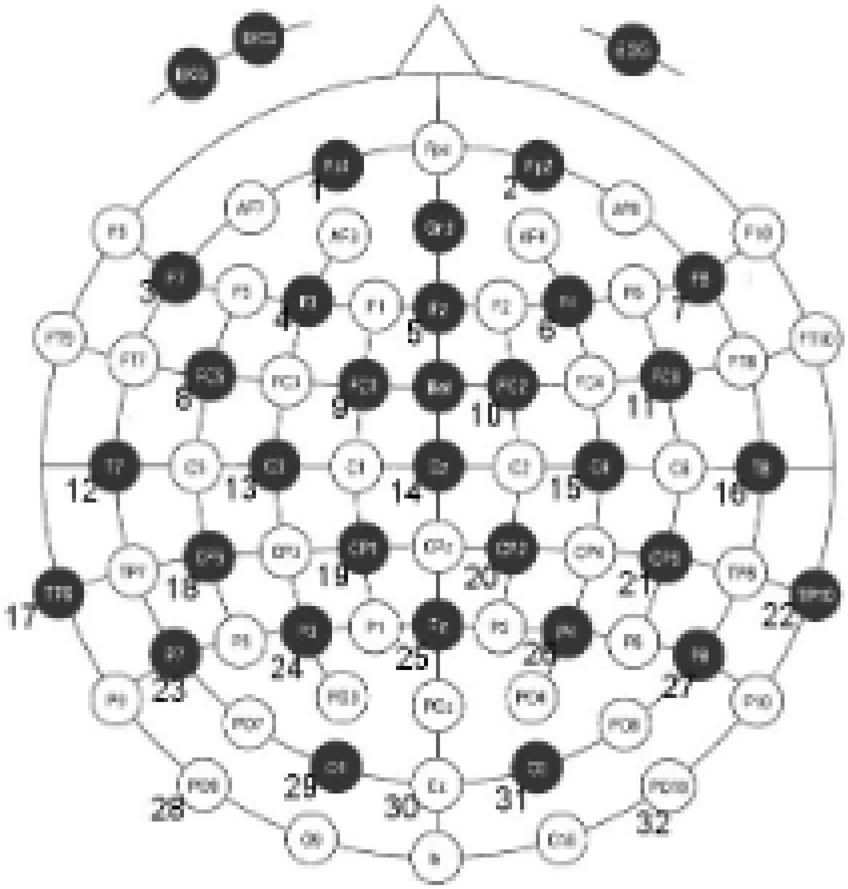


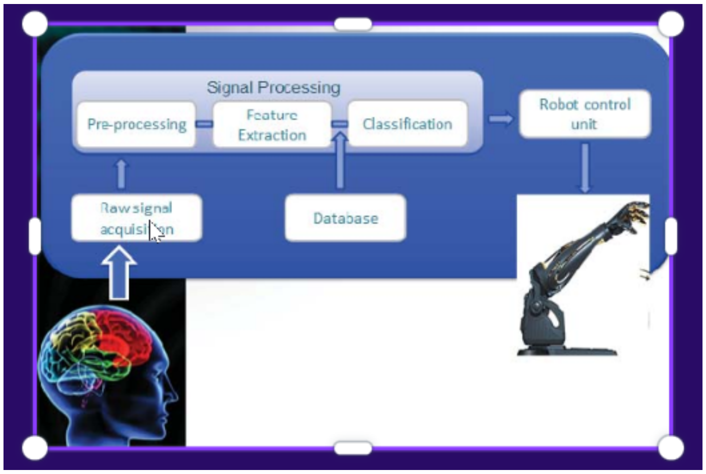
Fig :- EEG Recording of signals

[Ref: https://www.kaggle.com/c/grasp-and-lift-eeg-detection/data]

C h a p t e r 5

METHODOLOGY

In this section, we discussed about the whole methodology that we follow for the project feature extraction technique and prosposed model is described here,



5.1 Feature extraction: Wavelet transformation:
Wavelet transformation allows the decomposition of an EEG signal into different frequency sub-bands, enabling the analysis of both temporal and frequency information simultaneously. Here is a description of how wavelet transformation can be applied for feature extraction in EEG signals:

Wavelet Basis Selection: The first step in wavelet transformation is to select an appropriate wavelet basis. Different wavelet families, such as Daubechies, Symlets, and Morlet, have different properties and are suitable for different types of signals. The choice of wavelet basis depends on the characteristics of the EEG signals and the specific frequency components of interest.

Decomposition: Once the wavelet basis is selected, the EEG signal is decomposed into different frequency sub-bands using a multi-resolution analysis. This decomposition is achieved by applying a series of low-pass and high-pass filters to the signal at different scales or levels. Each level of decomposition captures different frequency components of the EEG signal.

Feature Extraction: After decomposition, the coefficients of the decomposed signal at each level are obtained. These coefficients represent the contribution of different frequency sub-bands to the original EEG signal. Depending on the specific application, different features can be extracted from these coefficients, such as statistical measures (mean, variance, skewness, etc.), energy, entropy, or higher-order spectral features.

Dimensionality Reduction: As EEG signals often consist of high-dimensional data, dimensionality reduction techniques, such as Principal Component Analysis (PCA) or Wavelet Packet Transform (WPT), can be applied to reduce the feature space while retaining the most relevant information. This helps in reducing computational complexity and improving classification performance.

Feature Selection: Depending on the classification or control task at hand, feature selection methods can be applied to identify the most discriminative features for accurate classification or control. Techniques like mutual information, correlation-based feature selection, or sequential forward/backward selection can be employed to select a subset of features that contribute the most to the classification performance.

By applying wavelet transformation and extracting relevant features from the decomposed EEG signal, the resulting feature set captures both temporal and frequency information. This approach allows for a more comprehensive representation of the EEG signals and can potentially improve the performance of subsequent classification or control algorithms.

5.2 Convolutional neural networks (CNN):-

convolutional layers are the building blocks of CNNs. They consist of a set of learnable filters (also called kernels) that slide over the input image in a grid-like fashion. Each filter performs a mathematical operation known as convolution, which involves element-wise multiplication and summation. The convolution operation captures local patterns or features within the image, such as edges, textures, and shapes. Multiple filters are used to extract different features simultaneously, resulting in multiple feature maps.

pooling layers are typically inserted after convolutional layers. They downsample the spatial dimensions of the feature maps while retaining the most important information. The pooling operation reduces the computational complexity of the network and provides a form of translation invariance, enabling the network to recognize patterns regardless of their exact location. The most common pooling operation is max pooling, which selects the maximum value within each pooling region..

$$Y[i, j] = \max(X[i:i+s, j:j+s]$$

Activation functions introduce non-linearities into the network, allowing it to learn complex relationships between the input data and the desired output. The most commonly used activation function in CNNs is the Rectified Linear Unit (ReLU). ReLU sets all negative values to zero and leaves positive values unchanged, promoting the network's ability to learn sparse and efficient representations.

$$\mathrm{ReLU}(x) = \max(0, x)$$

Fully Connected Layers: Fully connected layers are typically present at the end of the CNN architecture. They take the high-level features extracted from previous layers and use them to classify or predict specific outputs. These layers connect every neuron from the previous layer to every neuron in the subsequent layer.

$$Y = W*X + b$$

5.3 Long Short Term Memory (LSTM):-

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is designed to overcome the limitations of traditional RNNs in capturing and remembering long-term dependencies in sequential data.

The fundamental unit of an LSTM is the memory cell, which contains three main components: an input gate, a forget gate, and an output gate. These gates regulate the flow of information into, out of, and within the memory cell, allowing LSTMs to selectively retain or discard information based on its relevance.

The input gate of an LSTM determines which information from the current input and previous memory cell state should be stored in the memory cell. It is responsible for deciding which values need to be updated and to what extent. The input gate takes the input data and the previous hidden state as inputs, and applies a sigmoid activation function to them. The resulting values determine the amount of information to be stored in the memory cell..

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i)]$$

The forget gate allows the LSTM to selectively discard irrelevant information from the memory cell. It takes the input data and the previous hidden state as inputs and applies a sigmoid activation function. The output of the forget gate is multiplied element-wise with the previous memory cell state, resulting in the removal of irrelevant information.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f)$$

The update of the memory cell involves two steps. First, the input gate and the input data are combined, and a tanh activation function is applied to produce a vector of potential new values for the memory cell. Second, the new values are multiplied element-wise with the output of the input gate, allowing the LSTM to update the memory cell with relevant information while preserving the old memory.

$$c_t = f_t * c_{t-1} + i_t * g_t$$

The output gate determines which information from the memory cell should be outputted as the hidden state. It takes the input data and the previous hidden state as inputs, applies a sigmoid activation function, and combines it with the current memory cell state. The resulting values are passed through a tanh activation function to squash the output, which is then multiplied by the output gate to produce the final hidden state.

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o)$$

5.4 Deep reinforcement learning:

Implementing deep reinforcement learning on an EEG dataset involves combining reinforcement learning algorithms with deep neural networks to train an agent to interact with and learn from the EEG data. Here's a general outline of the process:

1. Define the Reinforcement Learning Problem: Determine the specific reinforcement learning problem you want to solve using the EEG dataset. This could include tasks such as brain-computer interfaces, neurofeedback training, or cognitive state detection.

2. Data Preprocessing: Preprocess the raw EEG data to prepare it for input to the deep reinforcement learning algorithm. This may involve filtering, artifact removal, normalization, and segmentation into appropriate time windows or epochs.

3. Define the Agent: Design the reinforcement learning agent that will interact with the EEG data. The agent can be based on algorithms such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), or Deep Deterministic Policy Gradient (DDPG). The agent typically consists of a deep neural network, which can be a convolutional neural network (CNN) or a recurrent neural network (RNN), depending on the nature of the EEG data.

4. Define the Reward Function: Define a reward function that provides feedback to the agent based on its actions and the observed EEG data. The reward function should be designed to guide the agent towards achieving the desired task or objective. It may involve metrics such as classification accuracy, performance on a specific EEG task, or other relevant measures.

5. Training the Agent: Train the deep reinforcement learning agent using the preprocessed EEG data. The agent interacts with the EEG data, takes actions based on its current state, and receives rewards from the environment. The training process involves optimizing the parameters of the neural network using techniques such as stochastic gradient descent or policy gradient methods.

6. Hyperparameter Tuning: Experiment with different hyperparameters of the reinforcement learning algorithm, such as learning rate, discount factor, exploration-exploitation trade-off, and network architecture. Use techniques like grid search or Bayesian optimization to find the optimal combination of hyperparameters.

7. Evaluation and Testing: Evaluate the performance of the trained agent on a separate test set or in real-time scenarios. Measure relevant metrics such as accuracy, task completion rate, or any other performance indicators specific to the reinforcement learning problem you are addressing.

8. Iterative Refinement: Analyze the results, iterate on the training process, and refine the agent's architecture and parameters as needed. This may involve adjusting the reward function, exploring different network architectures, or modifying the training strategy.

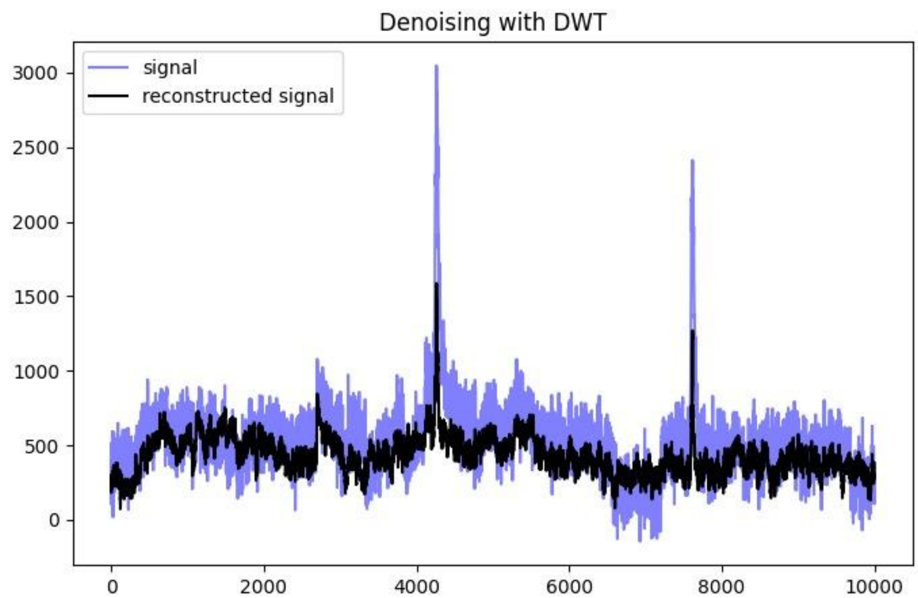
It's important to note that implementing deep reinforcement learning on EEG datasets can be a complex task and may require expertise in both reinforcement learning and EEG signal processing. Additionally, data availability and quality play a crucial role in the success of the approach. Proper preprocessing, careful design of the reinforcement learning problem, and thoughtful selection of algorithms and hyperparameters are key to achieving good results.

C h a p t e r 6

EXPERIMENTAL RESULTS

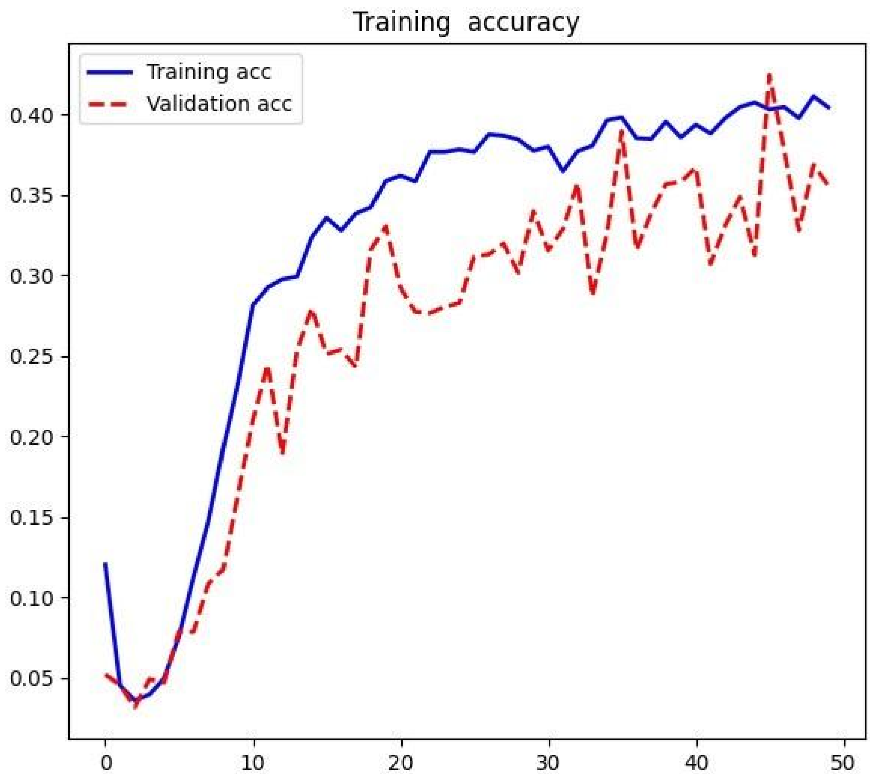
In this section we will discuss the results: -

6.1 Wavelet Transformation (feature extraction):

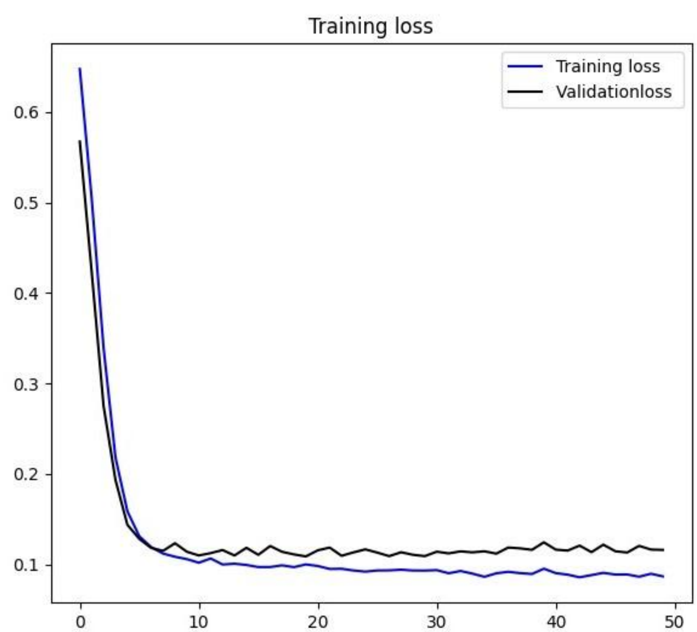


6.1 Result of Convolutional neural network :-

6.1.1 Training Accuracy and Validation Accuracy:-

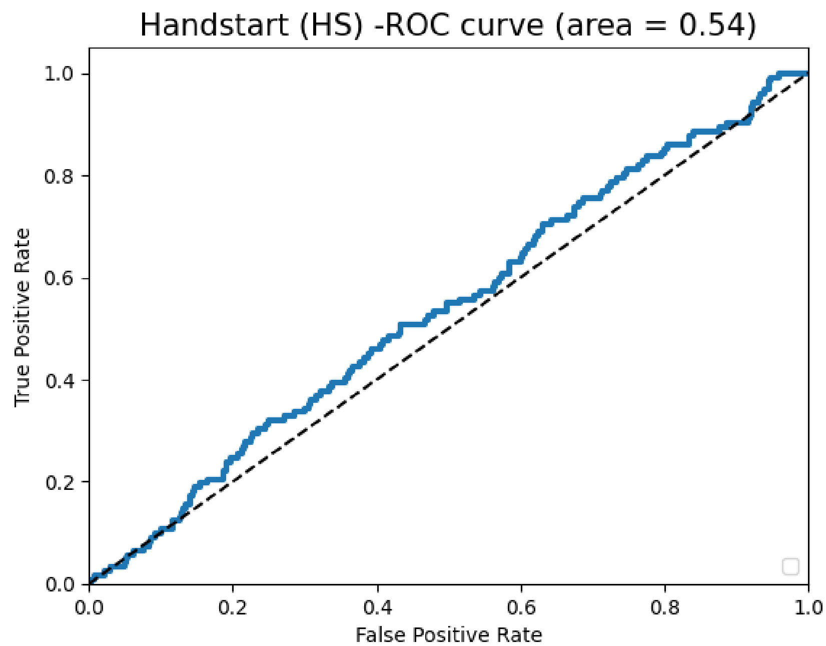


6.1.2 Training Loss and Validation Loss :-

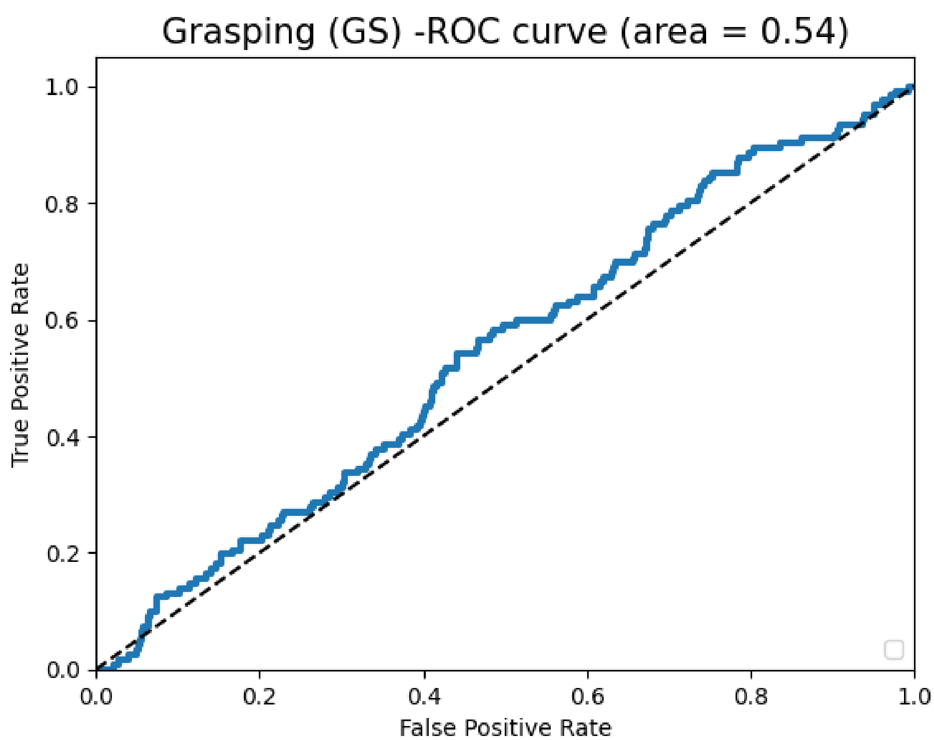


6.1.3 Receiver Operating Characteristic Curves(ROC curves): -

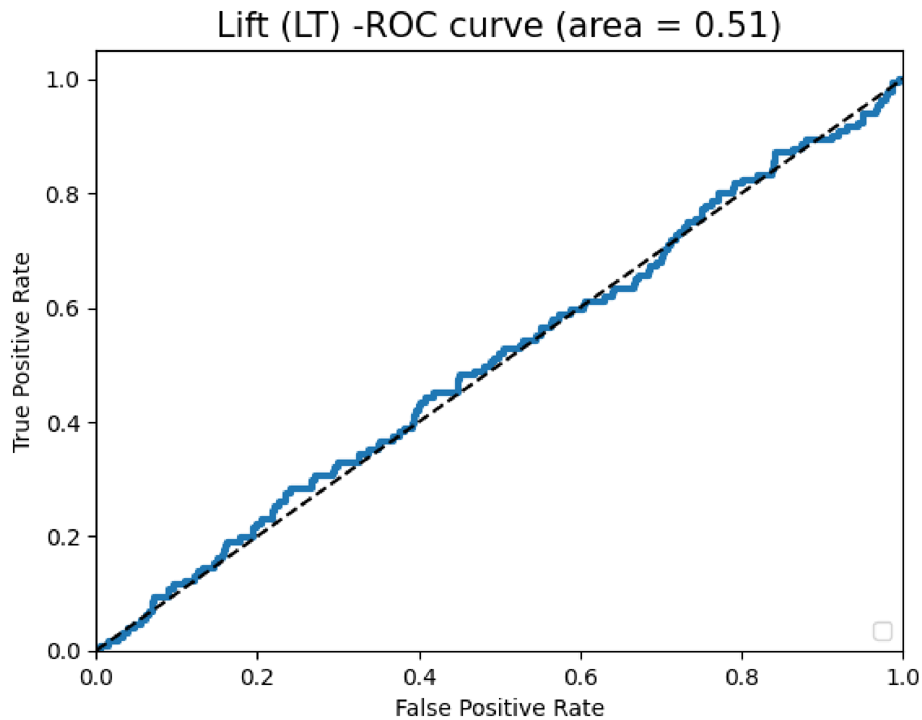
6.1.3.1 Roc Curve For **HandStart** class :-



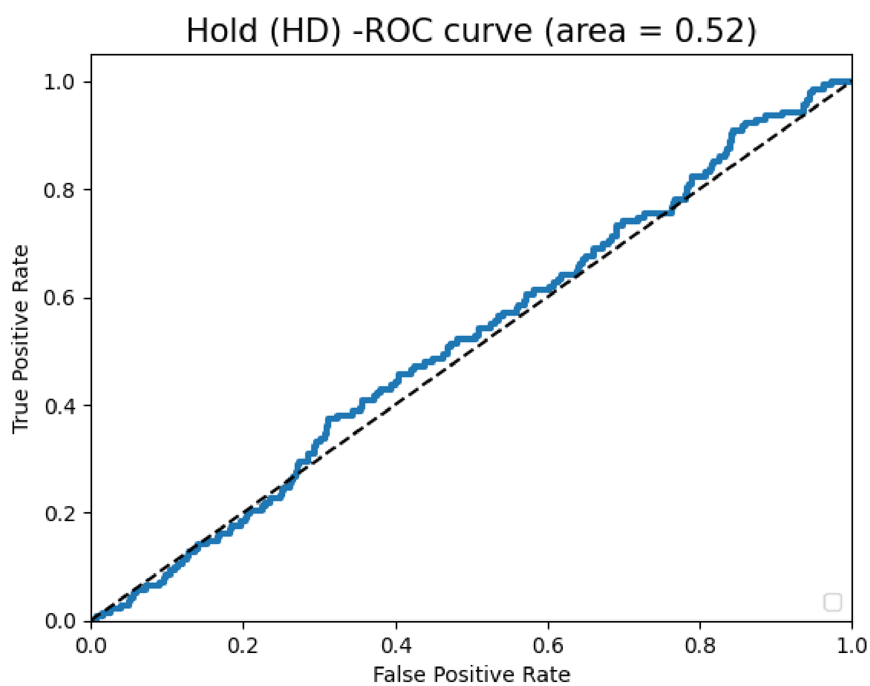
6.1.3.2 Roc Curve For **Grasping** class :-



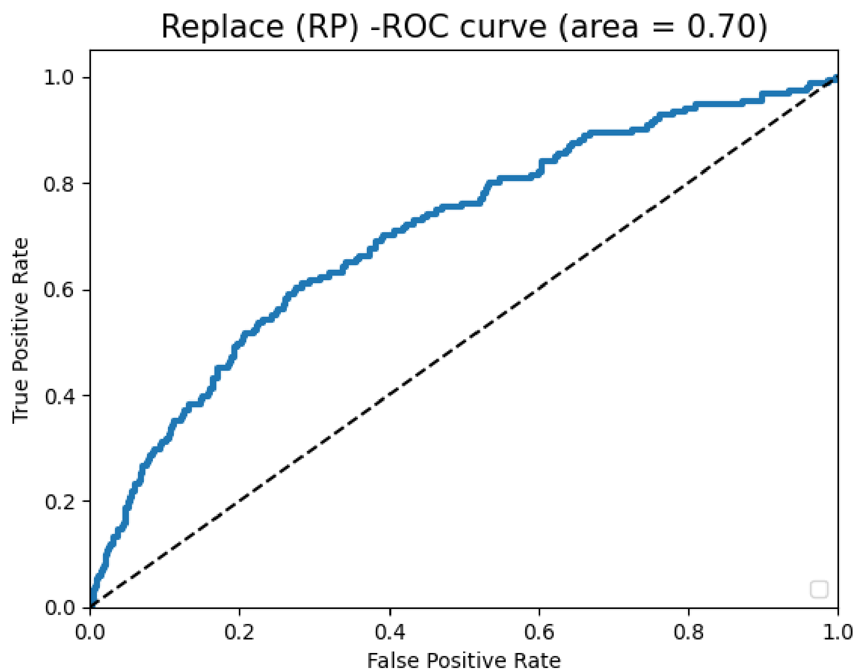
6.1.3.3 Roc Curve for **Lift** class :-



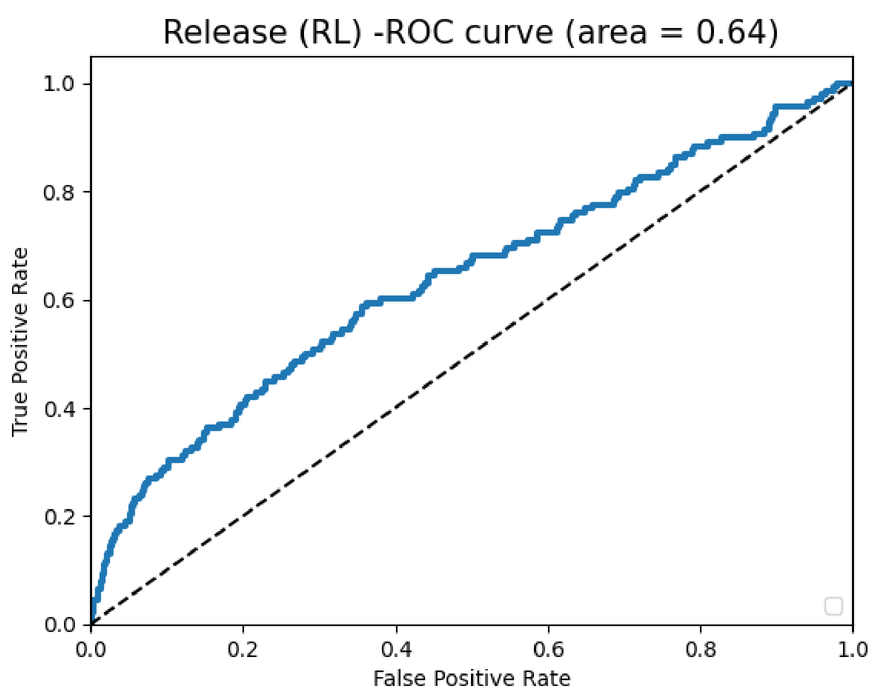
6.1.3.4 Roc Curve for **Holding** class:-



6.1.3.5 Roc Curve for **Replace** class :-

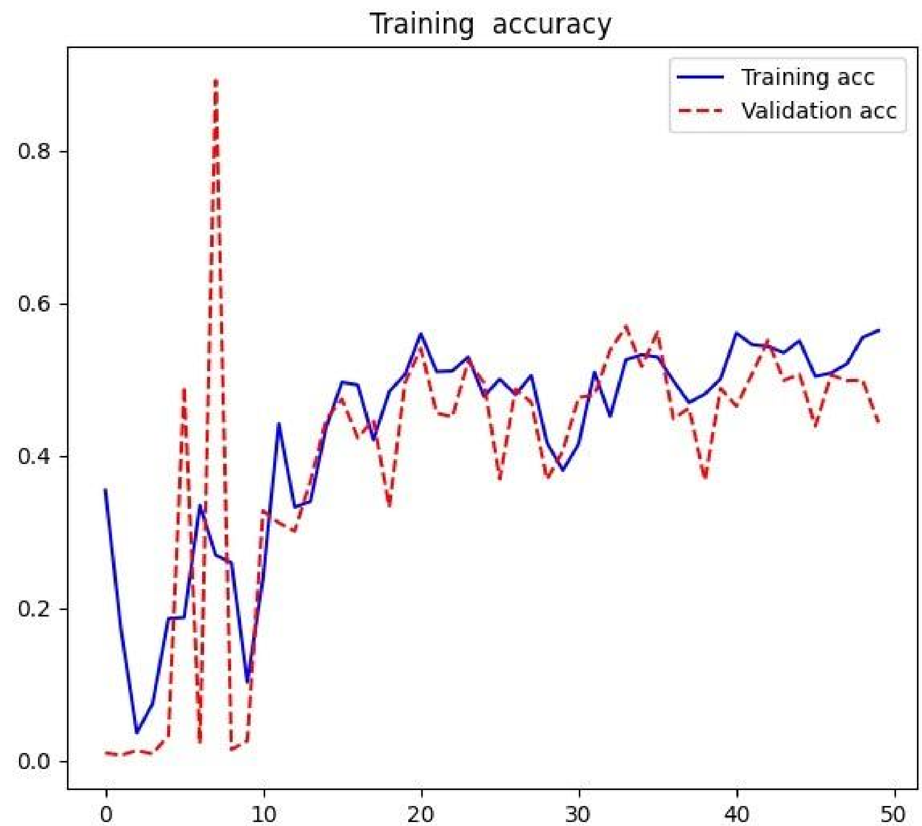


6.1.3.6 Roc curve for **Release** Curve :-

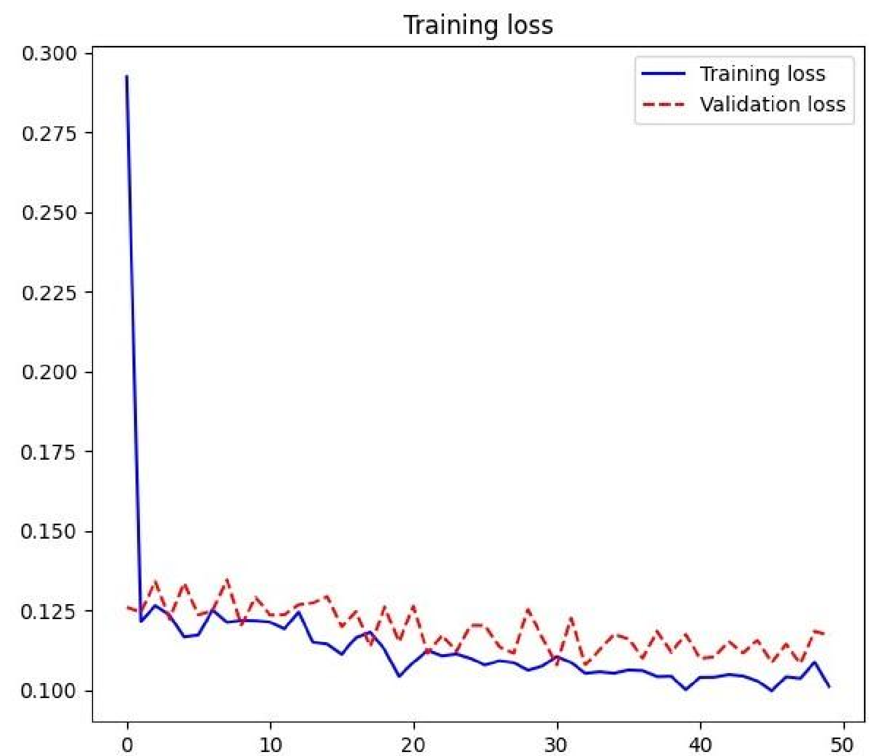


6.2 Long Short Term Memory Results :-

6.2.1 Training Accuracy and Validation Accuracy :-

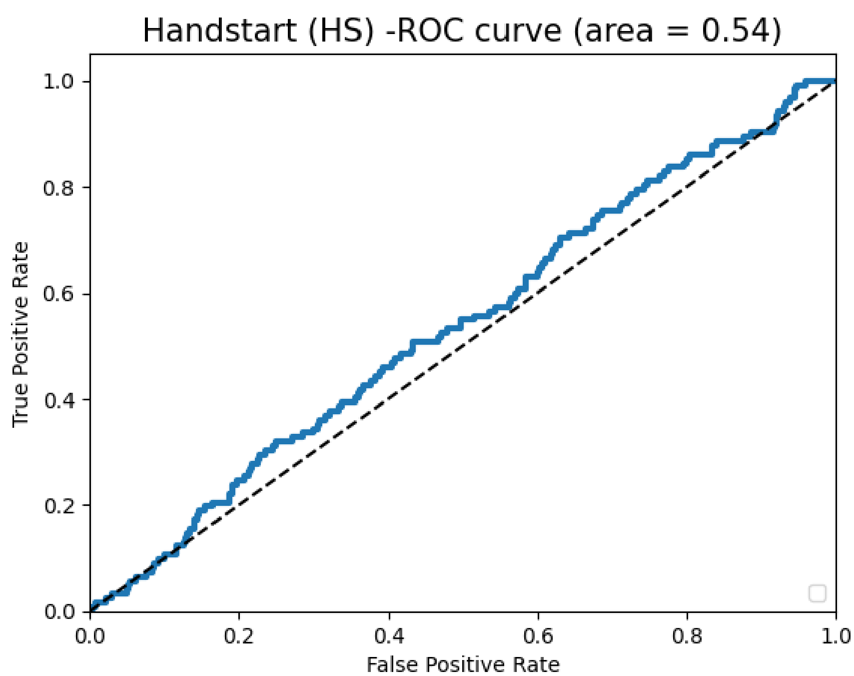


6.2.2 Training Loss and Validation Loss :-

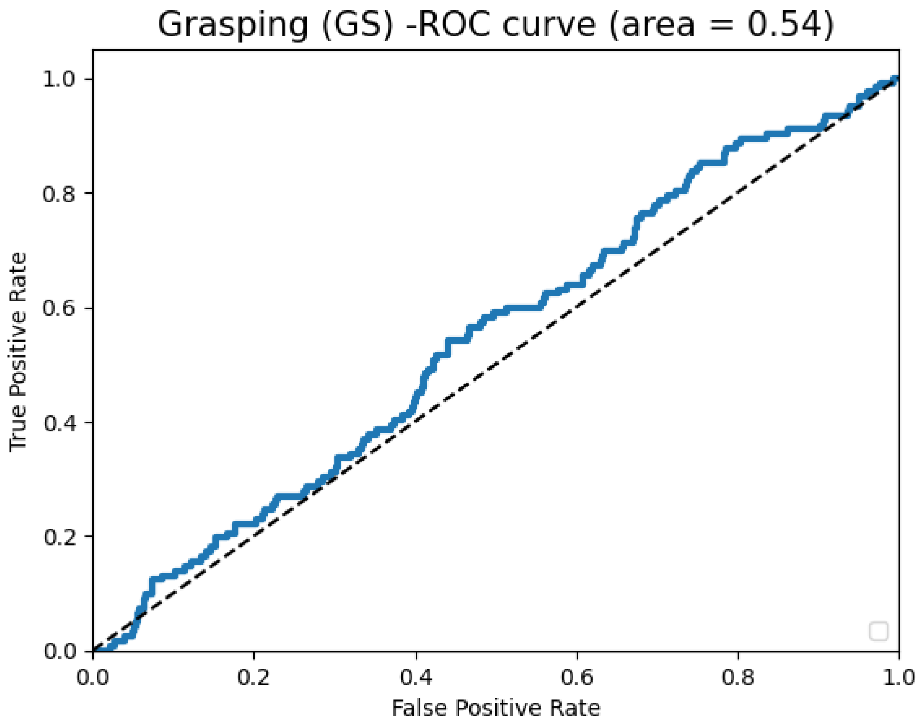


6.3.3 Roc curves for GAL Classes :-

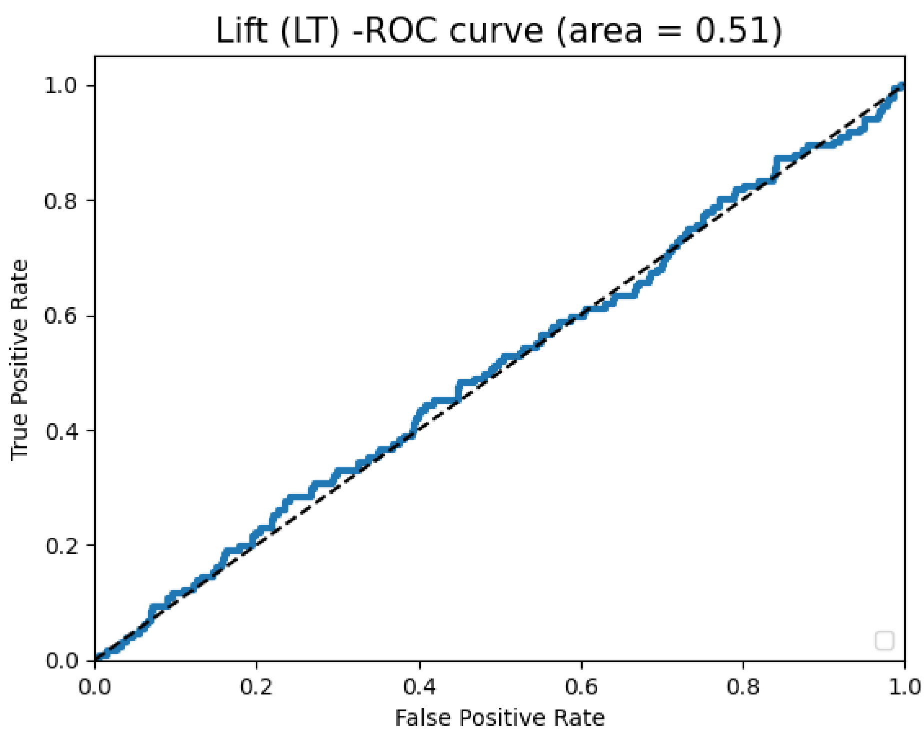
6.3.3.1 ROC curve for Handstart :-



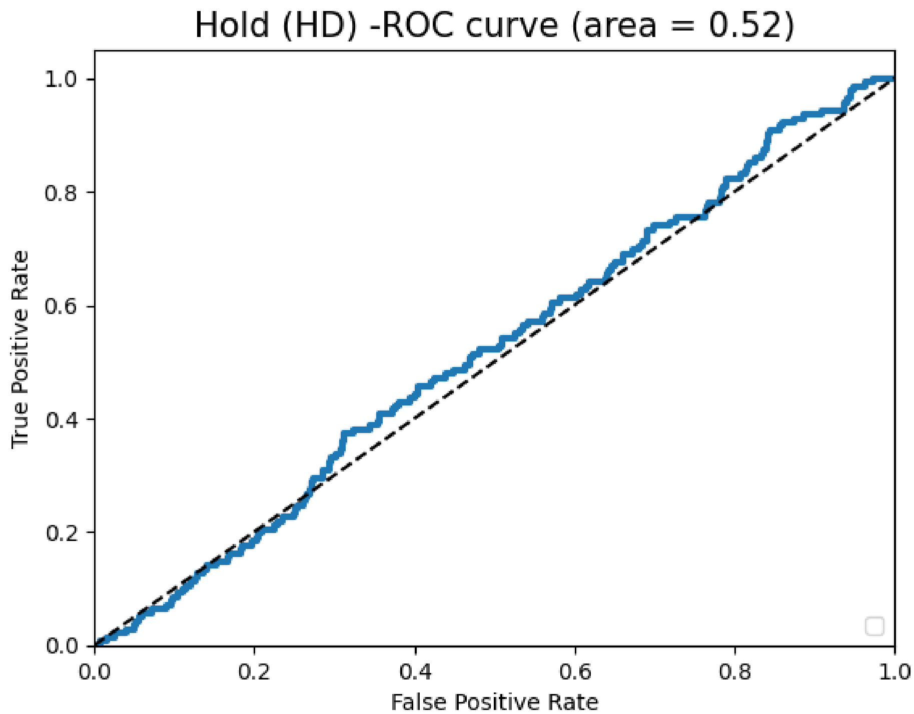
6.3.3.2 ROC curve for Grasping :-



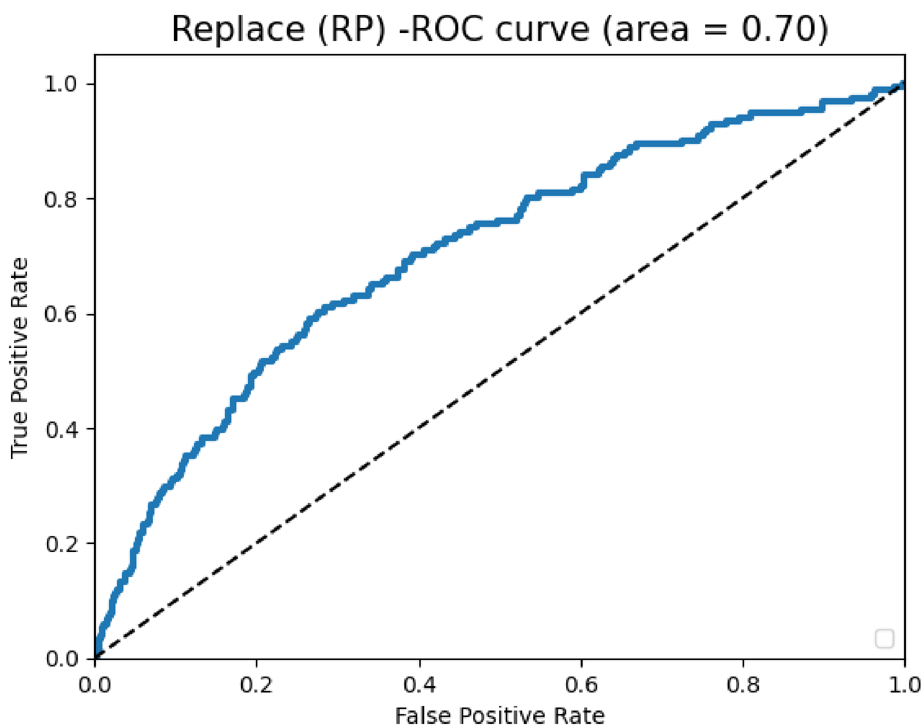
6.3.3.3 ROC curve for Lift :-



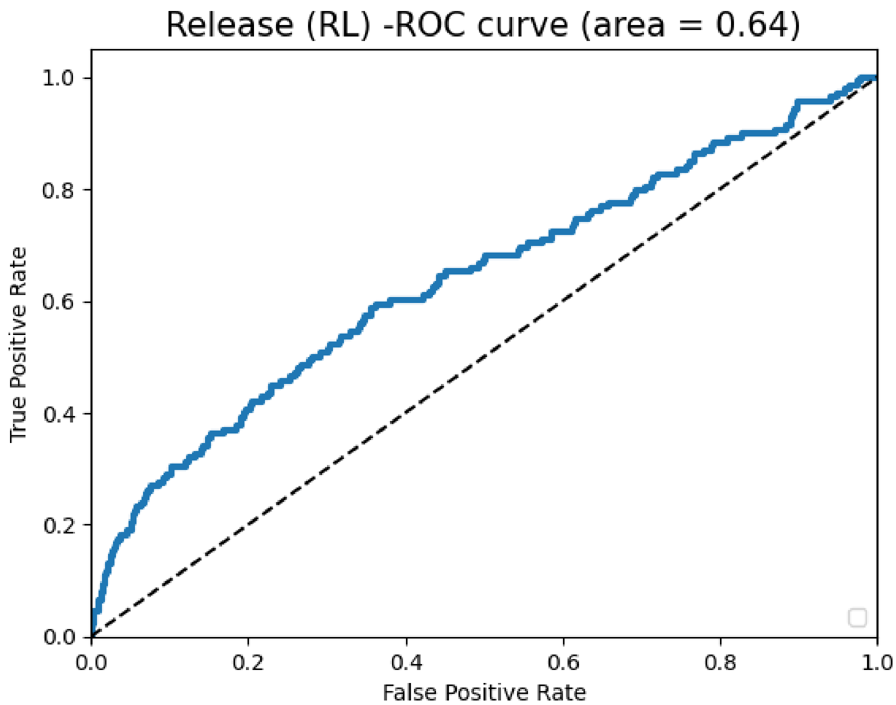
6.3.3.4. ROC curve for Hold :-



6.3.3.5 ROC curve for Replace :-



6.3.3.6 ROC curve for Release :-



6.3 Comparison between CNN and LSTM results :-

The Loss during the training of model by CNN is less thanloss during the training of model by LSTM. The validation accuracy of model by LSTM is ___________ the validation accuracy of model by CNN.

The proposed CNN-based model has outputted better results than the other LSIM-based model, notably 12.6 %, as the former has adequate feature learning capability. Furthermore, our testing results have pointed out that the CNN can produce what LSIM has been applied for and is excellent at predicting the events in the WAY-EEG-GAL dataset but in a much faster, more computationally effective fashion.

The layers, kernel size with its initialization and others of the proposed CNN-based detection model will be tuned in the future to obtain the best network for the same task and dataset. The optimum channels from the 32-channel EEG signal will also be estimated to reduce the computational burden for the real-time appliances.

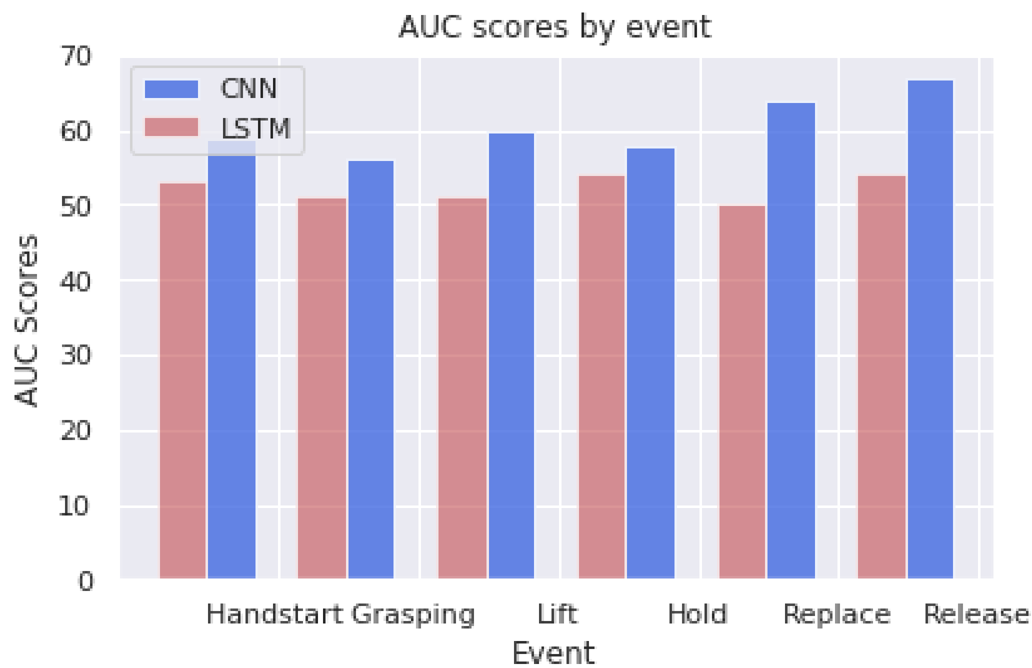


Fig :- **Comparison of CNN and LSTM by Area under the ROC Curves**

From above graphs And Results we conclude that the CNN performing better than LSTM

Chapter 7

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