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

In Partial Fulfillment of the Requirements for the
Degree of
Bachelor of Technology

By

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Approval Sheet

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Certificate

This is to certify that the thesis entitled, "Grasp and lift of an Object by EEG signals", submitted by Kummandas Meena(2020KUCP1056) ,Yogesh Meena(2020KUCP1032) ,Manish Kumawat(2020KUCP1034) in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in Computer Science & Engineering at Indian Institute of Information Technology Kota is an authentic work carried out by him under my supervision and guidance.

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Thank you

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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.OneVsRest with SGD and ClassifierChain with GaussianNB are two multi-label classification techniques employed in machine learning. OneVsRest with SGD utilizes a linear model with stochastic gradient descent, offering robust performance across multiple labels. On the other hand, ClassifierChain with GaussianNB adopts a probabilistic approach using Gaussian Naive Bayes, chaining classifiers to capture label dependencies. In comparative evaluations, OneVsRest with SGD consistently outperforms ClassifierChain with GaussianNB, showcasing its efficacy in handling multi-label classification tasks.

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Abbreviations

Chapter	Abbreviation	Description
1	EEG	Electroencephalogram
1	GAL	Grasp and Lift
1	WT	Wavelet tranformation
1	CNN	Convolutional neural network
1	LSTM	Long short term memory
4	ROC	Reciever operating characteristic curve
5	SGD	Stochastic Gradient Descent
1	EMG	Electromyographic signal
6	WPT	Wavelet packet transform
5	IIR	Infinte impulse response
5	DRL	Deep reinforcement learning
5	DQN	Deep Q network
6	AUC	Area under curve
6	PCA	Principal component analysis
6	DWT	Discrete Wavelet transform
2	BCI	Brain Computer Interface
2	VAE	Variational Autoencoder

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Ch a p t e r 1

INTRODUCTION

The rising interest in utilizing brain signals to control external devices, particularly through electroencephalography (EEG), presents promising avenues for individuals with motor disabilities to regain autonomy and dexterity. This project aims to explore the feasibility of using EEG signals to command six specific hand actions crucial for object manipulation tasks, offering potential applications in robotics and assistive technology. Leveraging advanced machine learning techniques like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and deep reinforcement learning, we endeavor to decode EEG signals associated with different hand actions, thereby enhancing control capabilities. In the realm of multi-label classification, we delve into the efficacy of methodologies such as OneVsRest with Stochastic Gradient Descent (SGD) and ClassifierChain with Gaussian Naive Bayes, scrutinizing their abilities to predict multiple labels accurately. By delving into the nuances of spatial feature extraction by CNNs and temporal context modeling by LSTMs, we aim to contribute to the advancement of EEG-based control systems, with a keen focus on fostering independence and quality of life for individuals with motor impairments. Additionally, we incorporate deep reinforcement learning techniques to further bolster the system's control capabilities, paving the way for adaptive and dynamic hand action control. This study endeavors to shed light on the strengths and limitations of various classification methodologies, ultimately striving towards the development of more effective and inclusive assistive technologies.

Multi-label classification is a challenging machine learning task where instances can belong to multiple classes simultaneously. In this context, two prominent techniques, OneVsRest with SGD and ClassifierChain with GaussianNB, have emerged to address the complexities of predicting multiple labels. 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
.
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.
OneVsRest with SGD leverages a linear model and stochastic gradient descent, offering scalability and efficiency in handling large-scale multi-label datasets. On the other hand, ClassifierChain with GaussianNB employs a probabilistic approach, utilizing Gaussian Naive Bayes and chaining classifiers to model label dependencies effectively. This study explores and compares the performance of OneVsRest with SGD and ClassifierChain with GaussianNB in multi-label classification scenarios, shedding light on their strengths and limitations in capturing label correlations and achieving high prediction accurac

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 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.

Multi-label classification has gained significant attention in the field of machine learning due to its applicability in various real-world scenarios. The OneVsRest with SGD technique has been widely studied and applied in the context of handling multi-label datasets efficiently. Its use of a linear model with stochastic gradient descent allows for scalability and adaptability to large-scale datasets. In contrast, ClassifierChain with GaussianNB has been explored for its probabilistic approach to multi-label classification, leveraging Gaussian Naive Bayes and chaining classifiers to model dependencies between labels effectively.

Previous research has delved into the strengths and weaknesses of these techniques. OneVsRest with SGD has demonstrated success in scenarios with numerous labels, offering competitive performance and computational efficiency. Meanwhile, ClassifierChain with GaussianNB has shown promise in capturing complex label dependencies, making it suitable for applications where the correlation between labels significantly impacts the predictive performance.

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.

C h a p t e r 4

DATASET

Data contains EEG recordings of subjects performing grasp-and-lift (GAL) trials. 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

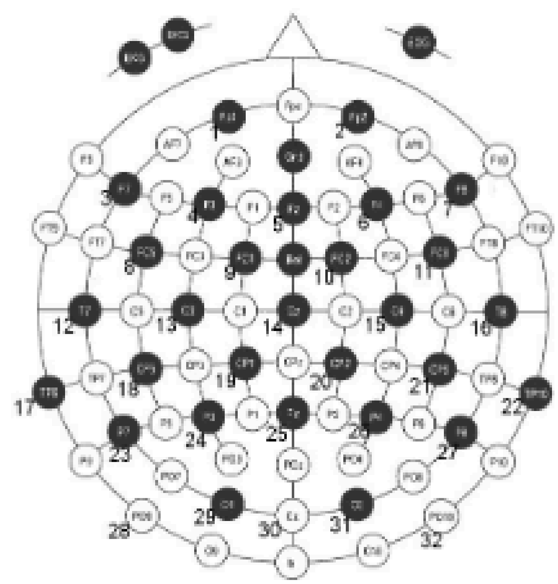

Fig. 1 :- EEG Recording of signals

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,

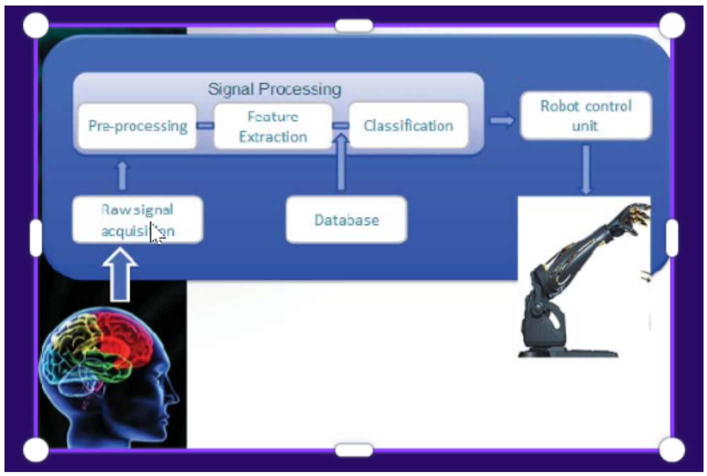

Fig. 2 :- Methodology of Model

The system's methodology consists of five main steps. The first step was Signal acquisition, that has been done using Emotiv headset. The second step was signal preprocessing, to remove the noises and unwanted data. The third step was features extraction from the EEG signals. The fourth step was classification of the signals to three classes that corresponding to the three arm movements.

5.1 Feature extraction:-

Wavelet transformation and Butterworth filters are fundamental techniques employed in the preprocessing of electroencephalogram (EEG) signals, pivotal in cognitive neuroscience research.

5.1.1 Wavelet Transformation:

Decomposition: Wavelet transformation enables the decomposition of EEG signals into different frequency sub-bands, facilitating the simultaneous analysis of temporal and frequency information. It involves selecting an appropriate wavelet basis, such as Daubechies or Morlet, based on signal characteristics and frequency components of interest.

Feature Extraction: Post-decomposition, coefficients representing the contribution of various frequency sub-bands to the original EEG signal are obtained. These coefficients serve as features for subsequent analysis, capturing both temporal and frequency information

.

Dimensionality Reduction: As EEG signals are often high-dimensional, techniques like Principal Component Analysis (PCA) or Wavelet Packet Transform (WPT) are applied to reduce feature space while retaining relevant information.

Feature Selection: Depending on the analysis task, feature selection methods, such as mutual information or correlation-based selection, are employed to identify discriminative features for classification or control.

5.2.2 Butterworth Filters:

Filter Design: Butterworth filters, categorized as infinite impulse response (IIR) filters, are designed based on parameters like filter type (low-pass, high-pass, or band-pass), order, and cutoff frequencies. The selection of these parameters balances noise reduction and signal preservation.

Filter Application: Implemented using Python libraries like scipy.signal, Butterworth filters are applied to raw EEG data to selectively allow specific frequency bands associated with brain activity while attenuating noise.

Frequency Refinement: Careful selection of cutoff frequencies refines the EEG signal, isolating relevant frequency bands of interest, such as delta, theta, alpha, beta, and gamma waves.
Feature Extraction: Post-filtering, various feature extraction techniques, including time-domain features like mean and variance, frequency-domain features like power spectral density, and time-frequency features extracted using wavelet transform, are applied to extract meaningful information from the EEG signal.

Integration with Machine Learning: The enriched EEG data, refined through Butterworth filtering and feature extraction, can be integrated with machine learning algorithms for tasks such as classification or regression, enabling the detection of patterns and relationships associated with cognitive states or neurological conditions.

Both wavelet transformation and Butterworth filters are indispensable tools in the preprocessing pipeline for EEG data, facilitating the extraction of relevant information and paving the way for deeper insights into brain function and cognition.

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 -   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:

Preprocessing: The EEG signal dataset is preprocessed to remove noise, filter out unwanted frequencies, and extract relevant features.

Agent-Environment Interaction: The DRL model consists of an agent and an environment. The agent takes the preprocessed EEG signals as input and interacts with the environment,

State Representation: The agent represents the current state of the EEG signals in a suitable format for the DRL model.

Action Selection: Based on the current state, the agent selects an action to perform.

Reward Calculation: After taking an action, the agent receives a reward from the environment. The reward indicates the desirability or performance of the action taken.

Learning and Optimization: The agent uses the received reward to update its decision-making policy or value function. This is done through techniques DQN-learning or policy gradient methods.

5.4.1 DQN Algorithm

The DQN (Deep Q-Network) process is a variant of Q-learning that combines deep neural networks with reinforcement learning

Here's an overview of how the DQN algorithm works:

Environment: The DQN algorithm operates in an environment where an agent can take actions and receives rewards based on its actions.

Q-Network: A deep neural network is used to approximate the Q-values, which represent the expected future rewards for each possible action in a given state.

Experience Replay: DQN utilizes an experience replay buffer to store the agent's experiences. Each experience consists of a state, action, reward, and next state.

Epsilon-Greedy Exploration: To balance exploration and exploitation, the DQN algorithm uses an epsilon-greedy strategy.

Training Process: The DQN algorithm uses a variant of the Q-learning update rule called the Bellman equation to update the Q-network's weights.

$$Q(s, a) = Q(s, a) + \alpha * (r + \gamma * \max(Q(s', a')) - Q(s, a))$$

Here, Q(s, a) Q-value for state s and action a, α is the learning rate, r is the received reward, γ is the discount factor. s' is the next state, and a' is the action taken in the next state.

Target Network: DQN introduces a target network that is a copy of the Q-network. This network is used to calculate the target Q-values during training, while the Q-network is used to select actions.

5.5 OneVsRestClassifier and SGDClassifier:-

Our approach involves the use of OneVsRestClassifier in conjunction with SGDClassifier for efficient multi-label classification.

OneVsRestClassifier

The OneVsRestClassifier strategy is implemented to address the multi-label nature of the EEG signal classification problem. For each event label, a separate binary classifier is trained. This simplifies the task by treating each label as an independent binary classification problem, predicting the presence or absence of a specific event.

SGDClassifier

The SGDClassifier is chosen as the base classifier within OneVsRestClassifier. This linear classifier employs the stochastic gradient descent optimization algorithm, making it well-suited for large datasets. The versatility of SGDClassifier allows it to adapt to different loss functions and penalties, offering flexibility in model configuration.

The combination of OneVsRestClassifier and SGDClassifier provides a pragmatic approach to EEG signal classification. While the independence assumption simplifies the task, The efficiency of SGDClassifier in handling large datasets contributes to the project's success in predicting grasp-and-lift events from EEG signals.

5.6 GaussianNB with ClassifierChain

we delve into the detailed implementation and evaluation of the ClassifierChain strategy coupled with the GaussianNB (Gaussian Naive Bayes) classifier. It extends the traditional binary relevance approach by considering label dependencies. Within this framework, GaussianNB is chosen as the base classifier. GaussianNB assumes that features follow a Gaussian distribution, making it suitable for continuous data like EEG signals.

ClassifierChain:

ClassifierChain is a problem transformation technique that takes label dependencies into account. It creates a chain of binary classifiers, each trained to predict a specific event label while considering the outputs of the preceding classifiers.

GaussianNB:

Gaussian Naive Bayes is a probabilistic classifier based on Bayes' theorem with the assumption of feature independence given the class.It is particularly effective for continuous features, making it suitable for EEG signal classification.

The combination of ClassifierChain and GaussianNB represents a sophisticated strategy for EEG signal classification. While the assumption of feature independence in GaussianNB may be limiting, the ClassifierChain approach compensates by considering label dependencies.

Chapter 6

EXPERIMENTAL RESULTS

6.1 Feature extraction:

6.1.1 Wavelet transformation :-

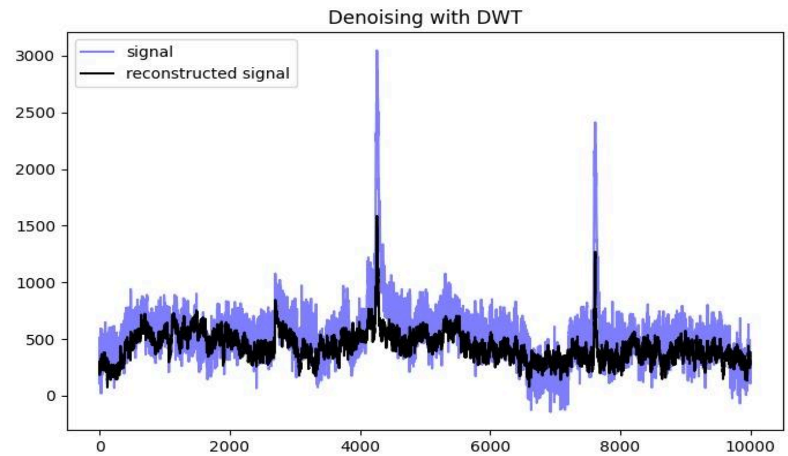

Fig 3 : Wavelet transformation of EEG signal

The blue signal represent the original signal and blue signal represent the reconstructed signal after preforming the wavelet transformation .

6.2.2 Butter Worth transformation :-

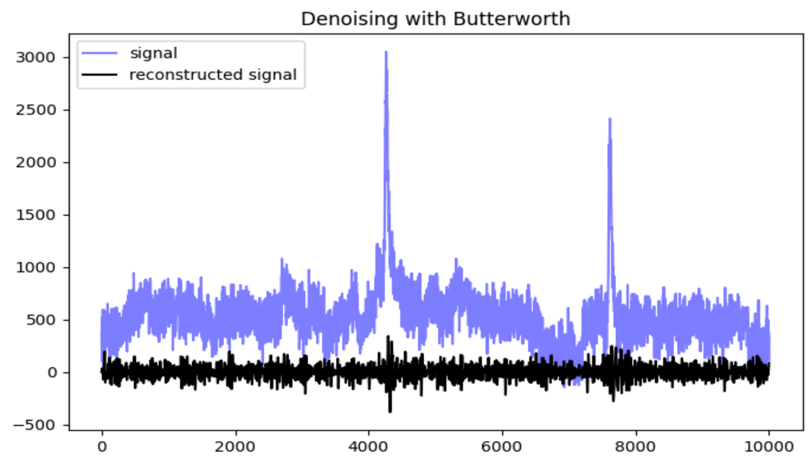

Fig 4 :- Butter worth transformation of Egg Signals

In this figure ,Blue signal represent the original signals and black signals represent the reconstructed signals.

6.2 Result of Convolutional neural network :-

6.2.1 Training Accuracy and Validation Accuracy:-

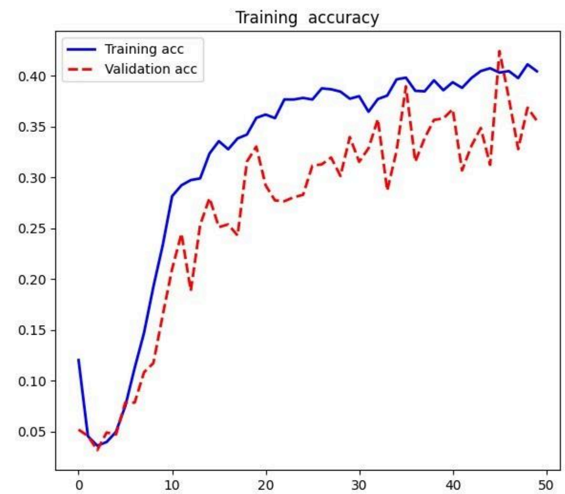

Fig 5 : Training Accuracy and Validation Accuracy

As the size of dataset and no of epochs is increasing ,the Training and Validation accuracy is increasing .

6.2.2 Training Loss and Validation Loss :-

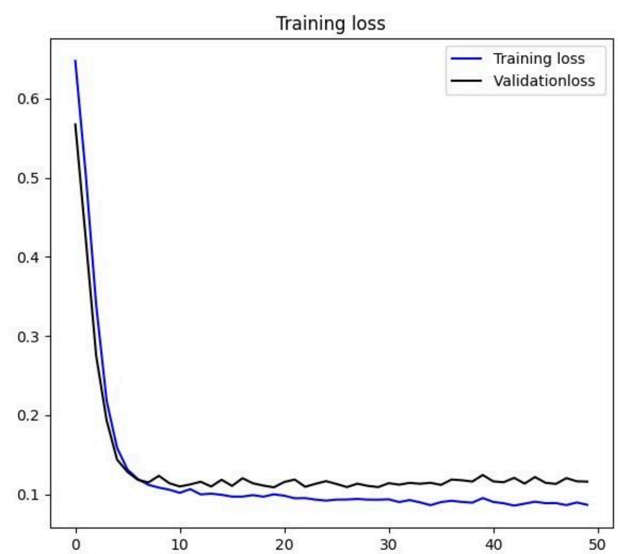

Fig 6 :- Training loss and Validation loss

From this Graph ,we conclude that training loss and Validation loss is decreasing as number of epochs and dataset is decreasing . The training loss is decreasing from the 0.68 to 0.9 . and the validation loss is decreasing from 0.56 to 0.12.

6.2.3 Receiver Operating Characteristic Curves(ROC curves): -

6.2.3.1 HandStart class :-

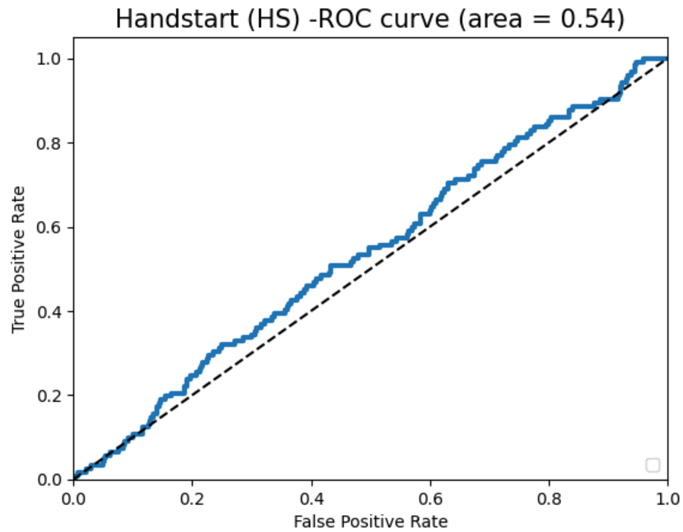

Fig 7 : - Roc curve of Handstart class

From this graph ,we can see that the handstart is performing at most of time .In starting the probability of performing the handstart action is equal to the not performing the action.

6.2.3.2 Grasping class :-

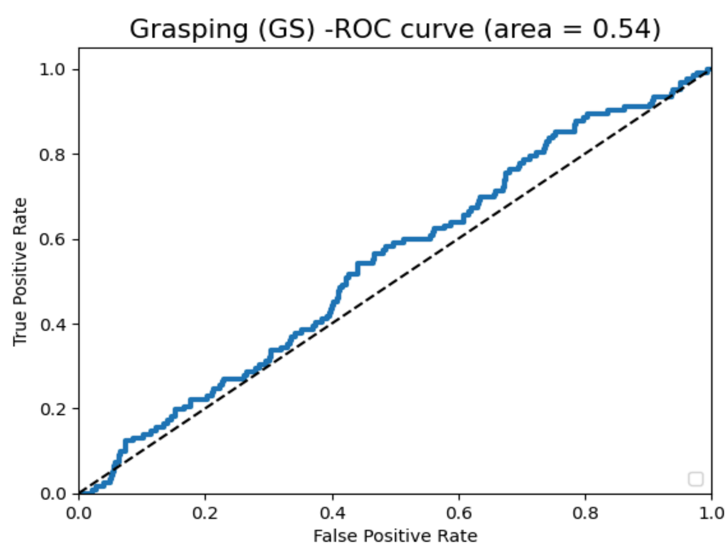

Fig 8 :- Roc curve of Grasping class

From this graph ,we can see that the handstart is performing at most of time .In starting the grasping task is not performing then ,after it is performing well.

6.2.3.3 Lift class :-

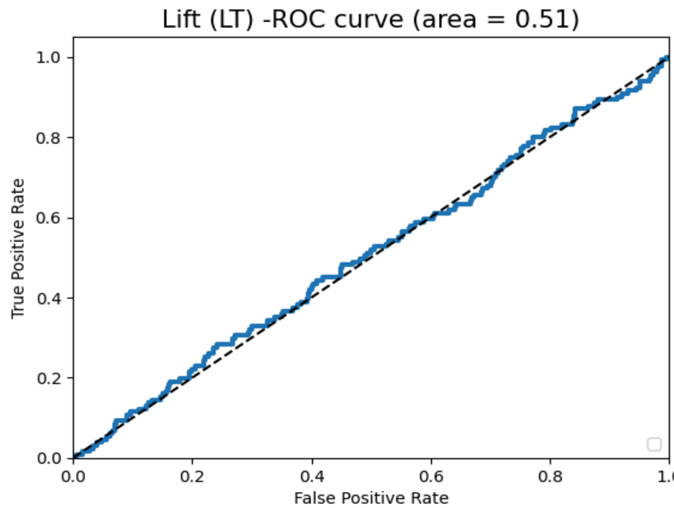

Fig 9:- Roc curve of lift class

From this graph ,we can see that the probability of handstart is low in comparison of grasp and handstart , At sometime ,it is not able to perform the action .

6.2.3.4 Holding class:-

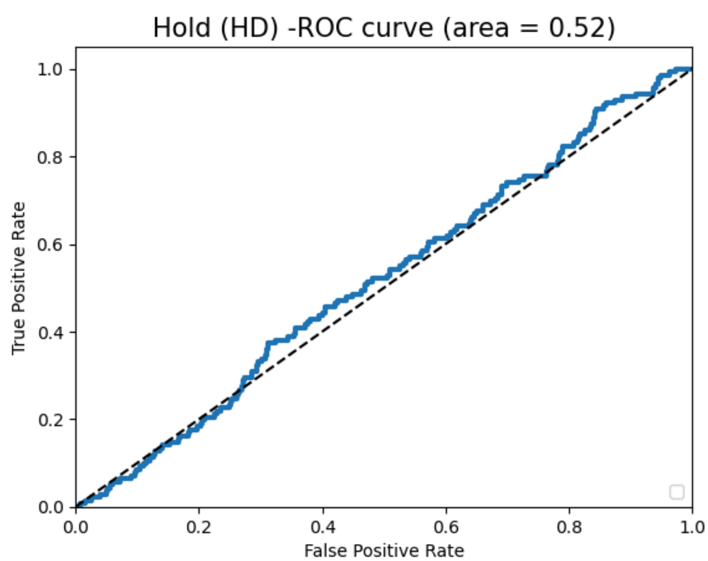

Fig 10: Roc curve of Holding class

From this graph ,we can see that the Holding is performing at most of time .In starting the Holding is not performing because the false positive rate is greater than true positive rate.

6.2.3.5 Replace class :-

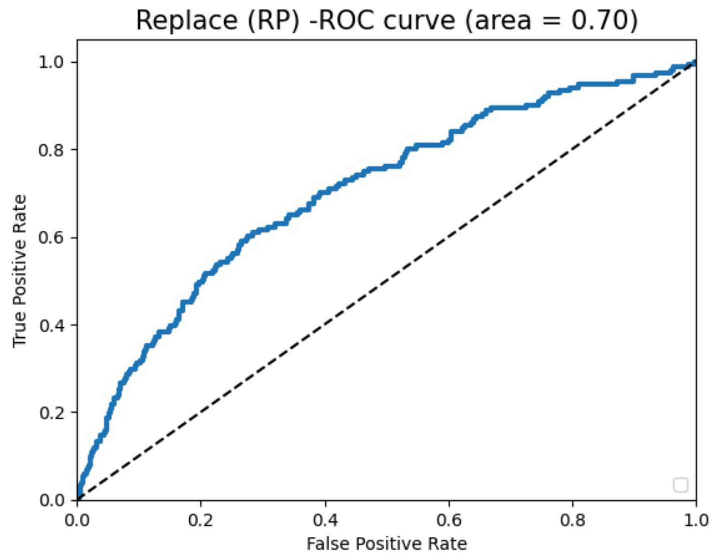

Fig 11:- Roc curve of Replace curve .

From this graph ,we can see that the Replace is performing at almost of time because the probability of true positive rate is greater than the false positive rate

6.2.3.6 Release Curve :-

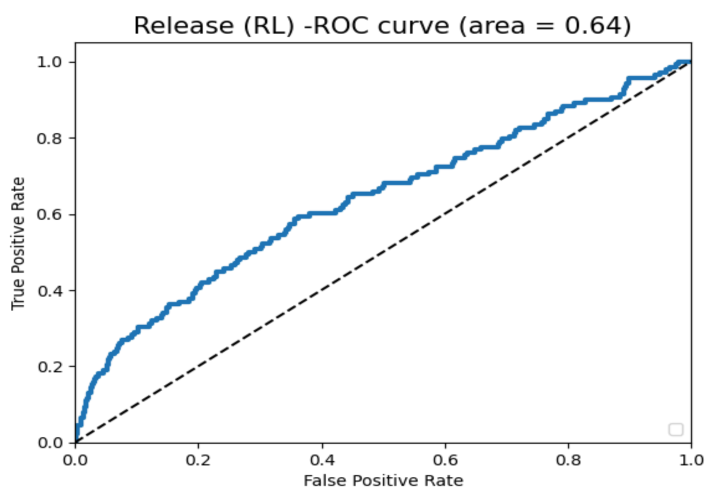

Fig 12:- Roc curve of Release class

From this graph ,we can see that the release task is performing at allmost of time .The true positive rate is greater than the false positive rate for all time .

6.3 Long Short Term Memory Results :-

6.3.1 Training Accuracy and Validation Accuracy :-

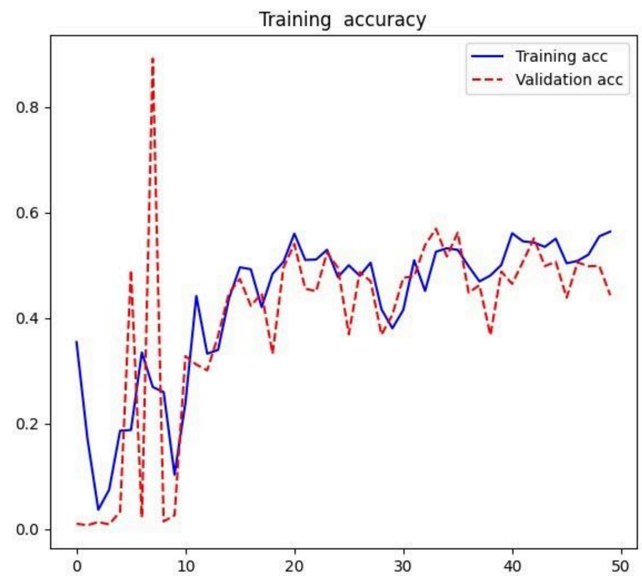

Fig 13: -Training and validation Accuracy

As the size of dataset and no of epochs is increasing ,the Training and Validation accuracy is increasing .

6.3.2 Training Loss and Validation Loss :-

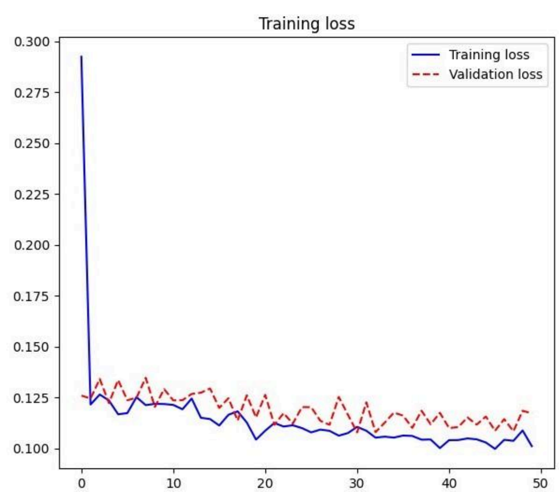

Fig 14:- Training loss and validation loss

As the size of dataset and no of epochs is increasing ,the Training and Validation loss is increasing .The training loss is nearly equal to the 0.15 and validation loss is nearly equal to the 0.120

6.4 **OneVsRestClassifier and SGDClassifier**

6.4.1 ROC curves of OneVsRestClassifier and SGDClassifier

6.4.1.1 Handstart :-

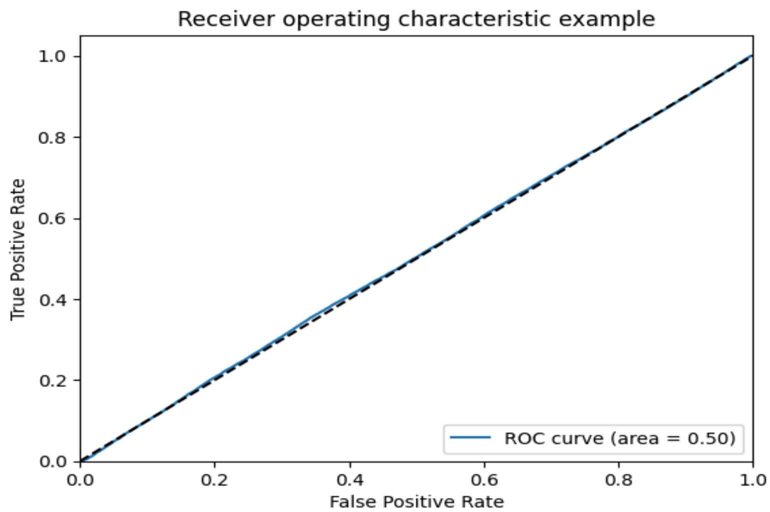

Fig 15:- ROC curve of handstart task

From this graph ,we can see that the handstart task is performing at 50 % .The true positive rate is equal to or slightly greater than the false positive rate .

6.4.1.2 Grasp:-

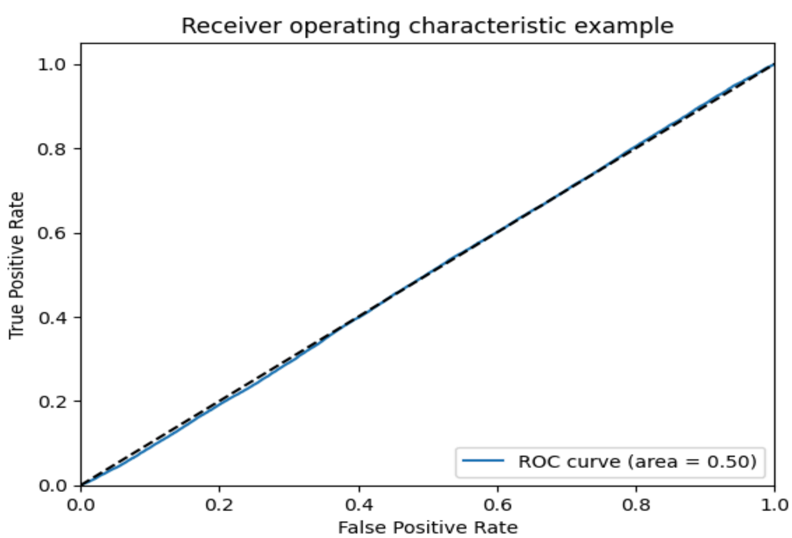

Fig 16:- ROC curve of grasp task

From this graph ,we can see that the grasp task is performing at 50 % rate .The true positive rate is equal to or slightly greater than the false positive rate .

6.4.1.3 Liftoff:-

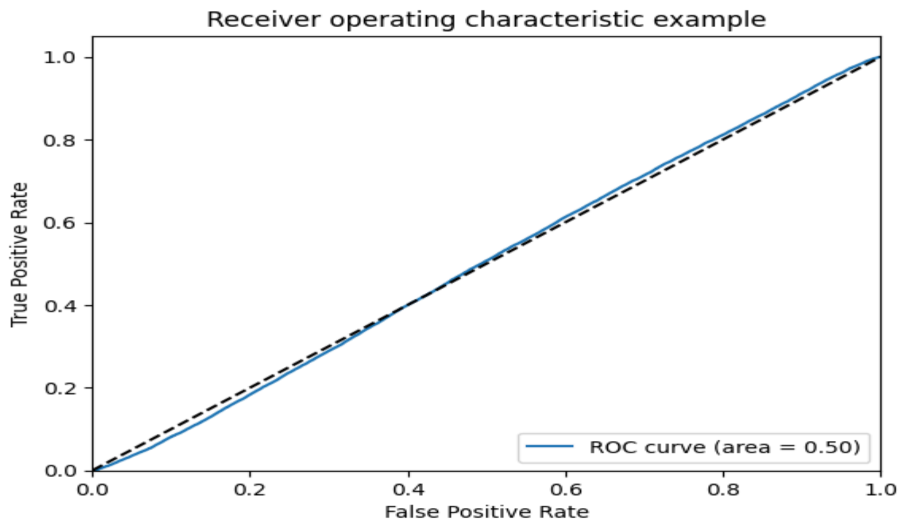

Fig 17:- ROC curve of liftoff task

From this graph ,we can see that the lift off task is performing at 50 % .The true positive rate is equal to or slightly greater than the false positive rate .

6.4.1.4 Holding the objects:-

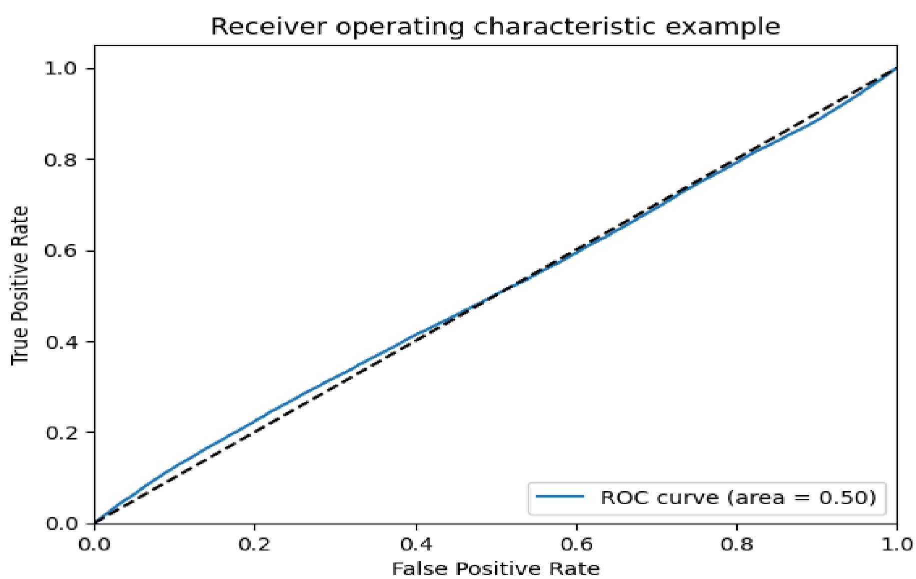

Fig 18 :- ROC curve of Holding the object task

From this graph ,we can see that the holding the task is performing at 50 % .The true positive rate is equal to or slightly greater than the false positive rate .

6.4.1.5 Replace :-

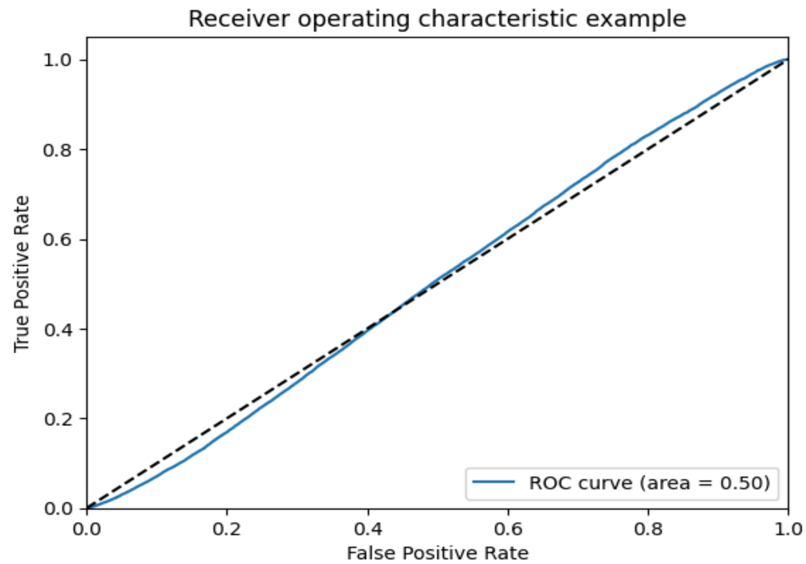

Fig 19:- ROC curve of Replace task

From this graph ,we can see that the replace task is performing at 50 % .The true positive rate is equal to or slightly greater than the false positive rate . and in starting the replace task is not happening.

6.4.1.6 Release :-

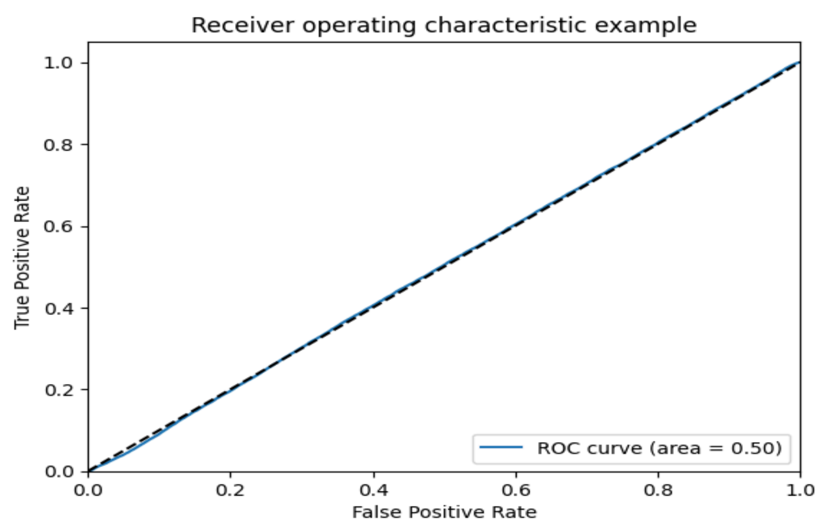

Fig 20 :- ROC curve of Release task

From this graph ,we can see that the Relase task is performing at 50 % .The true positive rate is equal to or slightly greater than the false positive rate .

6.6 Comparison between CNN and LSTM results :-

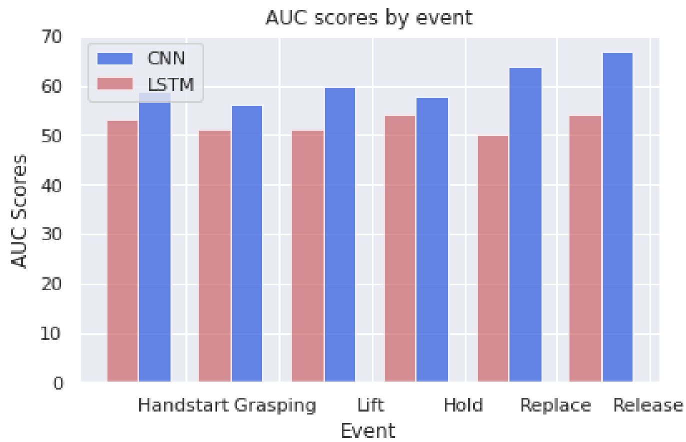

Fig 21:- Comparison of CNN and LSTM by Area under the ROC Curves

During the training phase, the CNN model exhibits lower loss values compared to the LSTM model. Conversely, when it comes to validation accuracy, the LSTM model showcases higher performance than the CNN model. However, in terms of event prediction, the CNN outshines the LSTM model by a significant margin of 12.6%, showcasing its superior feature learning capabilities. Moreover, efforts will be made to identify the most effective channels from the 32-channel EEG signal to alleviate computational complexity in real-time applications. Additionally, the CNN model demonstrates a higher Area Under Curve (AUC) for GAL events, implying better performance compared to the LSTM model in this regard.

6.7 Comparison between OneVsRestClassifier with SGDClassifier and GaussianNB with ClassifierChain :-

In the context of EEG signal classification, the choice between OneVsRestClassifier with SGDClassifier and GaussianNB with ClassifierChain depends on the nature of EEG data. OneVsRest with SGDClassifier is suitable for handling high-dimensional data, often seen in EEG signals, and is effective for tasks with numerous classes. However, its linear nature may struggle with capturing intricate non-linear relationships inherent in EEG patterns, necessitating careful feature scaling.OneVsRest with SGD have the higher accuracy than GaussianNB with classifierChain.On the other hand, GaussianNB with ClassifierChain is advantageous for multilabel EEG signal classification, where different brain activities may coexist. While GaussianNB assumes feature independence, which might not fully align with the complex relationships in EEG data, its interpretability can be valuable in certain applications.

C h a p t e r 7

CONCLUSION AND FUTURE WORK

The project findings reveal that convolutional neural networks (CNN) are effective in capturing spatial features, while long short-term memory networks (LSTM) excel in modeling temporal patterns. Multi-label strategies like OneVsRestClassifier and ClassifierChain, leveraging GaussianNB as a base classifier, demonstrate proficiency in handling simultaneous events in EEG signals. The use of wavelet transform and Butterworth filter for feature extraction proves valuable, showcasing diverse techniques' complementary roles. The upcoming exploration with LabelPowerset and GaussianNB aims to enhance accuracy by addressing intricate event relationships, providing a holistic approach to EEG signal classification. Overall, this study contributes to the optimization of predictive models for real-world applications involving grasp and lift movement detection.

In this comprehensive study, we investigated four distinct techniques for multi-label classification, namely Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), OneVsRest with Stochastic Gradient Descent (SGD), and ClassifierChain with Gaussian Naive Bayes (GaussianNB). Additionally, we explored the application of signal processing techniques, including Wavelet Transform and Butterworth filtering, coupled with appropriate preprocessing steps to enhance the performance of these models.

The CNN and LSTM models exhibited varying degrees of success across different events, as reflected in their Area Under the Curve (AUC) scores. While the CNN model demonstrated superior performance in events such as Replace and Release, the LSTM model outperformed in events like Handstart and Grasping. These findings emphasize the importance of considering the nature of the data and event characteristics when selecting deep learning architectures for multi-label classification

The traditional machine learning techniques, OneVsRest with SGD and ClassifierChain with GaussianNB, provided alternative perspectives. OneVsRest with SGD consistently demonstrated competitive AUC scores across multiple events, showcasing its versatility and efficiency in handling complex label structures. On the other hand, ClassifierChain with GaussianNB exhibited a probabilistic approach that leverages label dependencies effectively, yielding promising results in certain events.

Chapter 8
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