EEG Motor Imagery Classification using Graph Neural Network with Spatial Graph Convolution

Thesis to be submitted in partial fulfillment of the requirements for the degree

of

MTech

by

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CERTIFICATE

This is to certify that we have examined the thesis entitled **EEG Motor Imagery Classification using Graph Neural Network with Spatial Graph Convolution**, submitted by **Shukrayani Sanjay Redkar**(Roll Number: *19CS60R31*) a postgraduate student of **Department of Computer Science and Engineering** in partial fulfillment for the award of degree of MTech. We hereby accord our approval of it as a study carried out and presented in a manner required for its acceptance in partial fulfillment for the Post Graduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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Place: Kharagpur
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Shukrayani Sanjay Redkar
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Date:

ABSTRACT

Electroencephalogram (EEG) as a typical neuroimaging tool for the study of neuronal dynamics within the human brain. EEG signals measure the neuronal activities on different brain regions through electrodes. Existing studies don't exploit the topological structure of EEG signals effectively. Graph signal-based deep learning method for electroencephalography (EEG) to implement EEG-based motor imagery classification. We present some methods to effectively represent EEG data as signals on graphs, and learn them using graph convolutional neural networks. Experimental results for motor imagery classification using EEG responses. Effective schemes for graph signal representation of EEG also are discussed.

Keywords: Graph Neural Network, Motor Imagery Classification, EEG data, Conversion Of EEG data to graph structure.

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Chapter 1

Introduction

1.1 Motivation

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The brain-computer interface (BCI) is an alternative method of communication between a user and system that depends on neither the brain's normal output nerve pathways nor the muscles. The process generally begins by recording the user's brain activities and continues to signal-processing to detect the user's intentions. Then, the appropriate signal is sent to the external device, which is then controlled according to the detected signal. One of the important goals of BCI research is to enhance certain functions for a disable person via a new signal pathway. Electroencephalogram (EEG) signals produced while mentally imagining different movements can be translated into different commands. In this project, we refer to the brain potentials related to motor imagery tasks as control signals. In the near future, BCI has notable potential to become a major tool used by people with disabilities to control locomotion and communicate with surrounding environment and, consequently, improve the quality of life for many affected persons.Electrical field recording at the scalp (i.e. electroencephalography) is the more popular method to be of practical value for clinical use as it is simple and non-invasive. However, some aspects need future improvements, such as spatial resolution.

1.2 Scope And Objective

Graph signal processing is a way to study and analyze signals having irregular structures, where a signal residing on vertices of a graph (instead of regular intervals or

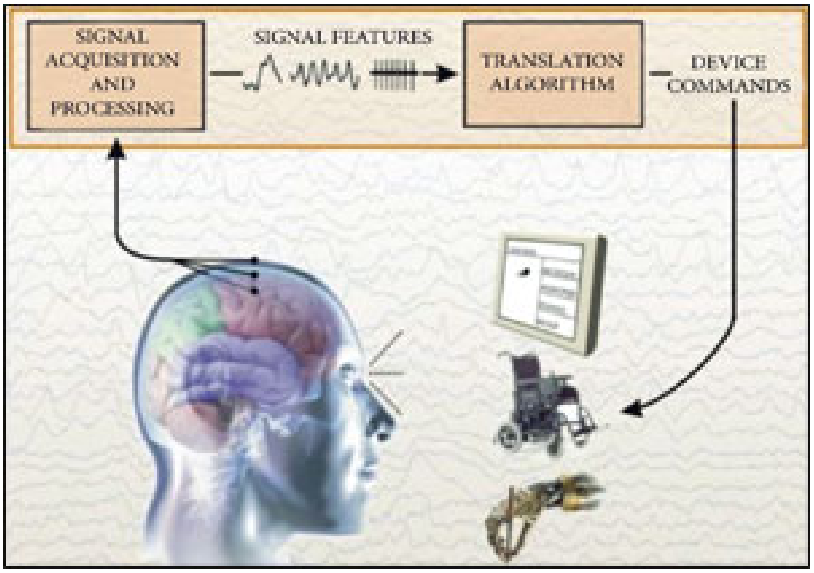


Figure 1.1: workflow of BCI system

grids) is defined and processed. The brain signal typically has an non-euclidean structure, which can be modeled as a graph signal. Since it contains much information of the human mental state, several applications such as neurological disease detection, emotion recognition, and behavior modeling have been developed. Our aim is to study this toplogical structure of Electroencephalogram signals and classify them. Electroencephalogram is widely used in this area to record the electrical signals on the scalp. Electroencephalogram technique is used because of its high temporal resolution, portability and noninvasiveness.

Objectives:
1.Explore different parameters to create topological graph where channels as nodes and strength of interaction as edges.
2.Design a graph convolutional neural network model to classify topological graph of EEG signals.
3.Compare model results with other standard ML and DL models.
4.To get the generalised results, collect multiple standard EEG motor imagery datasets from MOABB(Mother Of All BCI Benchmark datasets) dataset and execute model over these datasets and compare the results.

Chapter 2

Literature Survey

2.1 Neuroimaging

Neuroimaging is the process of creating the images of activity or structure of brain and regions of central nervous system[Bunge & Kahn (2009)].There are many available neuroimaging techniques and important details are mentioned in the figure 2.1 and 2.2.

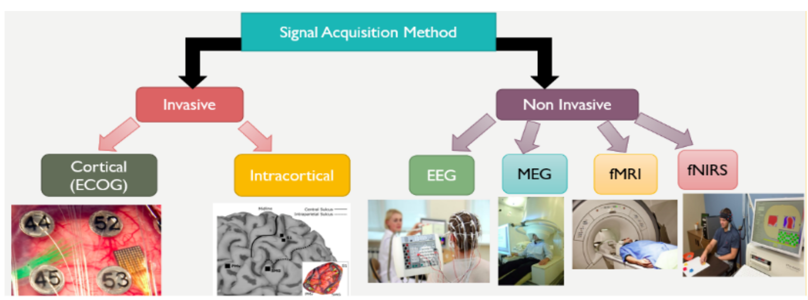


Figure 2.1: Neuroimaging techniques

In this study **electroencephalogram** technique is used. EEG technique in this area getting popularity because of its good time resolution, non-invasiveness and portability. EEG detects electrical activity of the brain. Electrodes are placed on the scalp. These electrodes detects the electrical signal which are result of activities of brain cells.

There are many applications of EEG signals and it is widely used in medical science descipline. In the recent few years its been used in the field of brain computer interface to control the surrounding environment without muscle movements. The electroencephalogram (EEG) measures the activity of large numbers (populations) of

Neuroimaging method	Activity measured	Direct/ Indirect Measurement	Temporal resolution	Spatial resolution	Risk	Portability
EEG	Electrical	Direct	~0.05 s	~10 mm	Non-invasive	Portable
MEG	Magnetic	Direct	~0.05 s	~5 mm	Non-invasive	Non-portable
ECoG	Electrical	Direct	~0.003 s	~1 mm	Invasive	Portable
Intracortical neuron recording	Electrical	Direct	~0.003 s	~0.5 mm (LFP) ~0.1 mm (MUA) ~0.05 mm (SUA)	Invasive	Portable
fMRI	Metabolic	Indirect	~1 s	~1 mm	Non-invasive	Non-portable
NIRS	Metabolic	Indirect	~1 s	~5 mm	Non-invasive	Portable

Figure 2.2: Details of Neuroimaging techniques

neurons. EEG based motor imagery task identification has been employed to manipulate the surrounding via neural activities. Traditional work on EEG data doesn't consider the topological relationship between nodes. But the neuroscience research suggest to work on topological relationship of electrodes to improve the efficiency.

2.2 Brain Connectivity:

Brain connectivity[Leisman et al. (2016)] refers to a pattern of anatomical links, statistical dependancies or of casual interactions between different regions of nervous system. This statistical or casual relationship can be measured by coherence, correlation etc. Brain connectivity can be studied and analyzed using network analysis aprroaches. Graph Theory is measurely deals with directed graphs and it can be applied to anatomical connectivity, structural connectivity and effective connectivity. Graphs are composed of vertices(brain regions) and edges(strength of connection between brain regions).

Brain Connectivity Analysis applications:
1.Brain connectivity[Leisman et al. (2016)] analysis can help to understand how human cognitive functions are associated with brain connectivity structure.
2.It can give more insight for pathophysiological processes in case of brain disconnection.

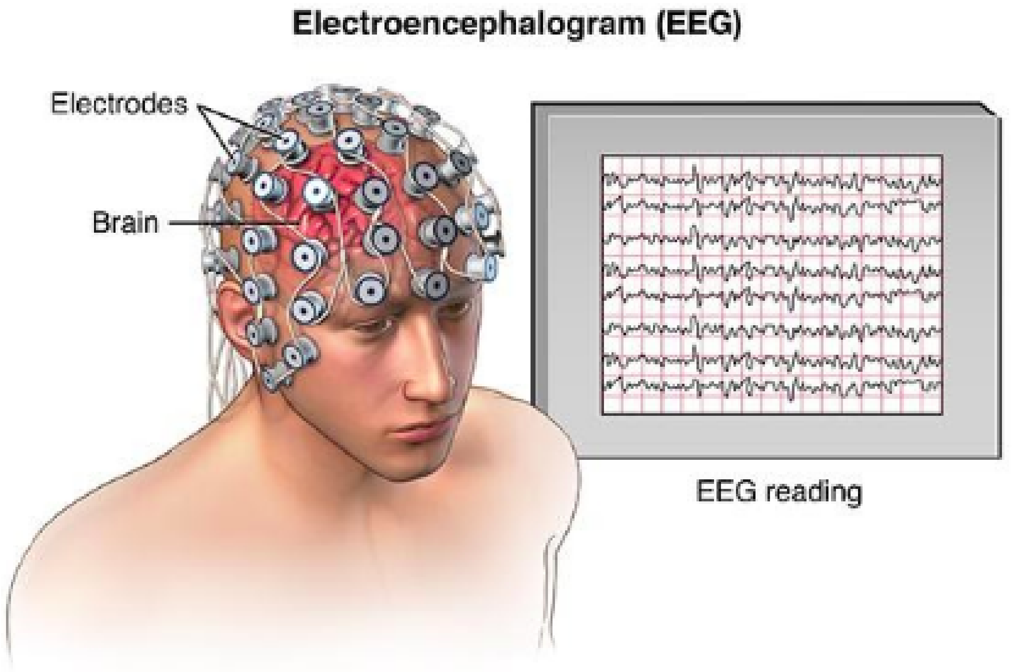


Figure 2.3: Electroencephalogram

3.It can monitor the impact of treatment in case of mental illness. brain connectivity.

2.3 Brain Computer Interface MI classification techniques

Motor imagery signals are recorded using EEG technique. As Motor Imagery based Brain computer Interface provides high degree of freedom, it helps disabled people to control the surrounding devices by performing sequence of Motor Imagery tasks. But challenges in the motor imagery classification is extracting features for every person while considering inter-subject variability. And keeping all these things in mind we need to increase accuracy of the classifier.

In all these methods features extracted from different domains such as statistical domain features, time domain features, wavelet based features etc.

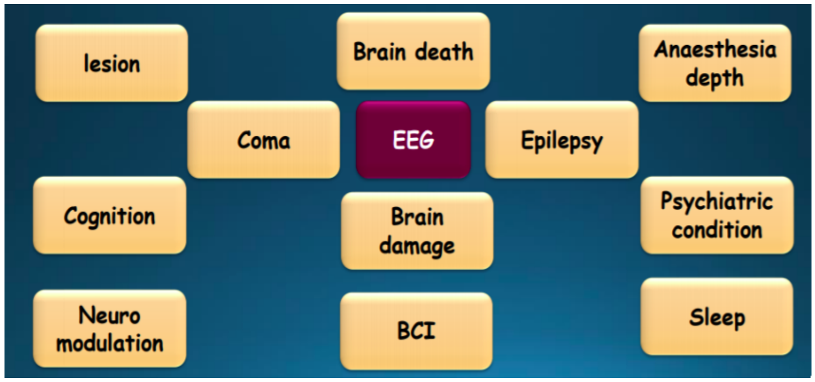


Figure 2.4: EEG applications

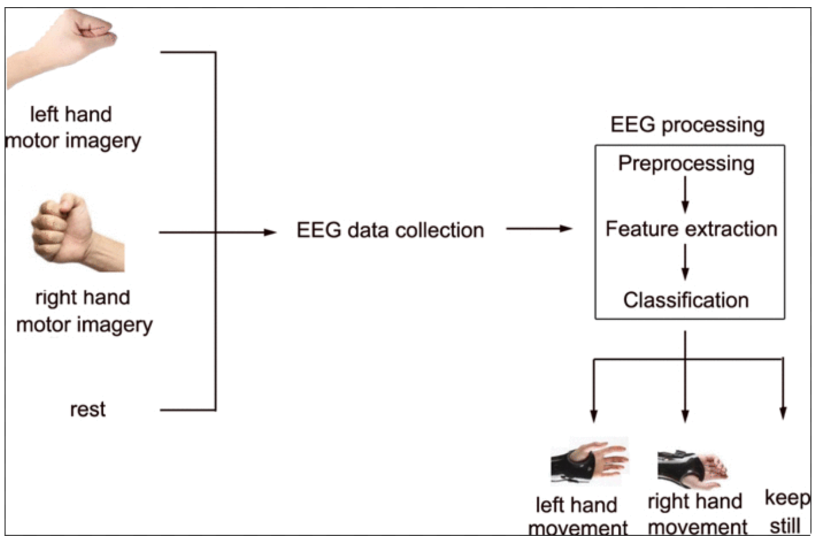


Figure 2.5: classification of motor imagery

Statistical Domain features gives the information about signal distribution. Statistical Domian features[Sreeja et al. (2017)] are mentioned below.

Table 1. Statistical features and their description.

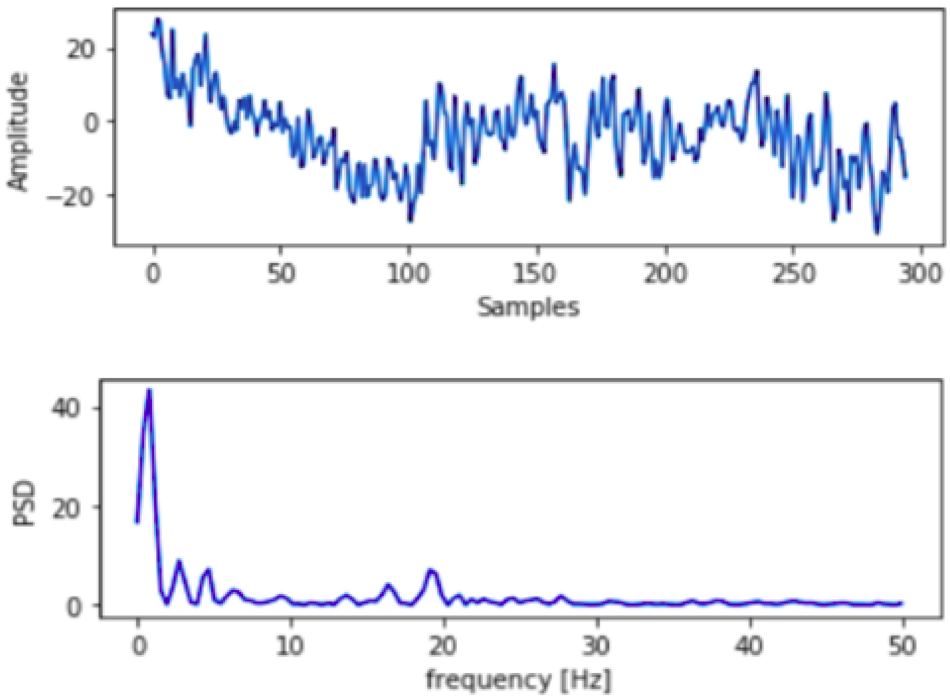
Parameters	Description
Mean	Mean value of the signal, $\mu_{X_i^{CSP}} = \frac{1}{N}\sum_{k=0}^{N-1} x_k$
Median	Median (middle) value of the signal
Standard deviation	Standard deviation of the signal, $\sigma_{X_i^{CSP}} = \sqrt{\frac{1}{N-1}\sum_{k=0}^{N-1}(x_k - \mu_{X_i^{CSP}})^2}$
Skewness	Asymmetry value of the signal, $S_{X_i^{CSP}} = \frac{\frac{1}{N}\sum_{k=0}^{N-1}(x_k-\mu_{X_i^{CSP}})^3}{{\sigma_{X_i^{CSP}}}^3}$
Kurtosis	Flatness measure of the signal, $K_{X_i^{CSP}} = \frac{\frac{1}{N}\sum_{k=0}^{N-1}(x_k-\mu_{X_i^{CSP}})^4}{({\sigma_{X_i^{CSP}}}^2)^2} - 3$
Maximum	Maximum positive amplitude
Minimum	Minimum negative amplitude

Time Domain Features captures the temporal information of signal. EEG provides good temporal resolution. So time domain features will play very important role in EEG motor imagery classification. Time domain features[Sreeja et al. (2017)] used for classification is:

Table 2. Time-domain features and their description.

Parameters	Description
Activity	Mean power/variance ($\sigma^2_{X_i^{CSP}}$)
Mobility	$\left(\frac{\sigma'_{X_i^{CSP}}}{\sigma_{X_i^{CSP}}}\right)$, where $\sigma'_{X_i^{CSP}}$ is the standard deviation of first derivative
Complexity	$\left(\frac{\sigma''_{X_i^{CSP}}}{\sigma'_{X_i^{CSP}}} / \frac{\sigma'_{X_i^{CSP}}}{\sigma_{X_i^{CSP}}}\right)$, where $\sigma''_{X_i^{CSP}}$ is the stand. devi. of second derivative
1st Diff. Mean and Max.	Mean and maximum value of the first derivative of the signal
2nd Diff. Mean and Max.	Mean and maximum value of the second derivative of the signal
Mean V-V slope	Mean of vertex to vertex (peak-peak) slope
Variance V-V slope	Variance of vertex to vertex (peak-peak) slope
Mean V-V amplitudes	Mean of vertex to vertex (peak-peak) amplitudes
Variance V-V amplitudes	Variance of vertex to vertex (peak-peak) amplitudes
Zero crossing	Number of times the signal crossing zero
Coeff. of variation	Ratio of standard deviation to the mean.

Frequency Domain Features captures information about brain waves during motor imagery tasks. Below are the examples of frequency domain features[Sreeja et al. (2017)]:



Chapter 3

Methodology

3.1 Objective

Processing of the electroencephalography (EEG) signals and extracting numerous forms of features made it possible to recognize the intention of a user performing a selection task among different options presented. Thus, the method can be applied to several specific tasks. The goal is to classify these activities in order to recognize the underlying MI task performed.

3.2 Flow Chart

In this study we have followed process as shown in the figure 3.1. Initially we have collected the data from BCI competition 4a. Channel selection, bandpass filtering and spatial filtering has been done on the dataset. After preprocessing we have extracted 52 features for every motor imagery task. Objective is to do the motor imagery classification through graph convolutional Network so for this purpose functional or effective connectivity must be measured. This connectivity is measured through many parameters like pearson correlation, partial correlation, phase locking value or granger causality etc. By using these parameters functional or effective connectivity can be represented in binary adjecency matrix or weighted graph matrix. Adjacency matrix along with features passed to the graph convolutional neural network. And output of graph convolutional neural network in terms of accuracy.

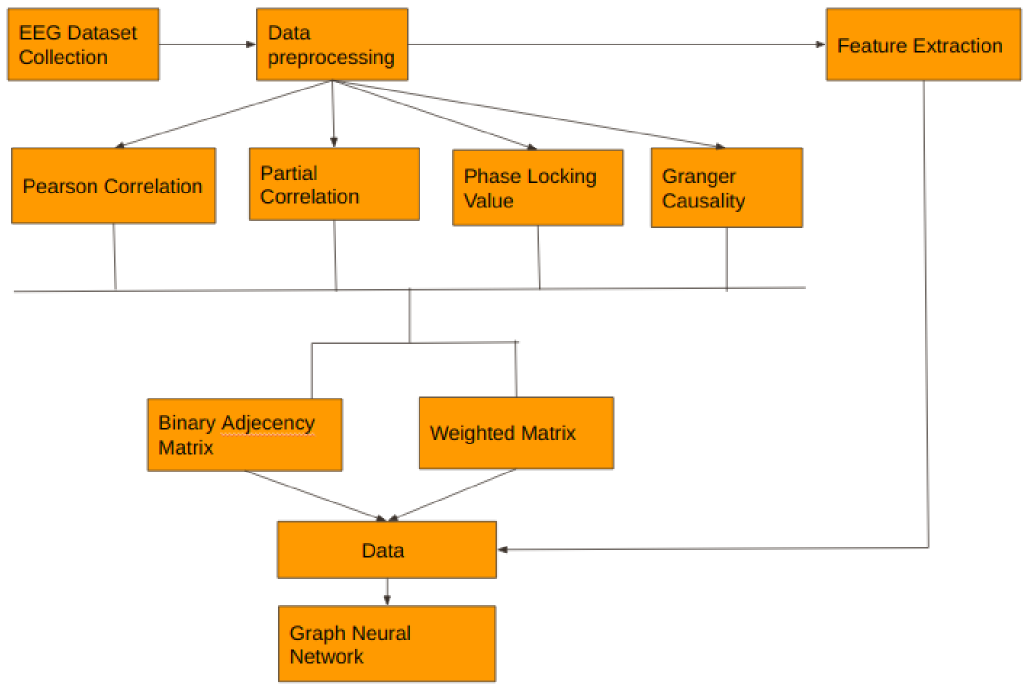


Figure 3.1: workflow

3.3 Experimental Procedure

Publically available BCI competition 4a dataset is used to validate this approach. This data set was recorded from five healthy subjects. Subjects sat in a comfortable chair with arms resting on armrests. Visual cues indicated for 3.5 s for the following 2 motor imageries. the subject should perform: (R) right hand, (F) right foot see figure 3.2. Time paradigm of one trial is shown in figure 3.3.

Format Of Data: Given are continuous signals of 118 EEG channels and markers that indicate the time points of 280 cues for each of the 5 subjects (aa, al, av, aw, ay). The figure 3.4 shows the respective number of training (labelled) trials "tr" and test (unlabelled) trials "te" for each subject.

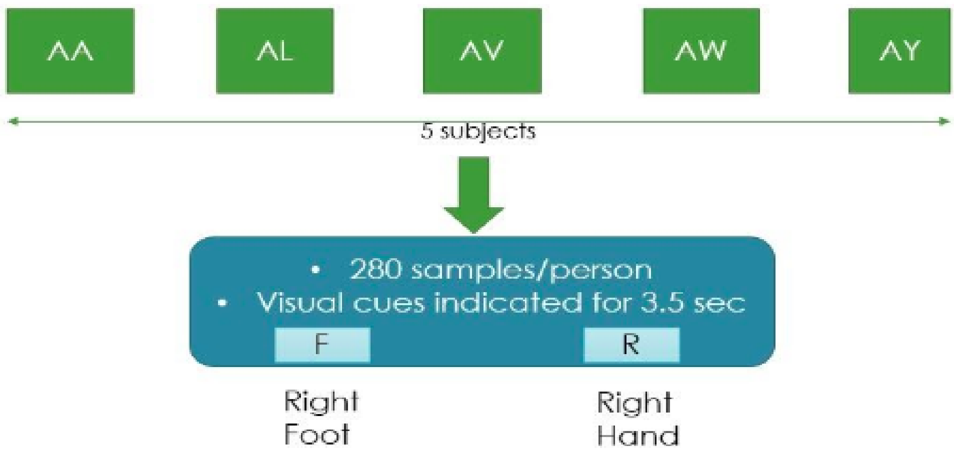


Figure 3.2: Experimental Procedure

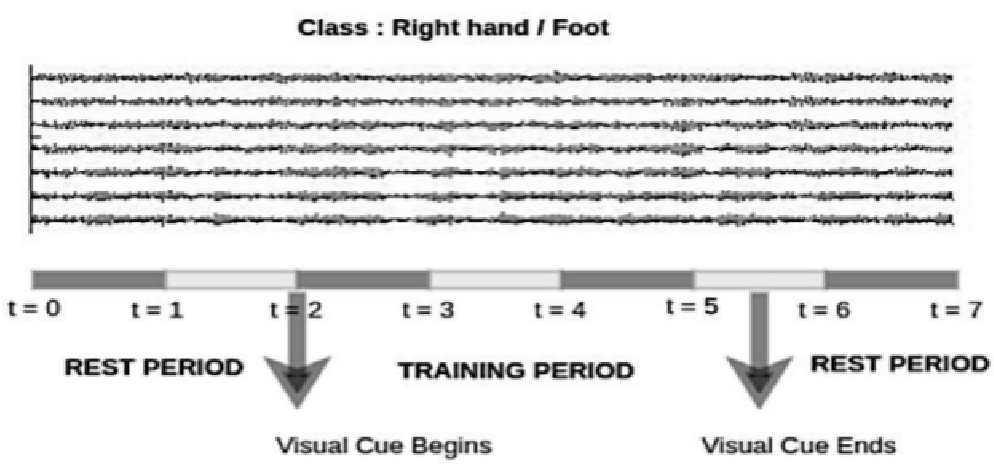


Figure 3.3: Time taken for a single trial

	#tr	#te
aa	168	112
al	224	56
av	84	196
aw	56	224
ay	28	252

Figure 3.4: Distribution of test and training data

3.4 Dataset Pre-Processing and Segmentation:

Channel Selection Dataset has recording of 118 channels because of which it is very large to process. Dataset consists of two class motor imagery so primary features can be extracted from premotor cortex, primary motor and supplementary motor cortex. Therefore 30 channels over motor cortex are considered for further processing. Irrelevant channels removal increases the efficiency of the system. The channels which are selected as FC2, FC4, FC6, CFC2, CFC4, CFC6, C2, C4, C6, CCP2, CCP4, CCP6, CP2, CP4, CP6, FC5, FC3, FC1, CFC5, CFC3, CFC1, C5, C3, C1, CCP5, CCP3, CCP1, CP5, CP3 and CP1[Sreeja et al. (2017)].

Data segmentation is done, where we have used 3 seconds data (300 samples) after the cue is displayed for each trial, considering that the person is moving the right foot or right hand on an average of 3 seconds. Each segmented data is known as epoch.

Bandpass Filtering: 30 channels selected data is passed through bandpass filter. Low frequency used is 7 Hz and high frequency used is 30 Hz.We have used this frequency range because mu and beta brain waves lies within this range.

Spatial Filtering: In MI based BCI projects mostly use common spatial filtering. CSP helps to compute the spatial filter or linear transform which will increase

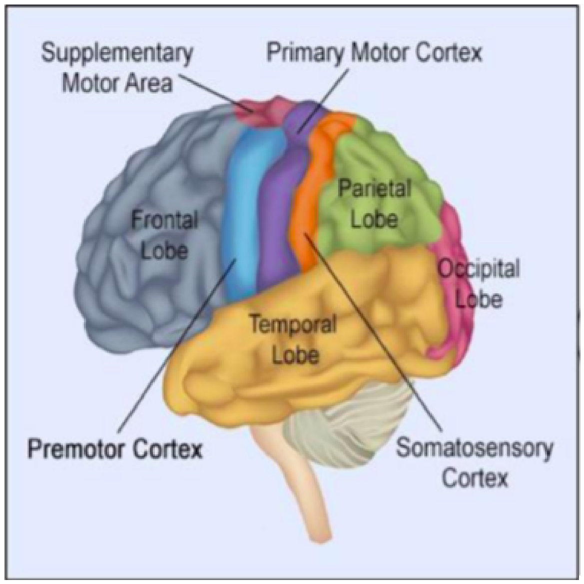


Figure 3.5: Motor Cortex of Brain

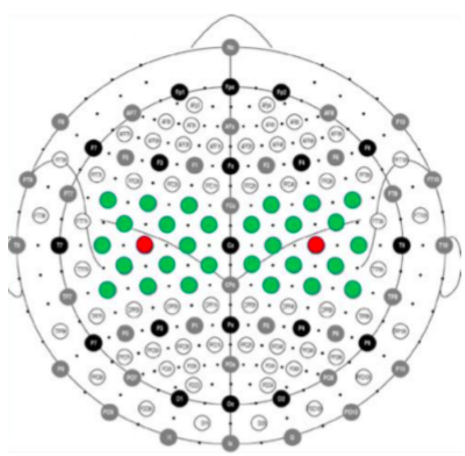


Figure 3.6: Electrodes shown in red and green are the channels selected for processing

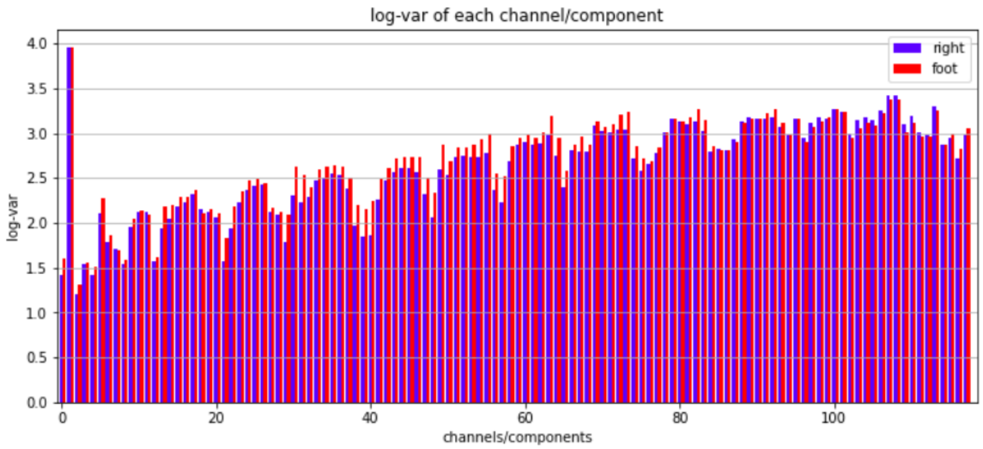


Figure 3.7: variance of two classes before applying CSP filter

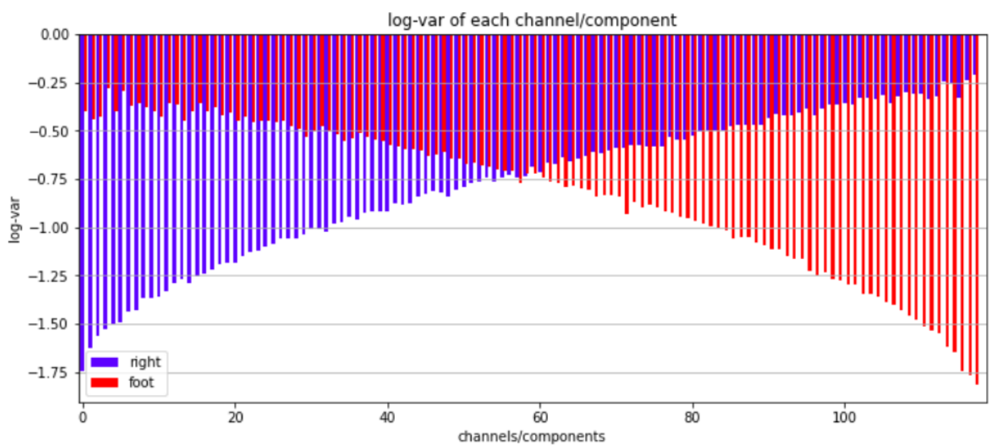


Figure 3.8: variance of two classes after applying CSP filter

the variance of first class while decrease the variance of second class. This will help us to create the distinction between two classes[Sreeja et al. (2017)]. CSP filter will also help to avoid volume conduction effect and to clean the noisy data. In figure 3.7 we can see there is very small difference in variance between same component of two classes because of which it is very difficult to distinguish two classes. Figure 3.8 the log-variance of each channel and here there is a clear distinction between two classes. Because of this overall performance of motor imagery classification is improved.

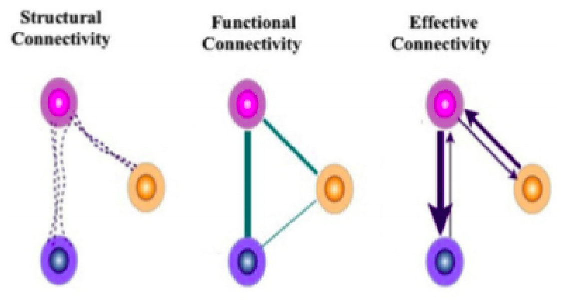


Figure 3.9: Different Types of Connectivity

3.5 EEG Brain Connectivity Analysis

Brain connectivity refers to pattern of anatomical links or statistical dependencies or causal interactions between different regions of nervous system. This connectivity is measured through coherence correlation or information flow.

Anatomical Connectivity refers to the connection of biological neural connection. It is formed trough synaptic contact between neighboring neurons. Relationship between the nodes depends on parameters like synaptic strength or effectiveness[Leisman et al. (2016)].

Functional Connectivity refers to the statistical dependancies between nodes. Functional connectivity can be measured using correlation, coherence etc[Leisman et al. (2016)].

Effective Connectivity describes the influence of one neuronal region on another neuronal region, thus causal connectivity is represented by information flow from one neuronal system to another. This relationship can be measured using techniques like granger causality[Leisman et al. (2016)].

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

r = correlation coefficient

x_i = values of the x-variable in a sample

$\bar{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\bar{y}$ = mean of the values of the y-variable

Figure 3.10: Pearson Correlation Coefficient

$$r_{xy \cdot z} = \frac{r_{xy} - (r_{xy}\, r_{yz})}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

Figure 3.11: Partial Correlation

3.6 Parameters for Connectivity Analysis

1.Pearson Correlation: Correlation coefficient is the measurement of strength of a relation-ship between two nodes. A correlation coefficient that is greater than zero indicates a positive relationship between two variables. A value that is less than zero signifies a negative relationship between two variables. Finally, a value of zero indicates no relationship between the two variables.

2.Partial Correlation: measures relationship between two variables X and Y while eliminating the effect of third variable Z.

3.Phase Lag Index: PLI is used to estimate the functional connectivity in EEG data. It removes the volume conduction effect. Phase lagged index values lies between 0 and 1 where 0 means no coupling because of volume conduction and 1 means lagged interaction.

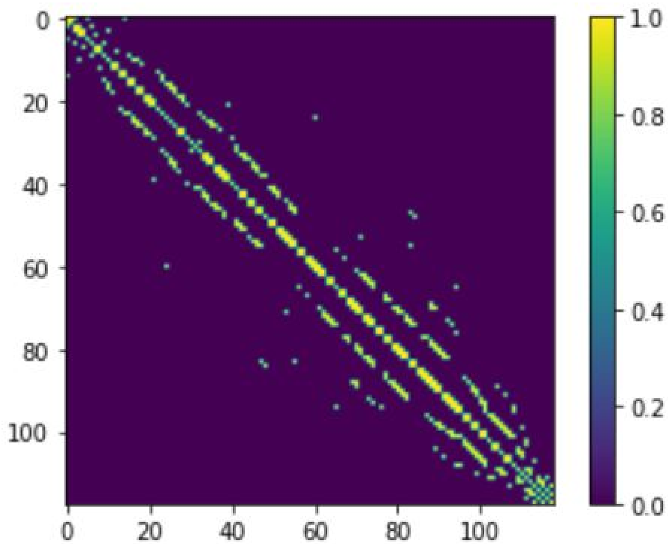


Figure 3.12: Adjacency matrix using pearson Correlation

Granger Causality: is a statistical concept of causality used for prediction. It is used for finding whether one time series is can be considerable in forecasting another. By using these parameters we can create **connectivity matrix** of 30*30, where nodes will be 30 representing 30 selected channels and edges represent the strength of the connection between two nodes.

In case of Binary connectivity matrix we are considering the threshold for pearson correlation as 0.3. If values present at cell(I,J) is greater than 0.3 then consider the edge between node I to J otherwise no edge. Same is followed for partial Correlation.

3.7 Graph Convolutional Network

Graph Covolutional Network is one variant of Graph Neural Network. Graph Neural Network is a neural network that operates on the graphs. Only difference in Graph Convolutional Network is that it has the property of local connectivity. It assumes the nodes which are close together are highly correlated. Spatial convolutions are similar to regular convolution in the way they spatially convolute over nodes. Convolutions

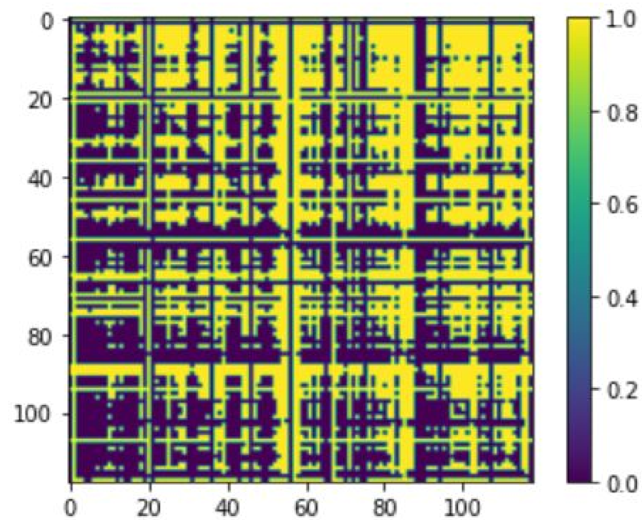


Figure 3.13: Adjacency matrix using Phase Locking Value

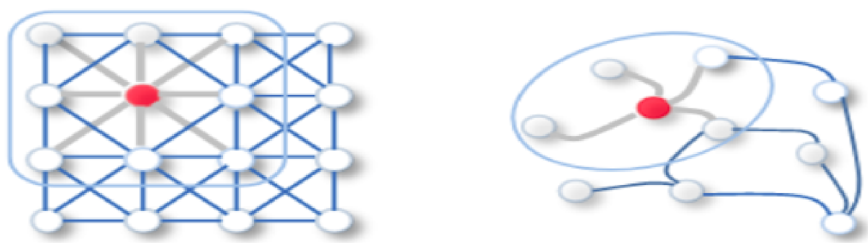


Figure 3.14: graph convolution with example

generate a new pixel from the pixel itself (the pixel placed in the same position as the new one) and it's surrounding pixels.

Input to the Graph Convolutional Network will be Adjacency matrix either binary or weighted matrix of size 30*30 , label of Motor Imagery task and feature Matrix. An input **feature matrix** N × F feature matrix, X, where N is the number of nodes and F is the number of features for each node. Weight of edge is present in adjacency matrix.[Lun et al. (2020)]

We have seen previously that clue is displayed for 3.5 sec. This 3.5 sec data can be very complecated as it may contains lots of distractions followed by artifacts, to reduce this effect we will divide this 350 rows into 50 rows each. First Input to GCN as shown in figure 3.14 is realtime raw EEG data of 30*50 matrix where 30 are the

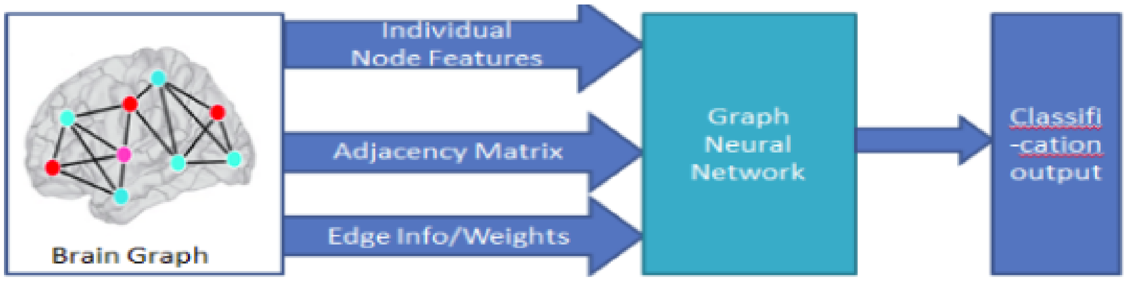


Figure 3.15: workflow of Graph Convolution Network

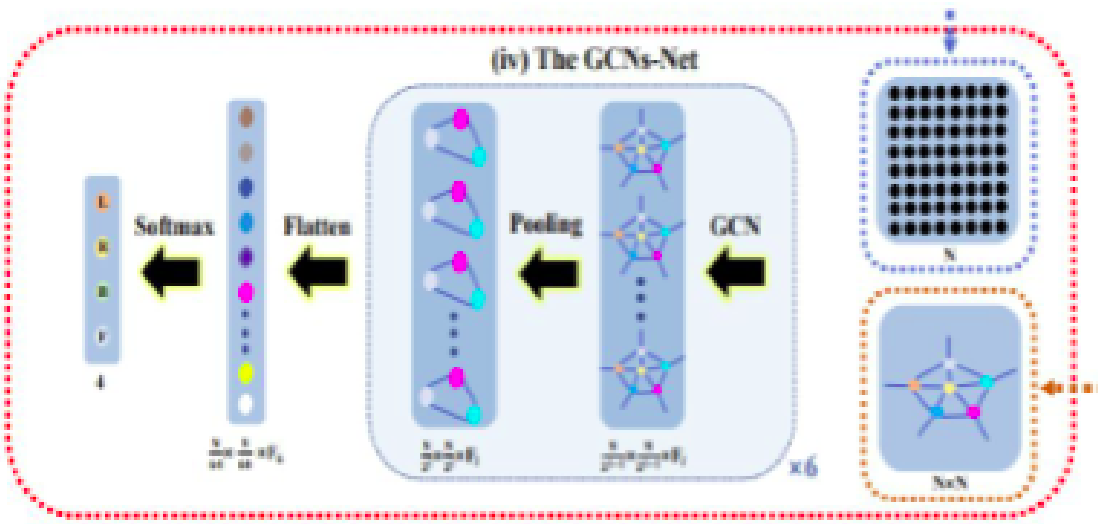


Figure 3.16: framework of Graph Convolutional Network

selected channels and 50 is the features per node. Second Input to GCN is a representation of the graph which has been computed through connectivity parameters.

Graph Convolutional Network can be used in many field like Computer Vision, Natural Language Processing and Science. It will be helpful to classify the patterns like molecular structures.Zhang et al. (2019)

3.8 Validation Of GCN Model

The Mother Of All BCI Benchmark(MOABB) project consists of the aggregation of many publicly available EEG datasets, converted to a common format and bundled in

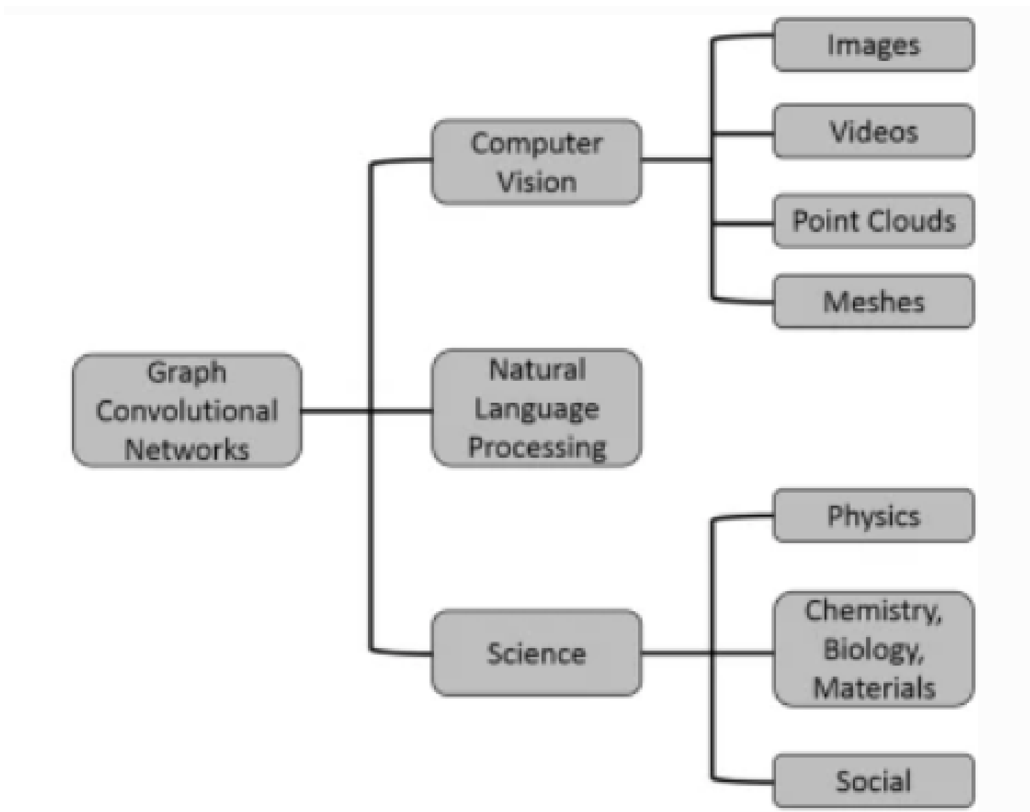


Figure 3.17: Applications of Graph Convolutional Network

Name	Imagery	# Channels	# Trials	# Sessions	# Subjects	Epoch
Cho et al. 2017	Right, left hand	64	200	1	49	0-3s
Physionet	Right, left hand	64	40-60	1	109	1-3s
Shin et al. 2017	Right, left hand	25	60	3	29	0-10s
BNCI 2014-001	Right, left hand	22	144	2	9	2-6s
BNCI 2014-002	Right hand, feet	15	160	1	14	3-8s
BNCI 2014-004	Right, left hand	3	120-160	5	9	3-7.5s
BNCI 2015-001	Right hand, feet	13	200	2/3	13	3-8s
BNCI 2015-004	Right hand, feet	30	70-80	2	10	3-10s
Alexandre Motor Imagery	Right hand, feet	16	40	1	9	0-3s
Yi et al. 2014	Right, left hand	60	160	1	10	3-7s
Zhou et al. 2016	Right, left hand	14	100	3	4	1-6s
Grosse-Wentrup et al. 2009	Right, left hand	128	300	1	10	3-10s
Total:					**275**	

TABLE I: Dataset attributes

the software package. Using this system the GCN model can be comparable over all standard datasets. In the table given below you can see details of all datasets. To generalise the conclusion of pruposed approach MOABB dataset will be perfect[Jayaram & Barachant (2018)].

Chapter 4

Implementation

4.1 Experiment 1

In this experiment we worked on different connectivity measurements for creating adjacency matrix where dataset we worked on is BCI 4a.

Implementation Details:
1. python3 version is required
2. For deep learning model implementation framework used is pytorch dgl library.
3. google colab is used to execute the graph convolution network model.
4. Graph Convolution Network has two hidden layer and activation function used is ReLu. Output layer uses Softmax function for output prediction. Dropout rate at each hidden layer is 0.25.
5.Feature matrix size is 30*52 (nodes = 32, and 52 features per node is computed)
Overall process is shown in the figure 4.1

4.2 Experiment 2

In this experiment we worked towards making the results generalised. For the generalisation purpose we have to apply prupused approach on two datasets. We have selected three datasets from Mother Of All BCI Benchmarks(MOABB). Those three dataset are: BNCI 2014-001, BNCI 2014-002 and AlexMI.

Implementation Details:

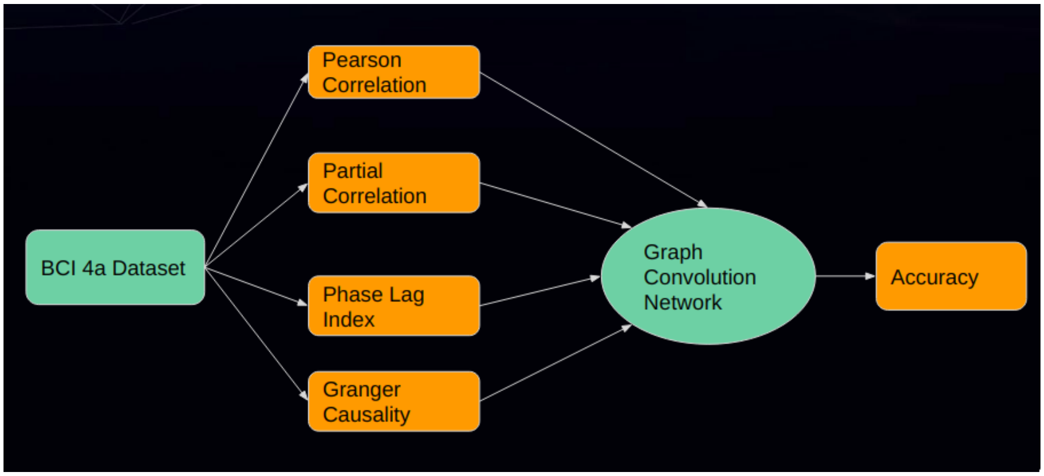


Figure 4.1: Details of Experiment 1

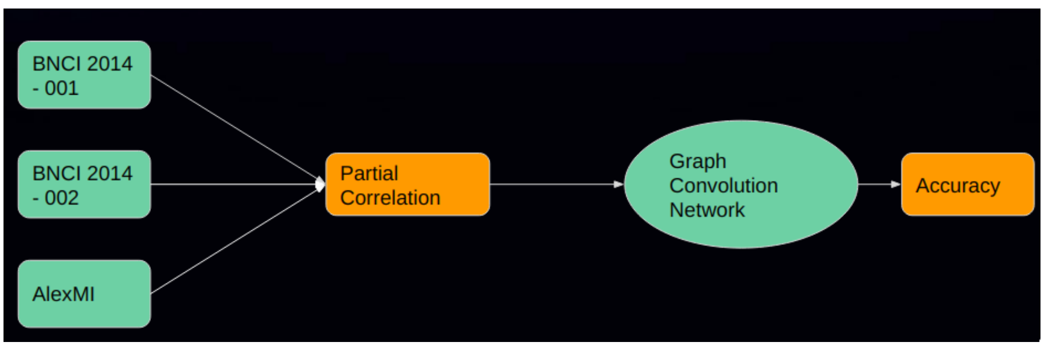


Figure 4.2: Details of Experiment 2

1. python3
2. For deep learning model implementation framework used is pytorch dgl library.
3. google colab is used to execute the graph convolution network model.
4. Graph Convolution Network has two hidden layer and activation function used is ReLu. Output layer uses Softmax function for output prediction. Dropout rate at each hidden layer is 0.25. Overall process is shown in the figure 4.2
5.Feature matrix size is n*52 (nodes = n, and 52 features per node is computed). Here number of nodes differ for every dataset.

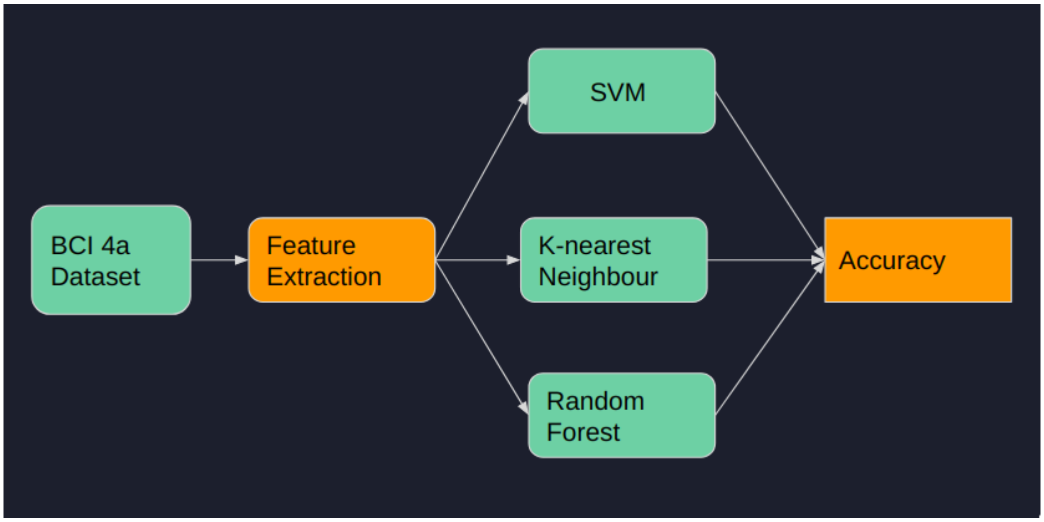


Figure 4.3: Details of Experiment 3

4.3 Experiment 3

To do the comparative analysis, tried to implement some standard machine learning model.

1. Dataset used here BCI 4a dataset.

2. 52 features computed across different domains like time domain, frequency domain etc.

3. google colab is used to execute all the machine learning algorithm.

Chapter 5

Results

As mentioned we have performed 3 experiments. All experiment results that we have obtained for motor imagery classification are subject wise. If we try to mix all the subjects data then model gets confused.

5.1 Experiment 1

Dataset - BCI Competition-III-IVa
Features - statistical features
Number Of Participants - 5
Number of Channels - 30
Sampling Frequency - 100Hz
Number of Samples per person - 280
Visual Cues Indicated for - 3.5 sec

Experiment 1.1 - Brain connectivity parameter used is Partial Correlation. Average accuracy in this experiment is 79.79%. Accuracy lies between the range of 66% to 88%. Subject AL obtained less accuracy as compared to other subjects it is because after applying CSP also noise removal didn't worked well.

Experiment 1.2 - In this experiment brain connectivity parameter used is phase lag index. Features selected are same as previous experiment. PLI as brain connectivity feature average accuracy achieved is 65.24%.

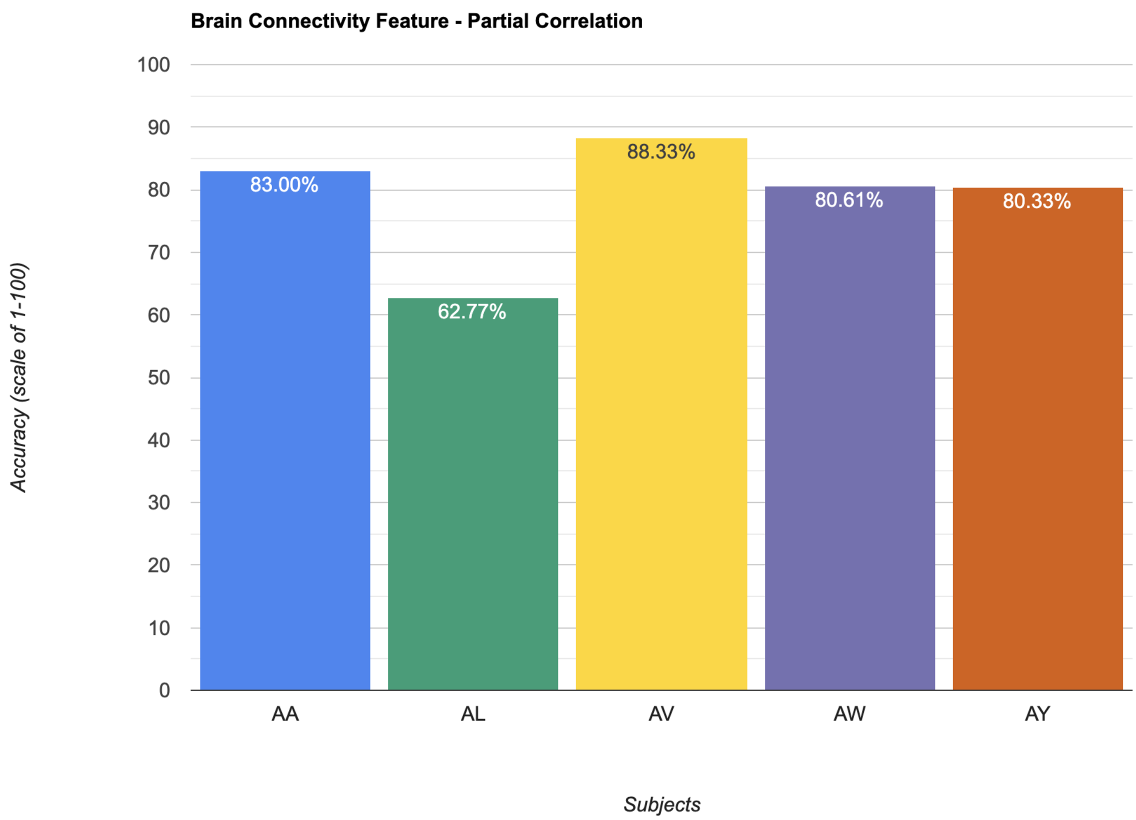


Figure 5.1: Experiment 1.1

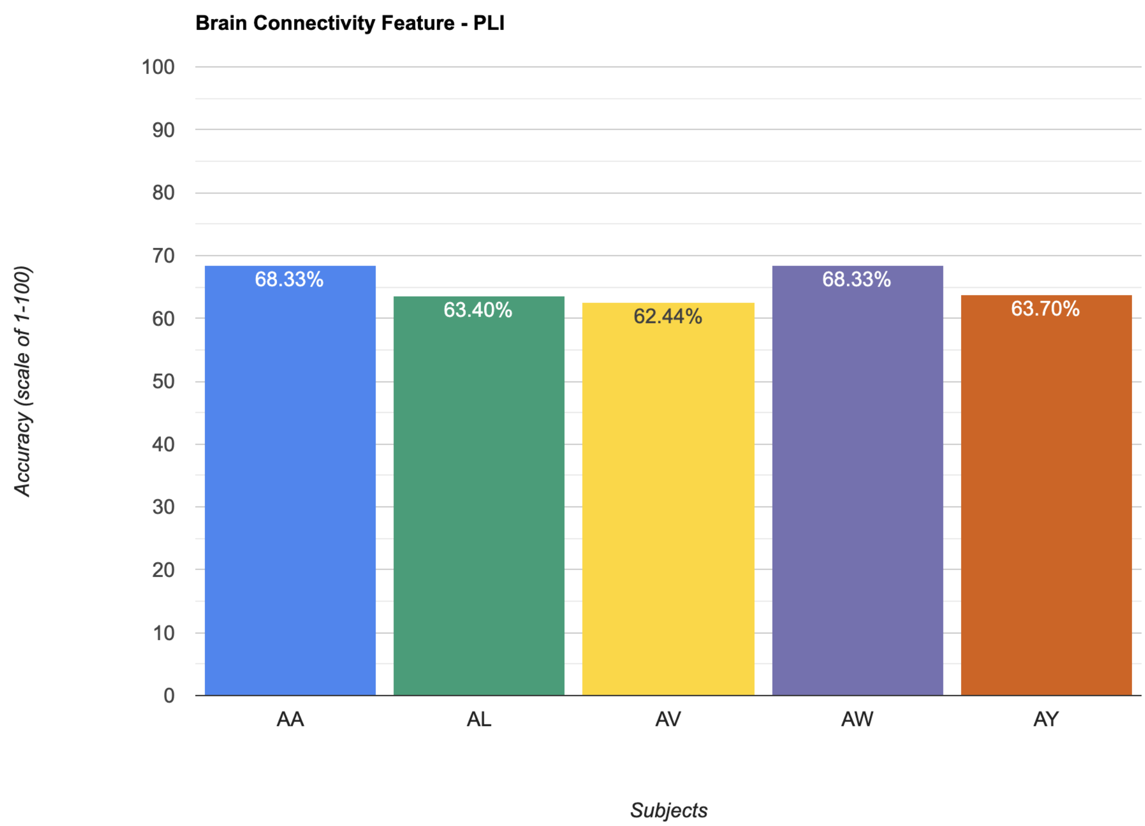


Figure 5.2: Experiment 1.2

Experiment 1.2 - Granger Causality which is a measure of effective connectivity is used in this experiment. Accuracy achieved is quiet similar as experiment 1.2. Average Accuracy obtained is 63.33%.

Comparison of results from Experiment-1
Figure 5.4 shows the comparative results of all the three sub-experiments of experiment-1. Partial Correlation works well as compared to other methods. That's why for further experiments we are going to use same method for validation purpose.

5.2 Experiment 2

5.2.1 Experiment 2.1

Dataset - BNCI-2014-001
Features - statistical features
Number Of Participants - 9
Number Of Channels - 22
Sampling Frequency - 250Hz
Number of Examples per person - 288
Visual Cues Indicated for - 4 sec
Average accuracy is 75.20%.

5.2.2 Experiment 2.2

Dataset - BNCI-2014-002
Features - statistical features
Number Of Participants - 6
Number Of Channels - 15
Sampling Frequency - 250Hz
Number of Examples per person - 160
Visual Cues Indicated for - 5 sec
Average accuracy is 75.00%.

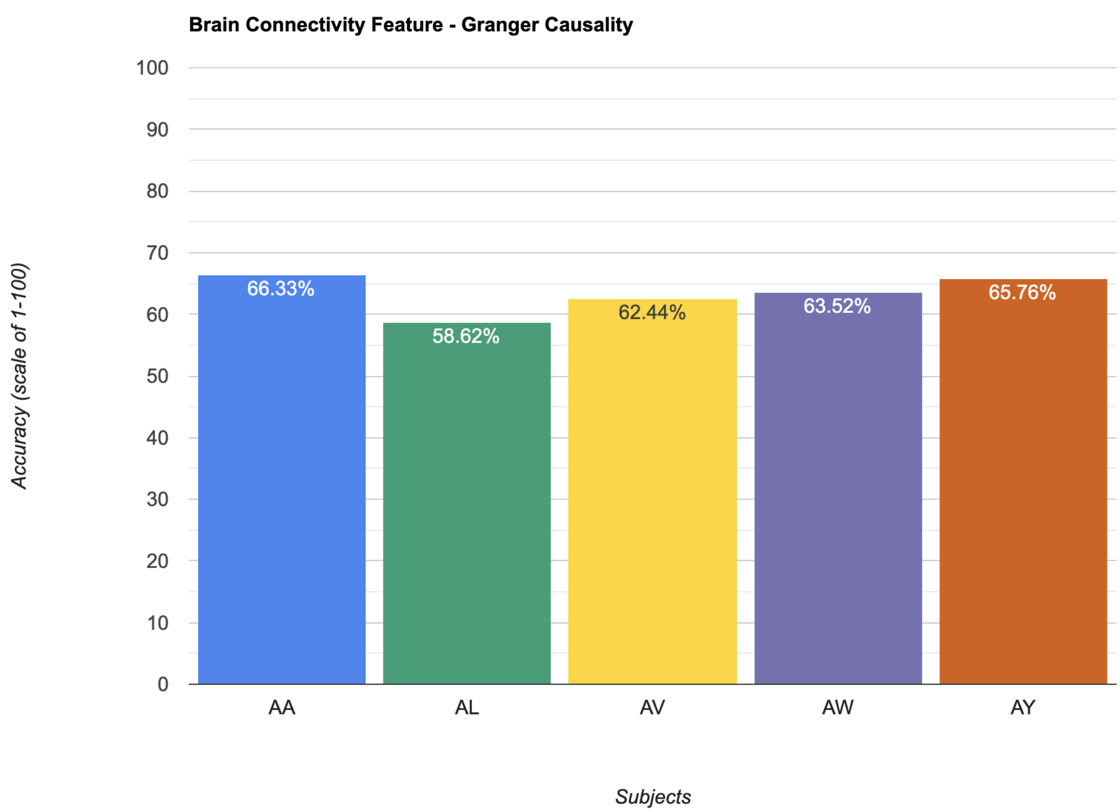


Figure 5.3: Experiment 1.3

5.2.3 Experiment 2.3

Dataset - AlexMI

Features - statistical features

Number Of Participants - 6

Number Of Channels - 16

Sampling Frequency - 512Hz

Number of Examples per person - 40

Visual Cues Indicated for - 3 sec

Average accuracy is 76.32%.

5.3 Experiment 3

Classification result from GNN is compared with traditional ML/DL approaches.

Dataset - BCI Competition-III-IVa

Features - statistical features

Number Of Participants - 5

Number of Channels - 33

Sampling Frequency - 100Hz

Number of Samples per person - 280

Visual Cues Indicated for - 3.5 sec

KNN method with 5 neighbours achieved highest accuracy of 88.76%.

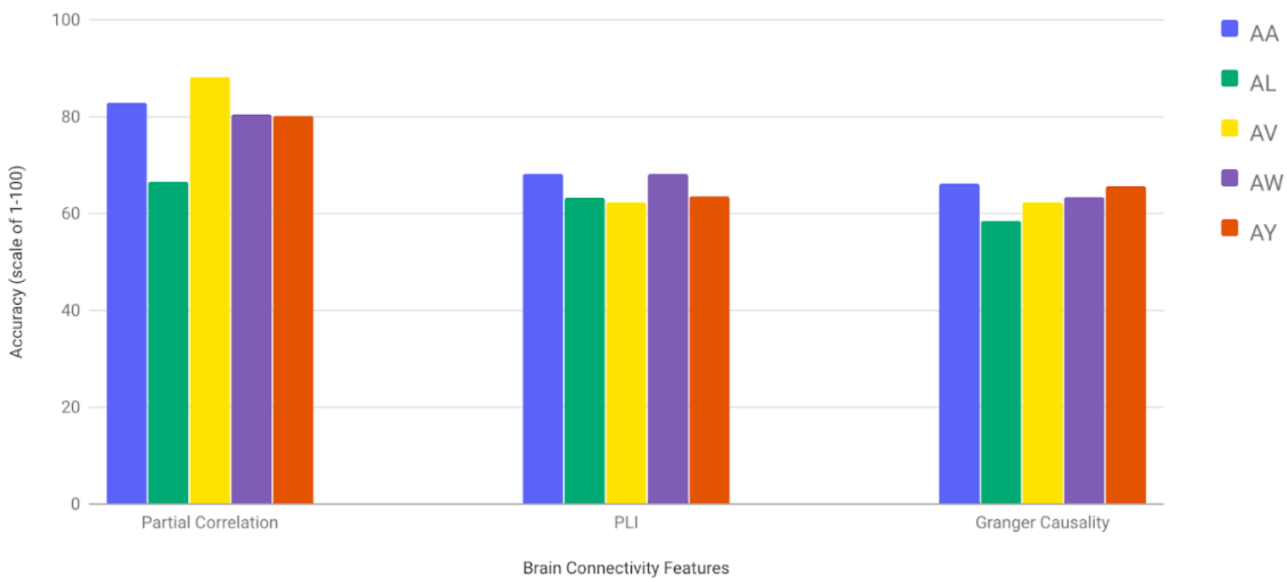


Figure 5.4: Comparison of results

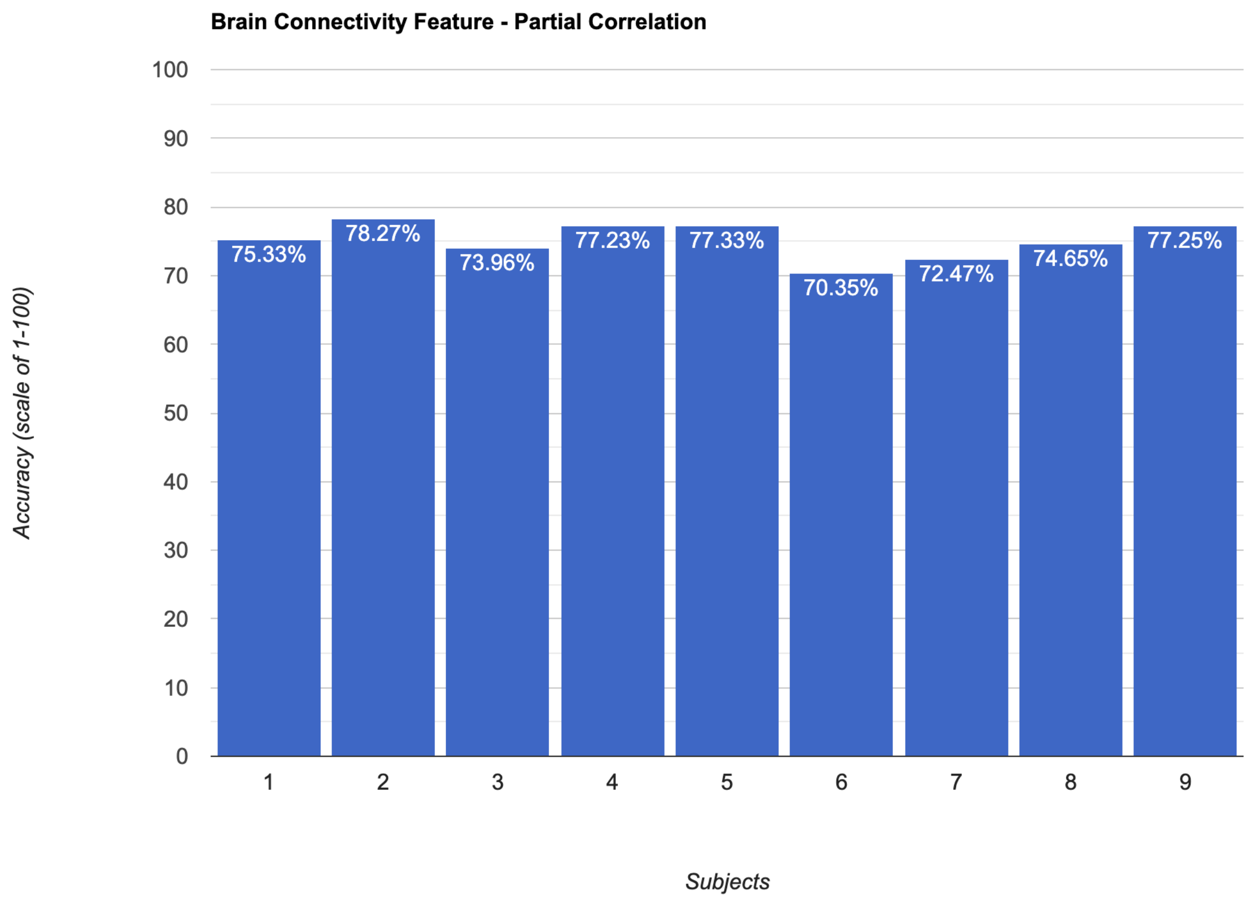


Figure 5.5: Experiment 2.1

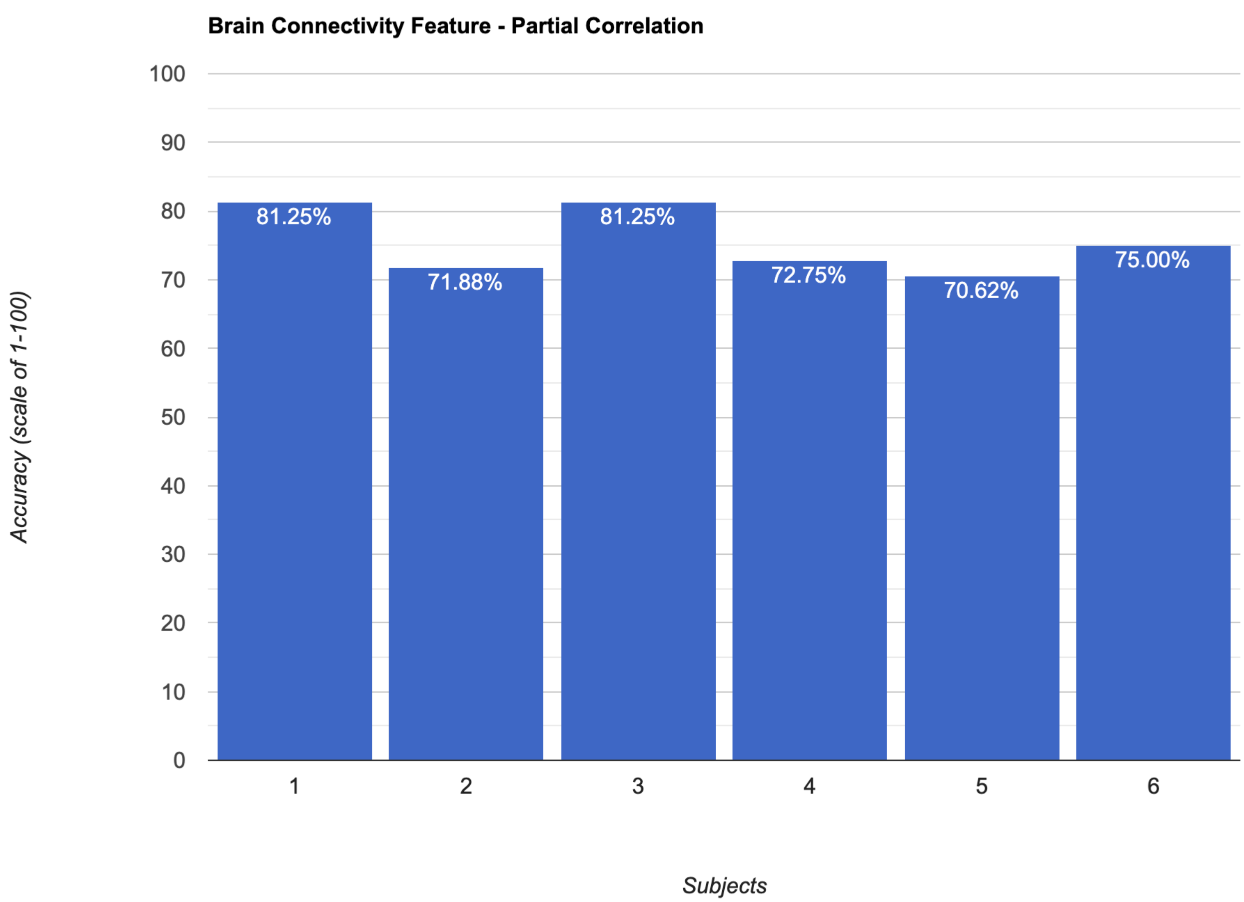


Figure 5.6: Experiment 2.2

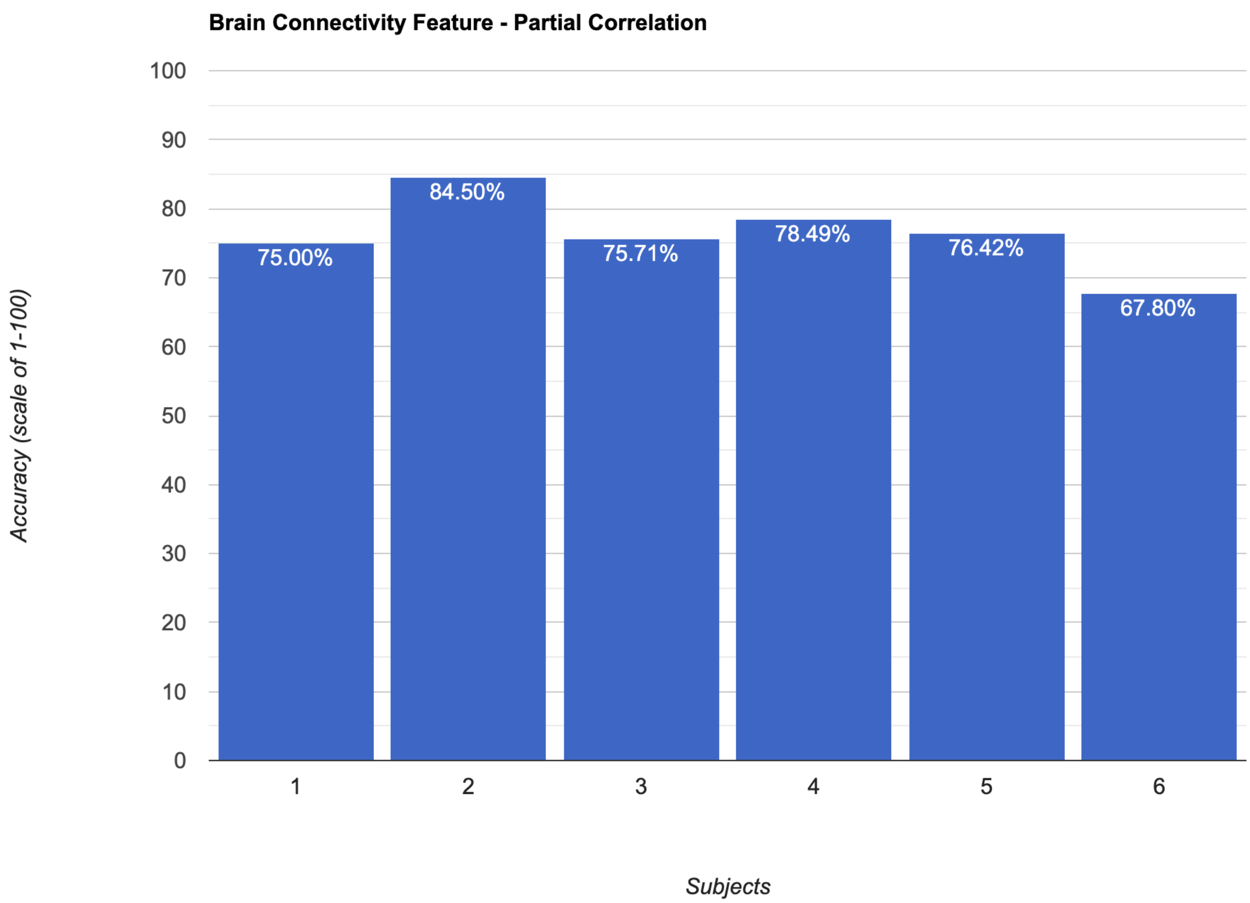


Figure 5.7: Experiment 2.3

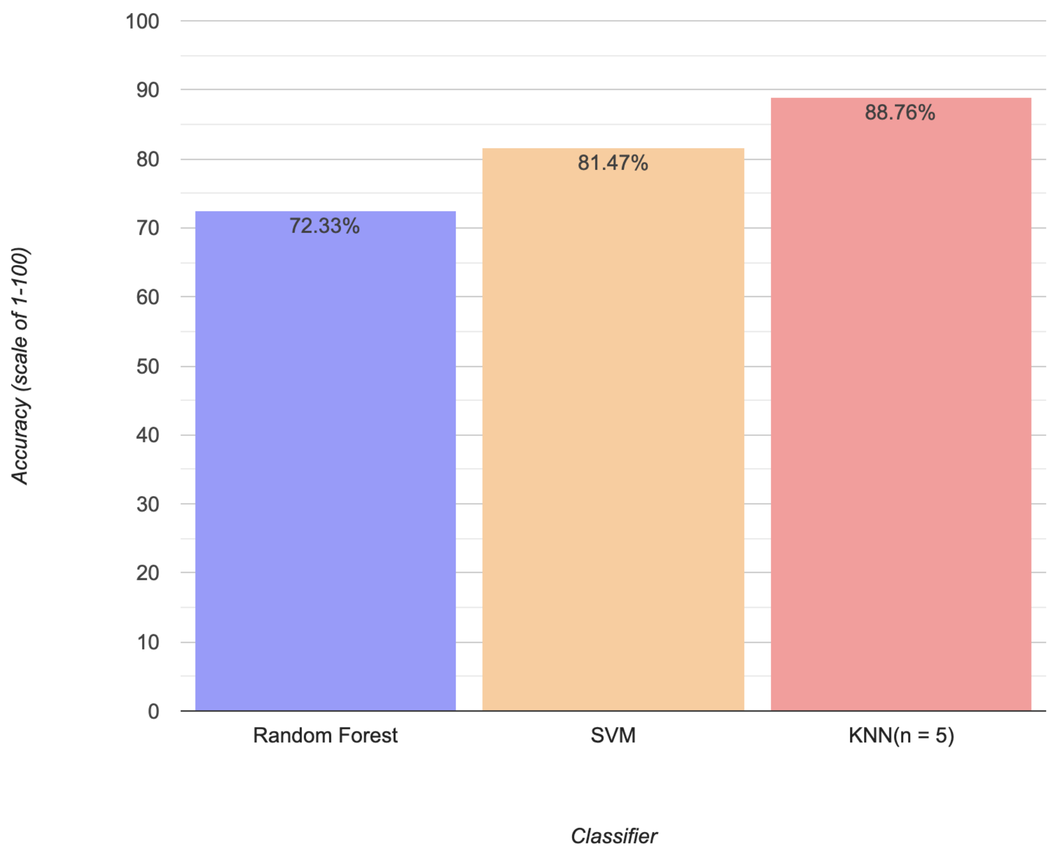


Figure 5.8: Experiment 3

Chapter 6

Conclusion

1.Motor Imagery classification task can be solved with graph convolutional network with good accuracy.

2.The EEG signals with 118 channels are of high dimension. To reduce computational complexity, constraints are applied on selecting channels.

3.it is important to note that the EEG signals produce variations among users at different sessions.

4.Adding edge weights features in the model may increase the accuracy and can beat the performance of KNN.

5.Partial Correlation with statistical features performs well as compared to other brain connectivity parameters. And gives the average accuracy of (79.79%).

6. Partial correlation obtained consistent results over all three datasets.

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