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

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Introduction

- Brain-computer Interfaces (BCIs) provides a direct connection between the human brain and a computer.
- EEG motor-imagery (MI) is the most popular and largely investigated approach for successful BCI.
- In this study, a Brain Connectivity Analysis approach is carried out to find out brain network alteration between different MI activities, such as left hand,right hand,or foot movements.
- To reduce the effect of volume conduction and noisy data cleaning, Common Spatial Patterns(CSP) of EEG channels is found out.
- Using the brain graphs thus obtained as features, a Graphical Neural Network (GNN) based classification technique is established.
- Classification result from GNN is compared with traditional ML/DL approaches.
- Further, to validate proposed methodology for BCI-MI classification, proposed model is implemented with 3 most popular BCI-MI dataset and classification performance is observed.

Motivation-Research Gap in BCI-MI

- A Brain Computer Interface(BCI) is a computer-based system that acquires brain signals, analyzes them, and translates them into commands that are relayed to an output device to carry out action.

- Traditional approaches for BCI-MI includes application of various ML/DL approaches on processed EEG data.Traditional work on EEG data does not consider the topological relationship/co-activation characteristic between channels.

- There has been a few efforts, where connectivity analysis has been employed to BCI-MI.

- These efforts do not consider all the aspects/modalities of network connectivity.

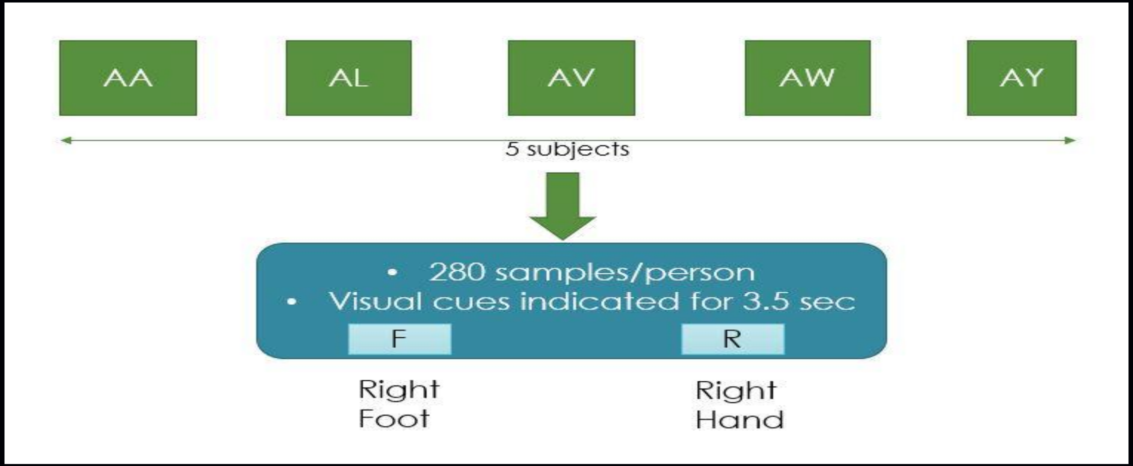
- Further, the topological nature of brain networks is not utilised while classifying using traditional ML/DL. Brain graph topology can be expertly utilised using Graphical Neural Network (GNN) models.

- To address the issue of MI generalization,proposed model has been tested on 4 popular datasets, containing total 26 subjects and multiple sessions.

Experimental Details of BCI-Competition-III, IVa dataset

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.

BCI competition III motor imagery dataset collected. 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 which of the following 2 motor imageries the subject should perform: (R) right hand, (F) right foot.



Data Collection

Number Of Channels : 118

Duration per trial : 3.5 sec

Sampling Frequency : 100Hz

Total Number Of Trials Per Subject:

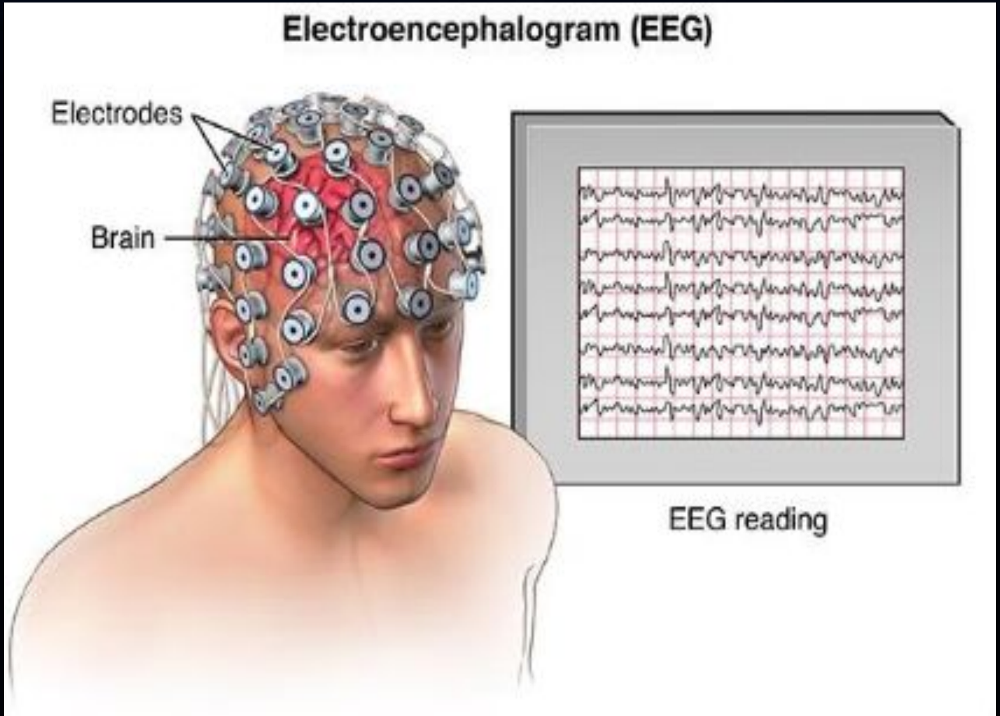
280

Total EEG Data Volume per person:

280*350*118

Total number of examples:

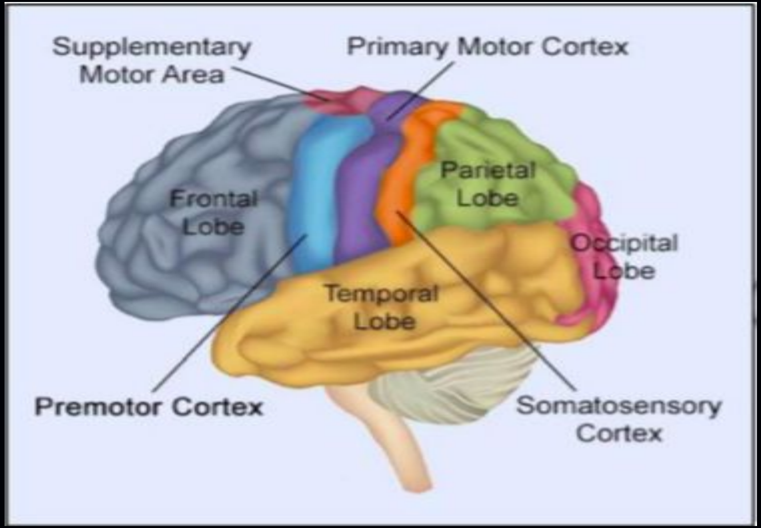
5*280*350*118

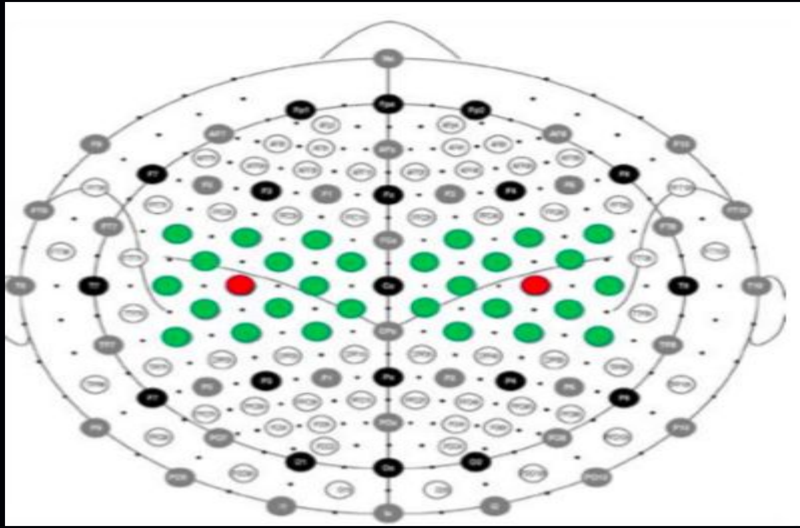


Data Pre-Processing

1.Channel Selection： Out of 118 channels, 30 channels over from premotor cortex, primary motor and supplementary motor cortex are considered for further processing. Irrelevant channels removal increases the efficiency of the system.

Channel selection scheme is inspired by the work of Sreeja S.R [2017]





Data Pre-Processing

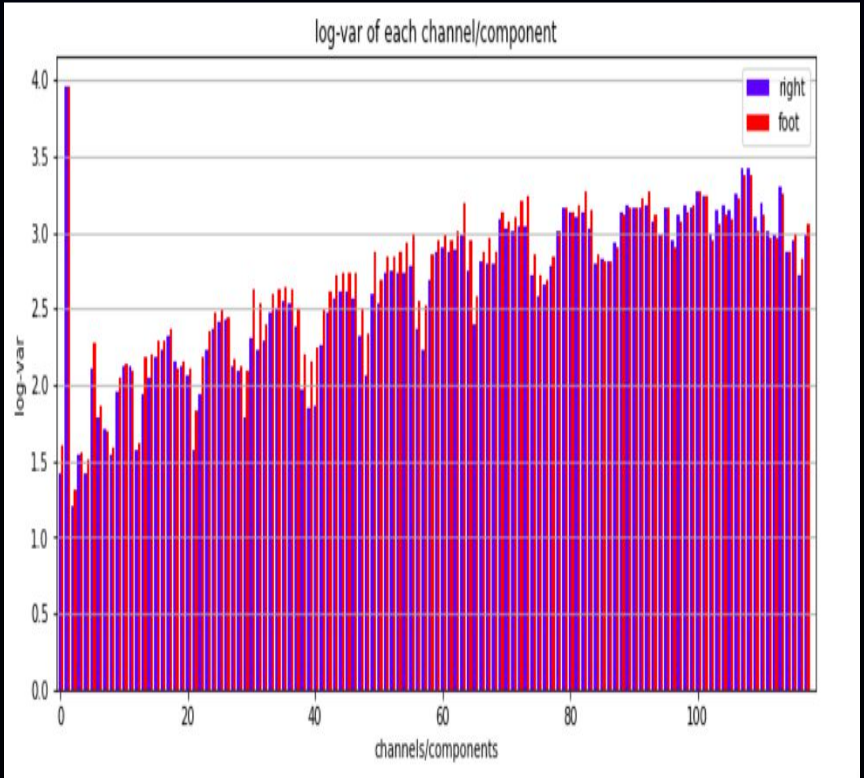
2.Bandpass Filtering : EEG data is passed through a band-pass filter between 7 and 30 Hz, as it is known from that mu (μ) and beta (β) rhythms lie within that frequency range.

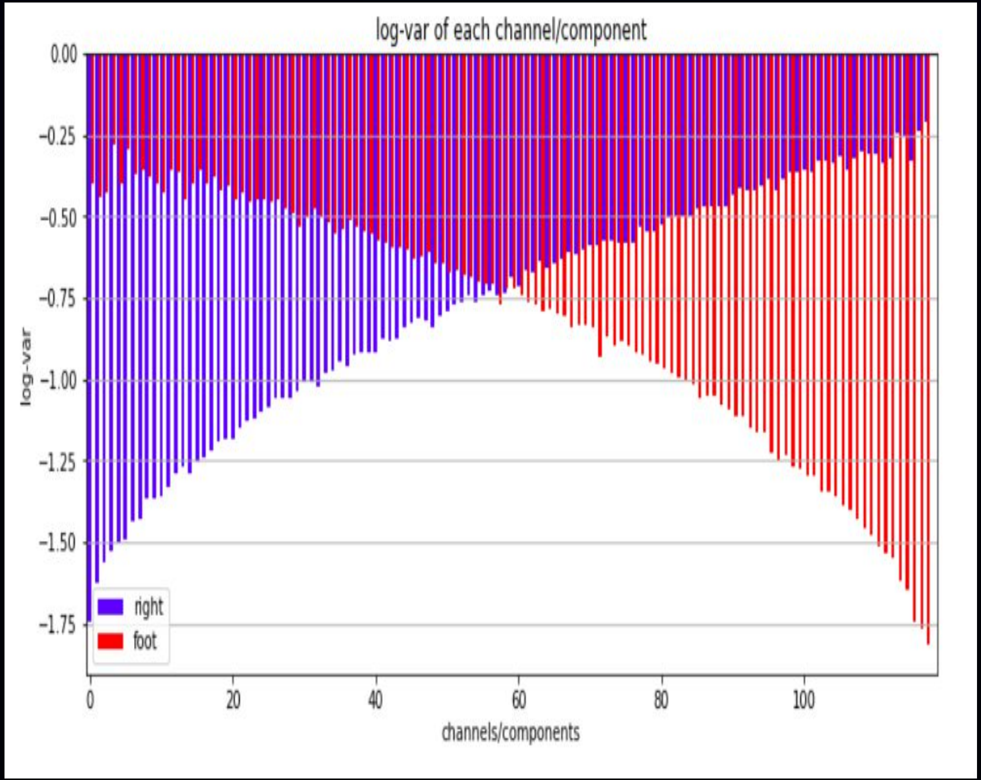
3. Spatial Filtering : CSP is one of the most commonly used spatial filters in building MI-based BCIs. Three second time samples are spatially filtered using a CSP filter. CSP aims to find the linear transforms or spatial filters, which maximizes the variance of one class while minimizing it for the other class. How CSP is applied to the given dataset, is explained in the next diagram.

Why CSP?

1. It is very popular spatial filter used in BCI domain.
2. Assuming data of two classes, for example, the motor imagery of right and left, CSP algorithm calculates spatial filters that maximize the ratio of variance of data stemming from the two classes. Consequently, the extracted signals are optimally discriminating two different EEG classes.
3. Common Spatial Pattern scheme is inspired by the work of Sreeja S.R [2017]

Data Pre-Processing





Node-Features for GNN model

Node/channel Features(Approach 1): With similarity with standard DL approaches, RAW EEG channel data (A vector of size 300) can be used as node features.

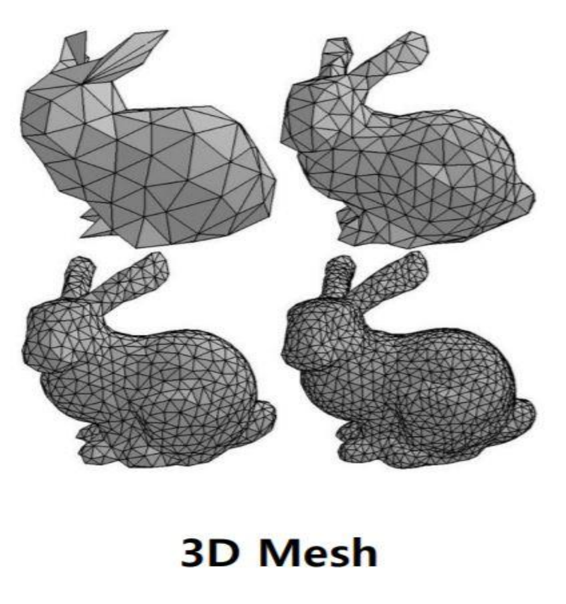
Node/channel Features(Approach 2): We also tried another approach where we have computed 52 features from different domains like:

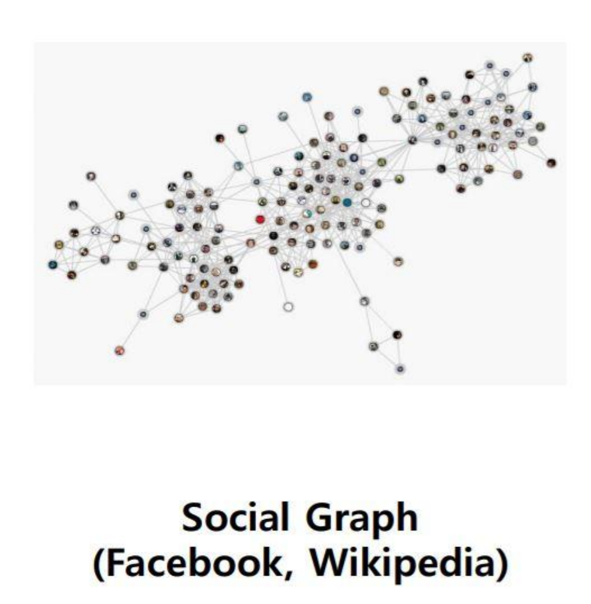
1. Time Domain Features
2. Frequency Domain Features
3. Statistical Features
4. Wavelet Based Features

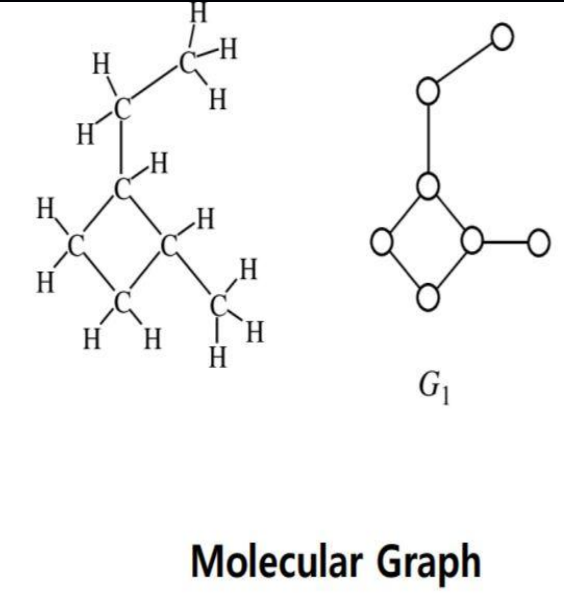
We have created adjacency matrix(30*30) using brain connectivity parameters. And this matrix along with features passed to the GNN model. GNN model performs classification. Efficiency of this model is measured by the accuracy.

GNN on Irregular Data Structure

In many research areas data is modelled as graph, 3D mesh(non Euclidean data structure).

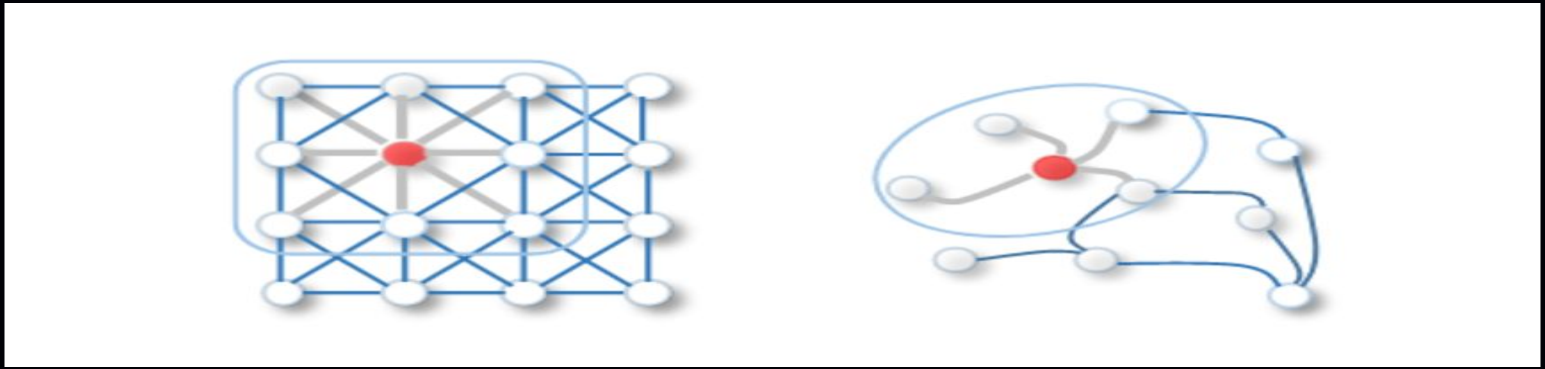




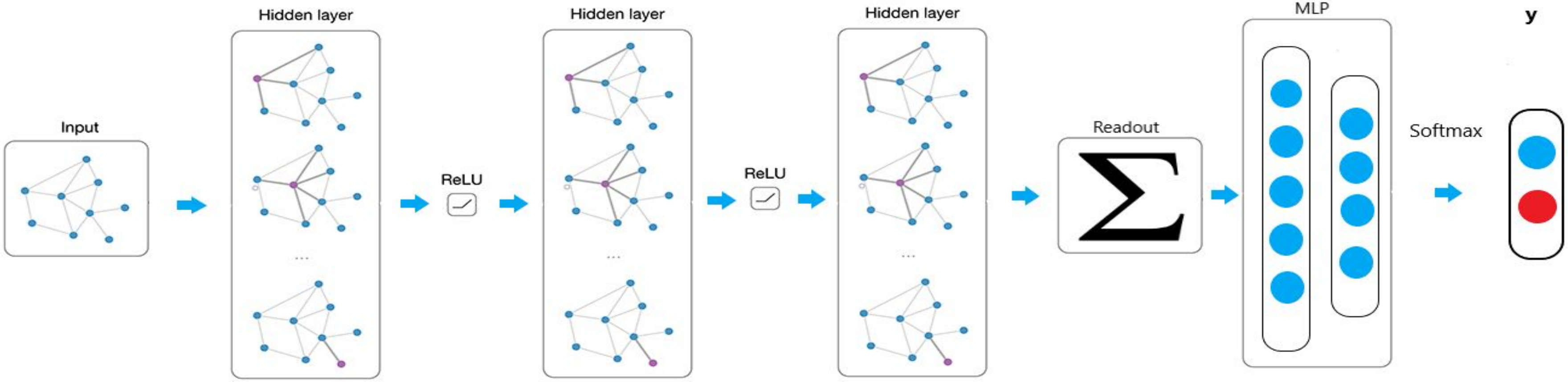


Graph Convolution Network

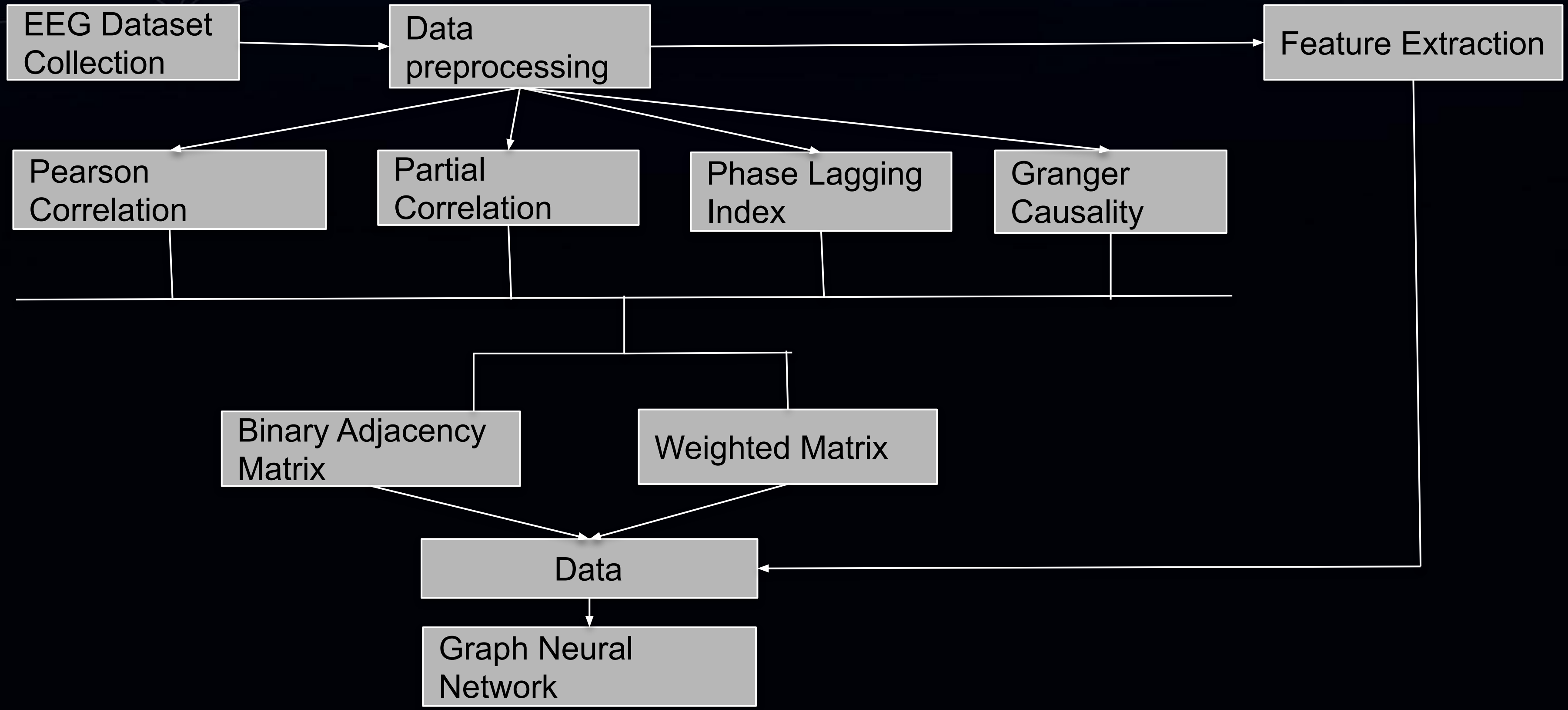
- Graph Neural Network is a neural network that operates on the graphs.
- Graph Convolutional Network is one variant of Graph Neural Network.
- GCN has property of local connectivity. It assumes the pixels which are close together are highly correlated.
- Spatial convolutions are similar to regular convolution in the way they spatially convolute over nodes. Convolutions generate a new pixel from the pixel itself (the pixel placed in the same position as the new one) and it’s surrounding pixels.



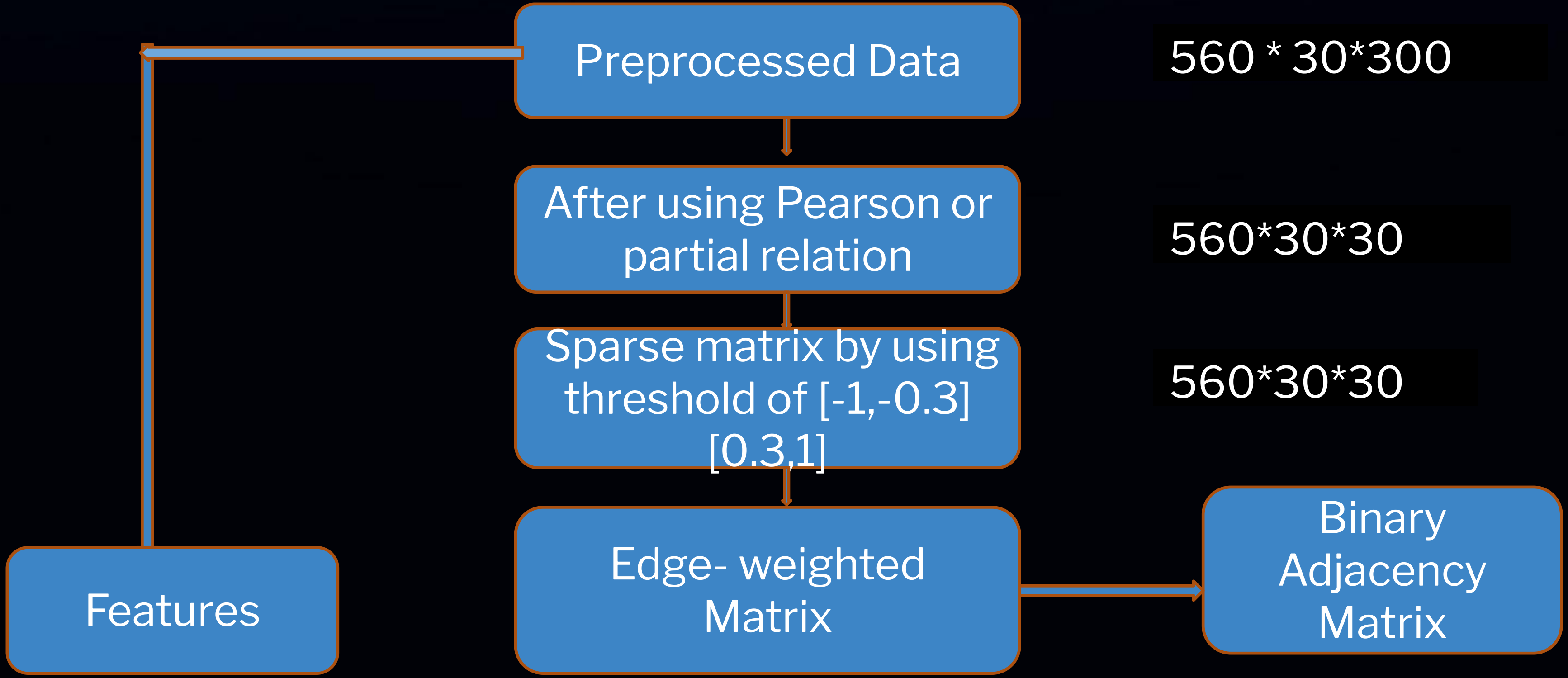
GCN Model


Input
Hidden layer
ReLU
Hidden layer
ReLU
Hidden layer
Readout
MLP
Softmax
y

Process Followed



Process


Preprocessed Data
560 * 30*300
After using Pearson or partial relation
560*30*30
Sparse matrix by using threshold of [-1,-0.3] [0.3,1]
560*30*30
Edge- weighted Matrix
Binary Adjacency Matrix
Features

Input Graph to GCN

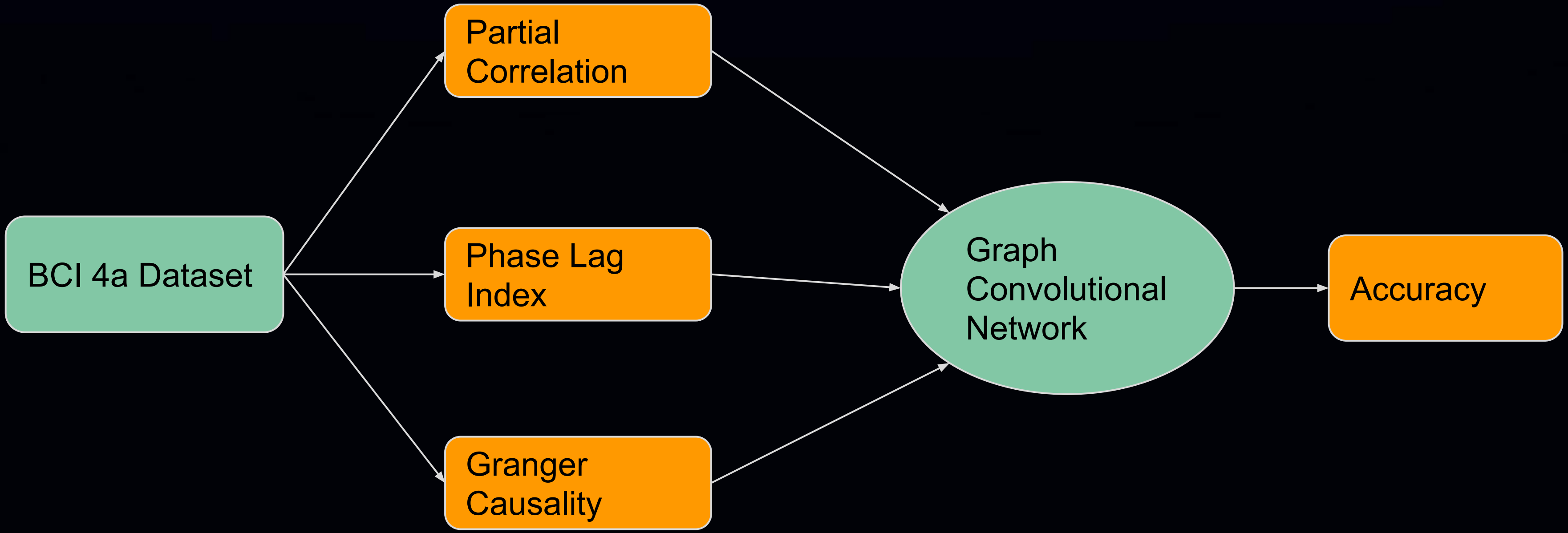
Adjacency Matrix

Features

GNN

Output:
Right Foot/Right Hand

Experiment 1



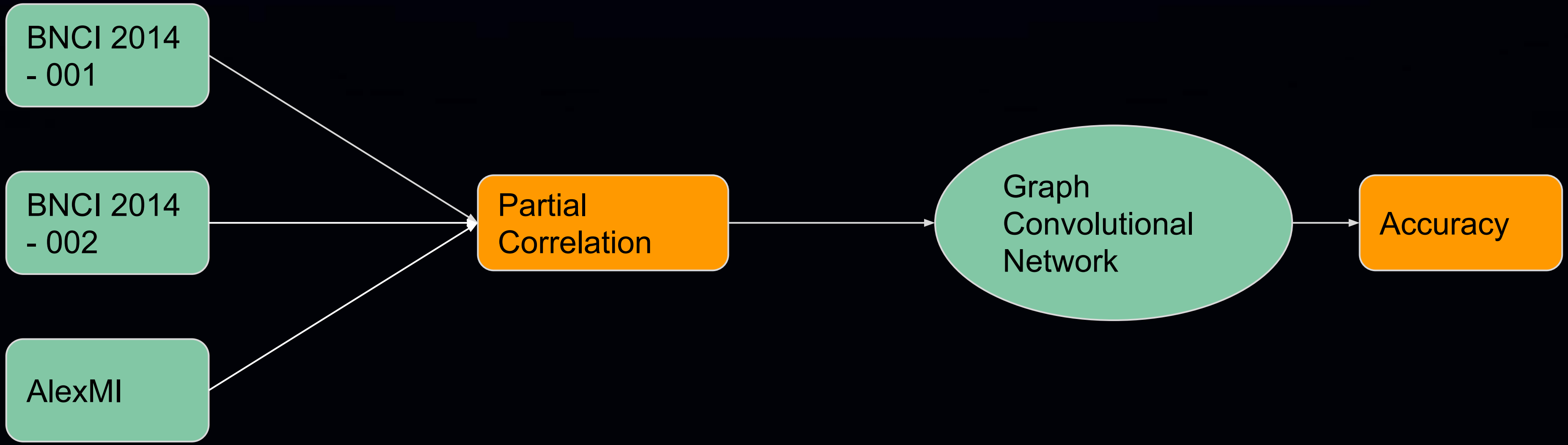
Validity of performance of the framework - MOABB Dataset for MI

- The MOABB project consists of the aggregation of many publicly available EEG datasets, converted to a common format and bundled in the software package.
- Using this system the GCN model can be comparable over all standard datasets.
- We have picked 3 datasets for validation purpose: BNCI-2014-001,BNCI-2014-002 and Alexandre motor imagery.

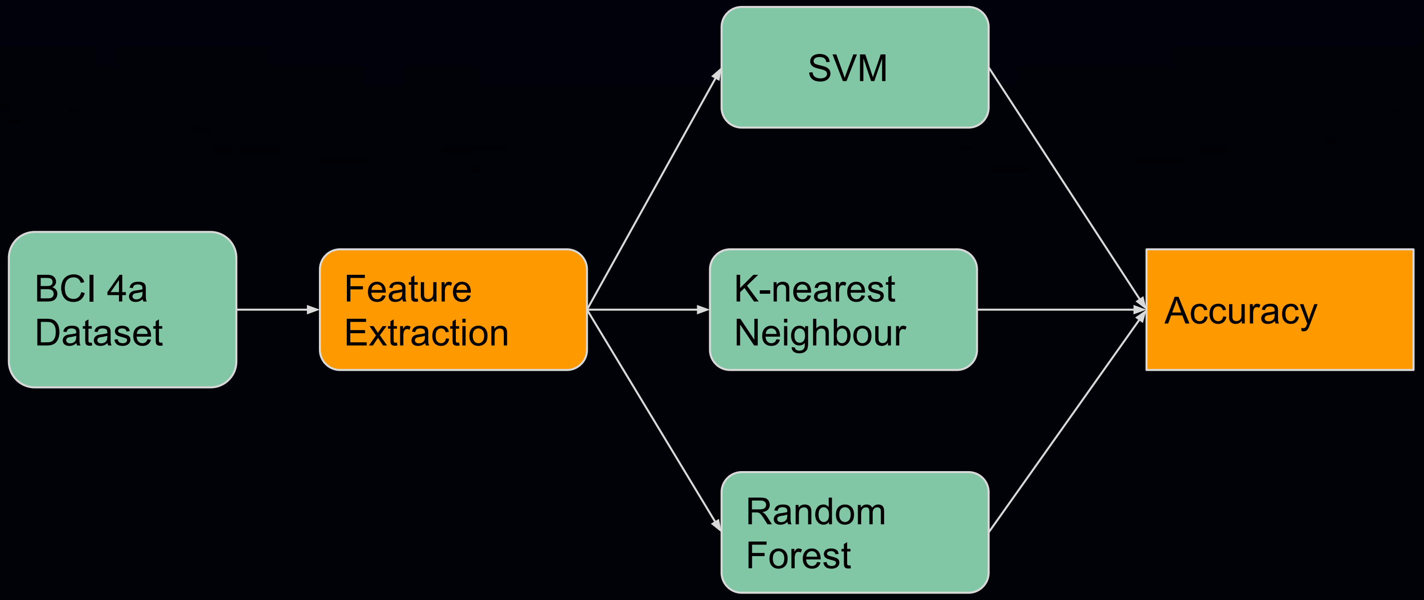
Name	Imagery	# Channels	# Trials	# Sessions	# Subjects	Epoch
Cho et al. 2017	Right, left hand	64	200	1	49	0-3s
Physionet	Right, left hand	64	40-60	1	109	1-3s
Shin et al. 2017	Right, left hand	25	60	3	29	0-10s
BNCI 2014-001	Right, left hand	22	144	2	9	2-6s
BNCI 2014-002	Right hand, feet	15	160	1	14	3-8s
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

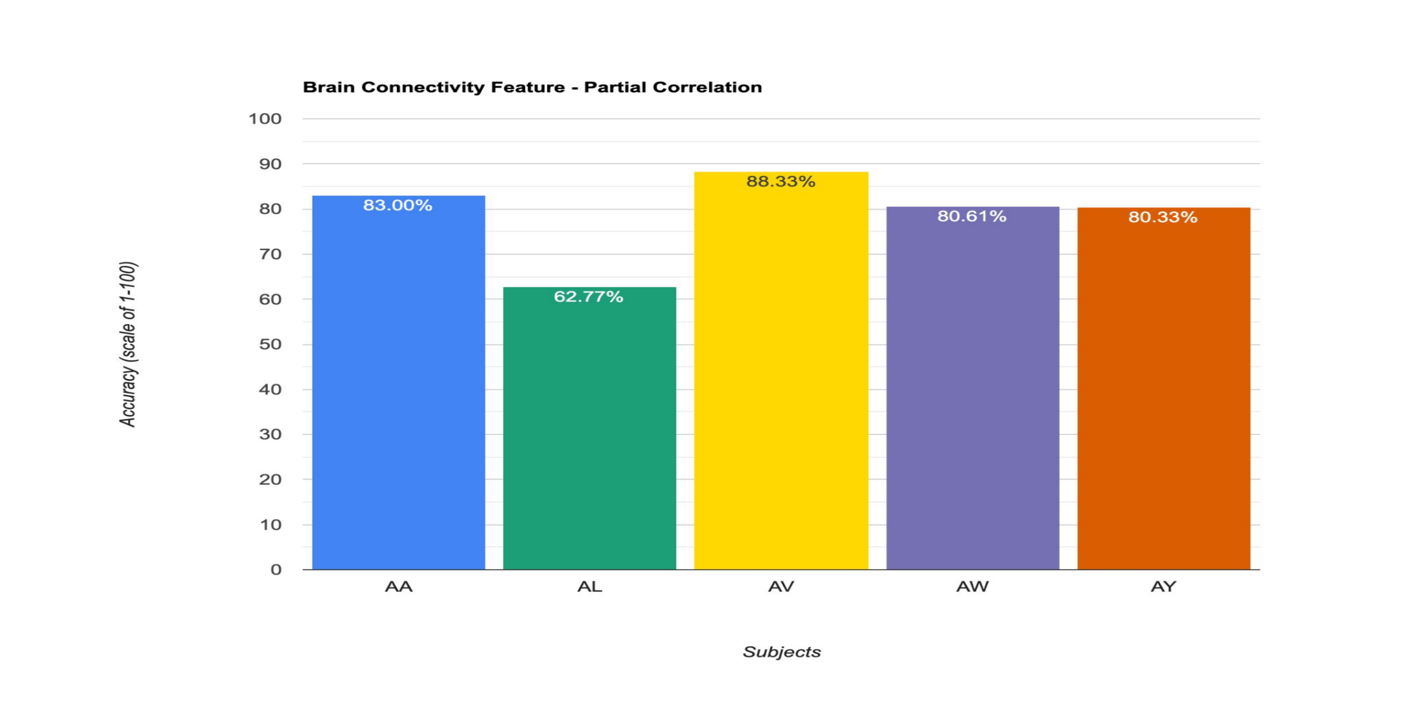
Experiment 2



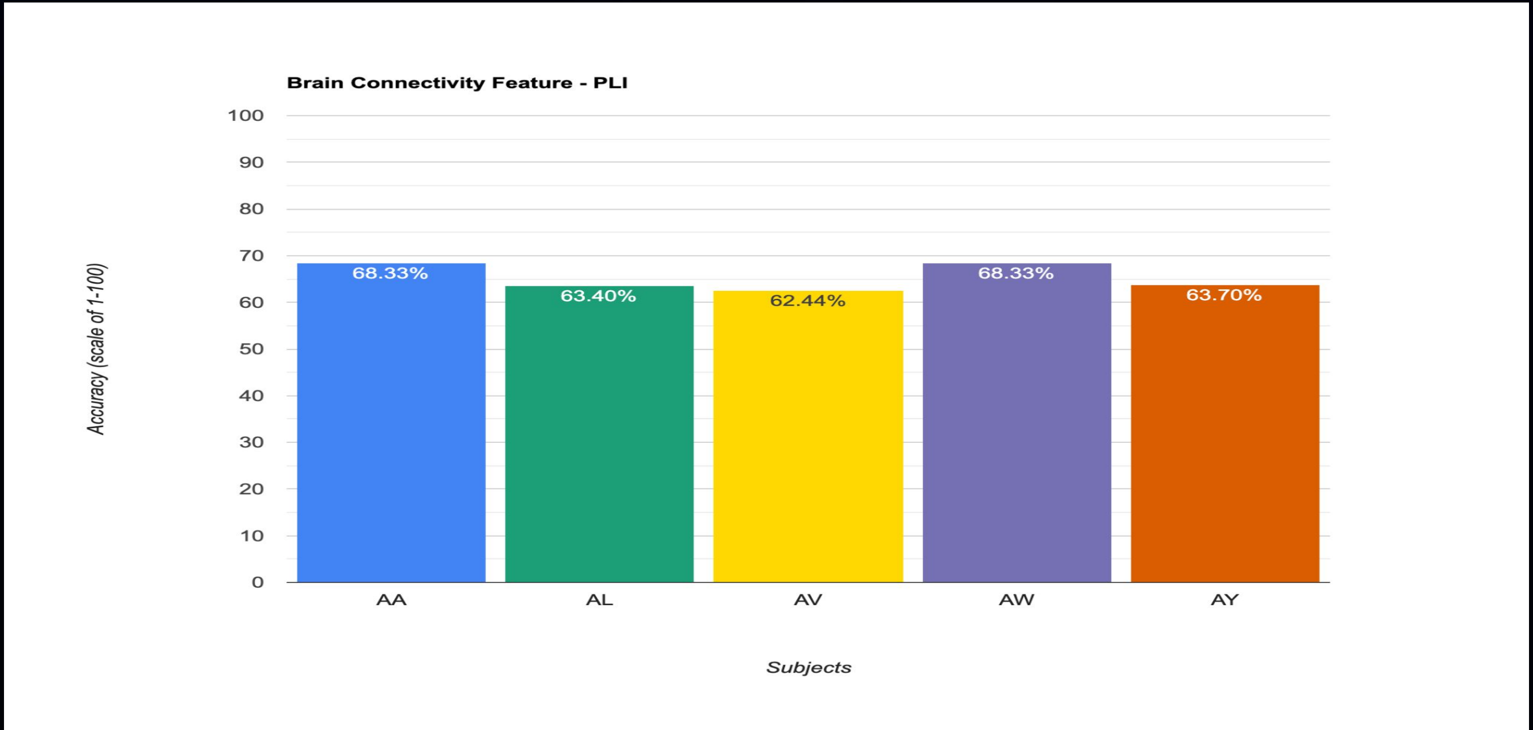
Experiment 3



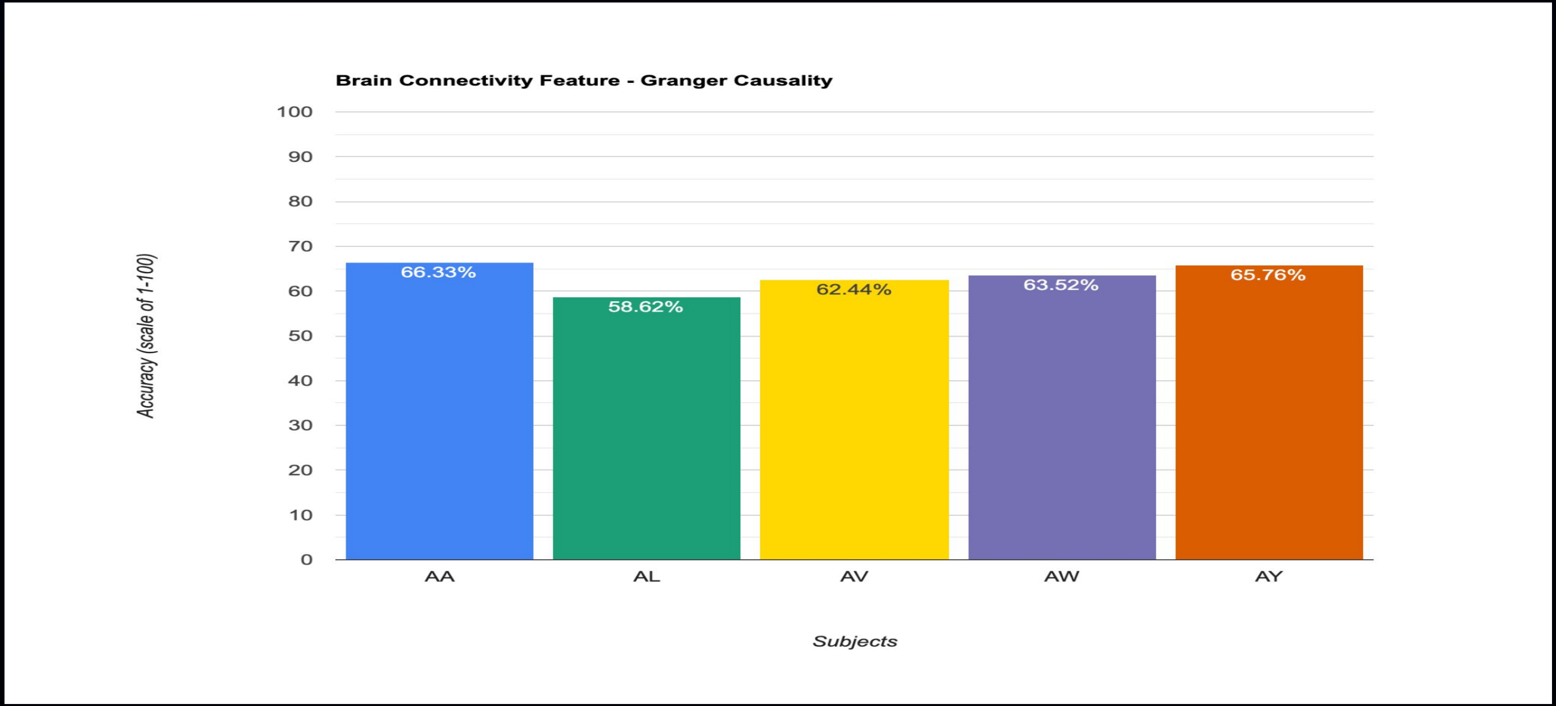
Results - Experiment 1- BCI Competition - iii-4a-Partial correlation



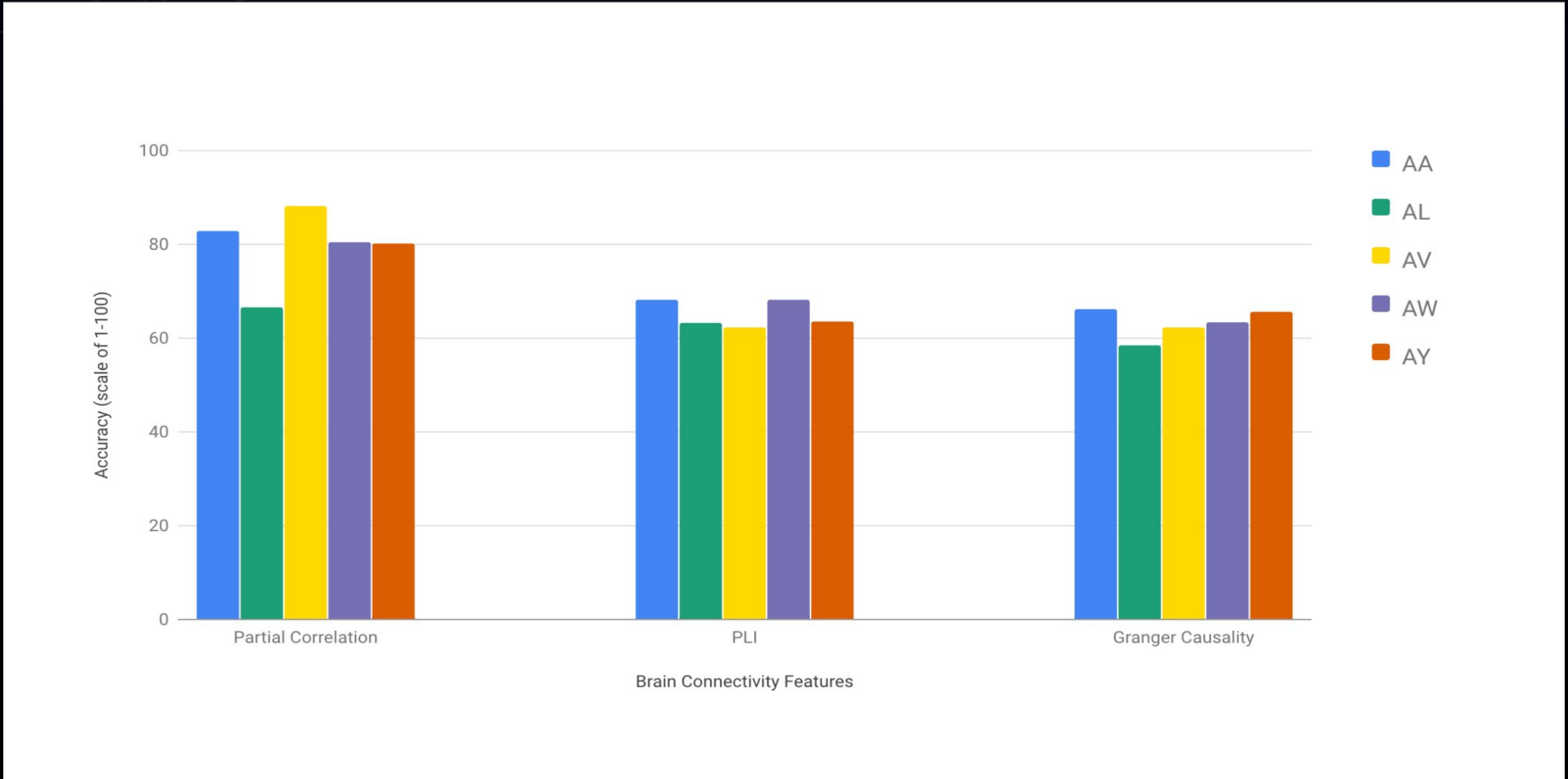
Results - Experiment 1-BCI Competition - iii-4a-PLI



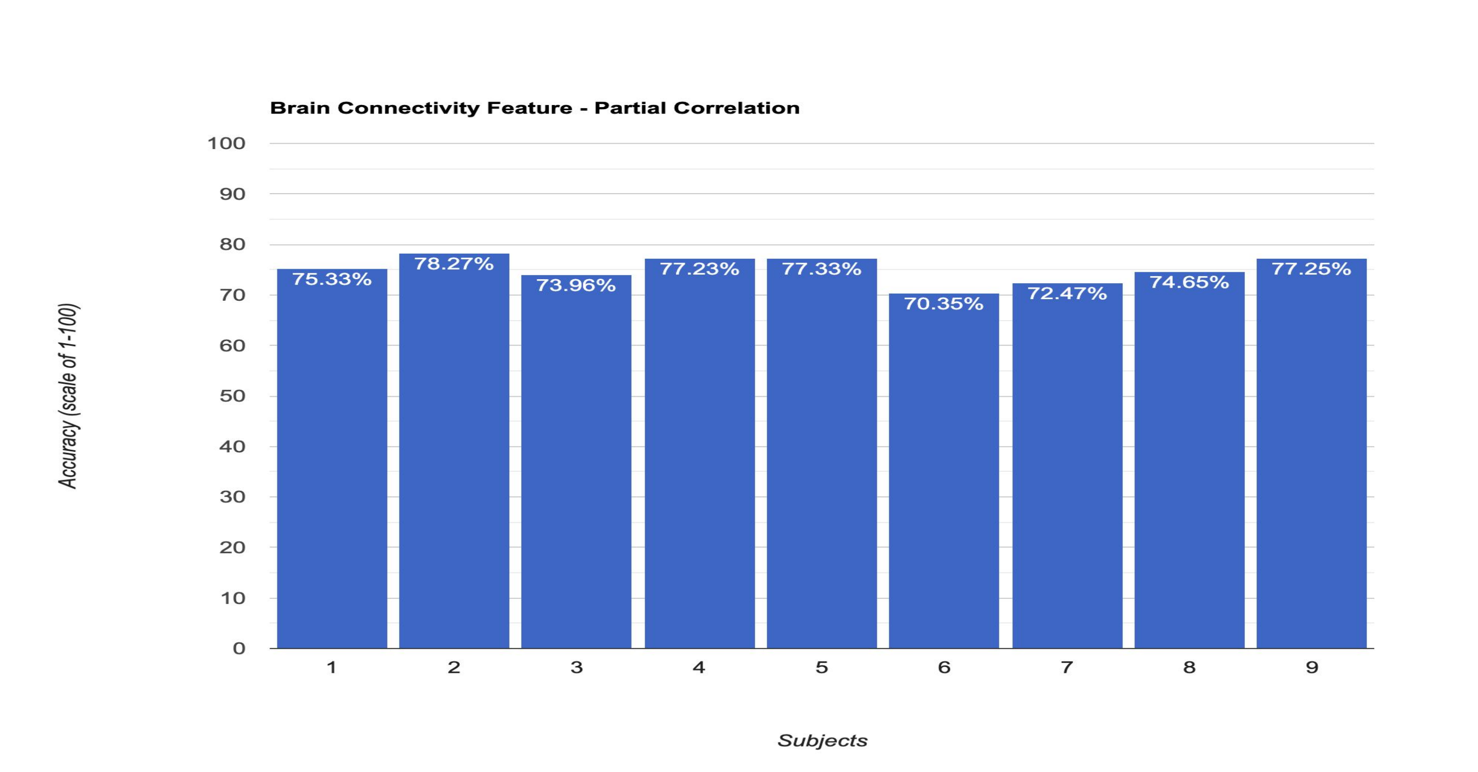
Results - Experiment 1-BCI Competition - iii-4a-GC



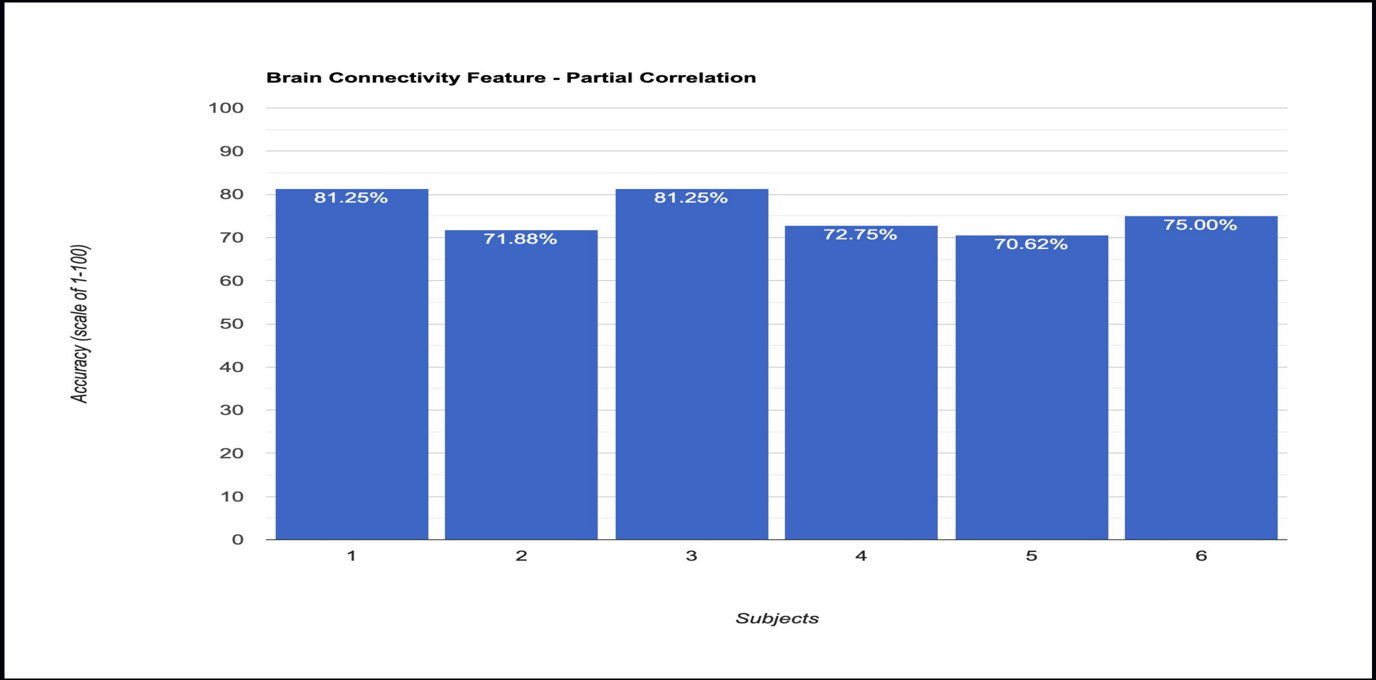
Result Comparison - Experiment 1



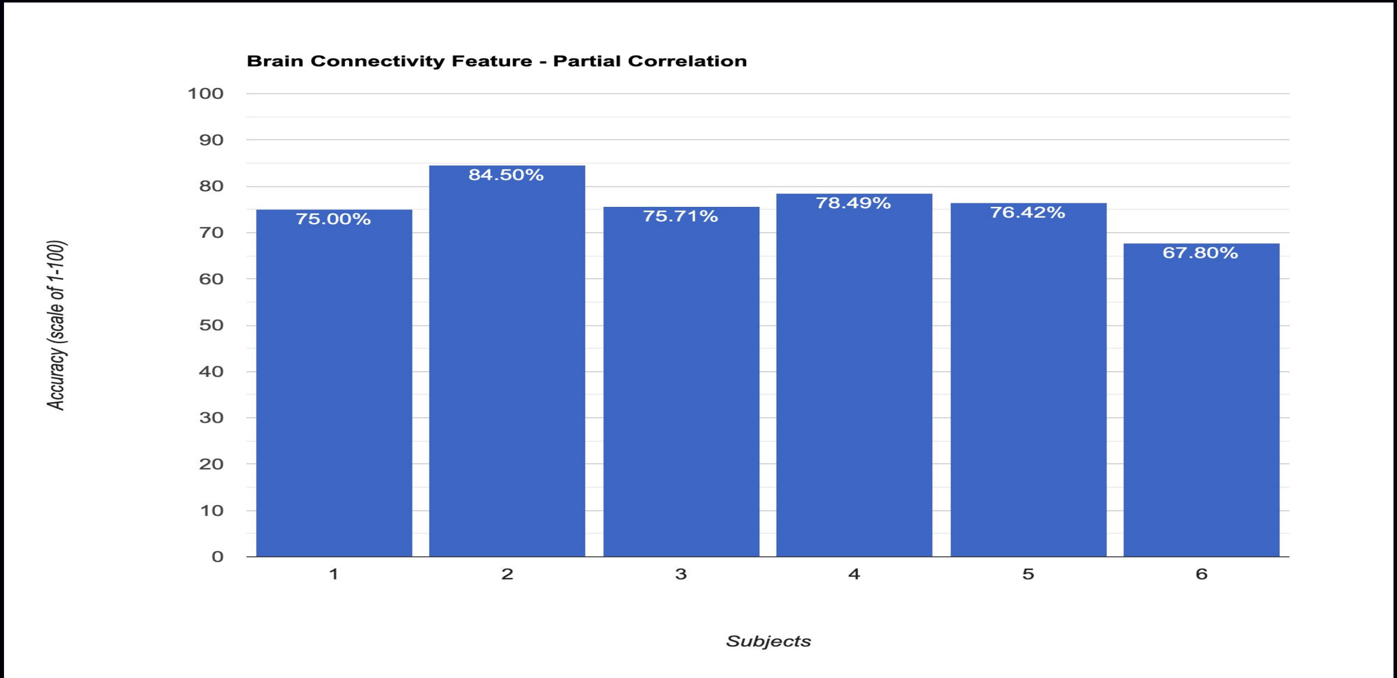
Results - Experiment 2-Validating best model found in Experiment I, with BNCI-2014-001 dataset



Results - Experiment 2-Validating best model found in Experiment I, with BNCI-2014-002 dataset



Results - Experiment 2-Validating best model found in Experiment I, with AlexMI dataset



Results - Experiment 3-Validating proposed model with traditional ML, for BCI Competition - iii-4a dataset in experiment-I

Dataset	Classifier	Accuracy
BCI Competition - iii-4a	Random Forest	72.33
BCI Competition - iii-4a	SVM	81.47
BCI Competition - iii-4a	KNN(n=5)	88.76

Conclusion

1. Motor Imagery classification task can be solved with graph convolutional network with good accuracy.
2. Results we obtained is subject wise. If we mix the data of all subjects model gets confused.
3. Adding edge weights features in the model may increase the accuracy and can beat the performance of KNN.
4. Partial Correlation with statistical features performs well as compared to other brain connectivity parameters. And gives the average accuracy of (79.79%).

References

1. S. R. Sreeja, Debasis Samanta, Pabitra Mitra, Monalisa Sarma, JJCIT(2018) ,”Motor Imagery EEG Signal Processing And Classification Using Machine Learning Approach”.

2. Leisman, G., Moustafa, A. & Shafir, T. (2016), ‘Thinking, walking, talking: The development of integratory brain function’, Frontiers in Public Health 4(10.3389).

3. Christopher Morris, Martin Ritzert, Matthias Fey, William L. Hamilton, Jan Eric Lenssen, Gaurav Rattan, Martin Grohe “Weisfeiler and Leman Go Neural: Higher-order Graph Neural Networks**”.**

4. Ioannis Xygonakis,[1,2] Alkinoos Athanasiou,[1] Niki Pandria,[1] Dimitris Kugiumtzis,[2] and **Panagiotis D. Bamidis ,** **“**Decoding Motor Imagery through Common Spatial Pattern Filters at the EEG Source Space**”.**

Thank You