Analyzing Functional Connectivity Networks in the Brain and the Relationship of Node-Level Characteristics

by

PATEL DHAIRYA BHAVESHKUMAR
202111044

A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of

MASTER OF TECHNOLOGY
in
INFORMATION AND COMMUNICATION TECHNOLOGY
to

DHIRUBHAI AMBANI INSTITUTE OF INFORMATION AND COMMUNICATION TECHNOLOGY

June, 2023

Declaration

I hereby declare that

i) the thesis comprises of my original work towards the degree of Master of Technology in Information and Communication Technology at Dhirubhai Ambani Institute of Information and Communication Technology and has not been submitted elsewhere for a degree,

ii) due acknowledgment has been made in the text to all the reference material used.

PATEL DHAIRYA BHAVESHKUMAR

Certificate

This is to certify that the thesis work entitled **Analyzing Functional Connectivity Networks in the Brain and the Relationship of Node-Level Characteristics** has been carried out by **PATEL DHAIRYA BHAVESHKUMAR** for the degree of Master of Technology in Information and Communication Technology at *Dhirubhai Ambani Institute of Information and Communication Technology* under my/our supervision.

PROF. MUKESH TIWARI
Thesis Supervisor

PROF. BAKUL GOHEL
Thesis Co-Supervisor

Acknowledgments

I want to thank my mother, **Mrs. Bhavisha Patel**, and sister, **Tisha Patel**, for always believing in me and supporting me in my endeavors. My father, **Mr. Bhavesh Patel**, has always emphasized the need to compete and improve professionally.

I want to thank **Prof. Mukesh Tiwari**, my thesis advisor, for his essential advice and assistance during the study process. I was able to complete the goals of this research with his support and skills.

I also want to thank **Prof. Bakul Gohel** for his advice and assistance in getting this research done. His insightful comments and recommendations helped me polish my work and raise its caliber.

I am grateful to my panel members, **Prof. V. Sunitha, Prof. Saurish Das Gupta, Prof. Rahul Muthu, Prof. Priyanka Singh, and Prof. Sanjay Shrivastav**, for their valuable time and insightful feedback during my stage presentations. Their teaching provided good knowledge, which was helpful during the thesis work, and they will be there with me as I grow.

I am grateful to my friends **Ruchita, Krutika, Hemani, Divya, Nisarg, Shreyas, Juned, Abhishek, Harsh Prajapati, Vraj, Harsh Sharma, Jeegar, Shrey, Devesh, Vinay, Maulik, Raghav, Ateendra, Kevin, Rahul, Parth and Utkarsh** who helped me directly or indirectly in this journey.

Contents

Abstract

It might be difficult to comprehend how the brain functions and how its structure and function interact because it is the body's most complicated organ. Recent advances in the non-invasive measurement techniques of brain signals and large-scale computing originating from advances in complex systems have enabled high-resolution temporal and spatial data analysis, thereby providing new insights into the functional connectivity of the different brain regions.

High-resolution temporal data, such as those obtained from EEG, can provide significant insights into the dynamics of the brain at very short time scales. These signals, however, are non-stationary and complex. This has resulted in applications of methods outside those of conventional statistics.

During the previous two decades, developments in the field of complex networks have provided a range of methods to analyze EEG data and thereby construct a picture of the brain's functional network. Complex networks provide a simple representation of the connectivity between the different EEG channels regarding nodes and edges. The connectivity is obtained by looking at the amplitude or phase relationship between the signals from different channels. Different network measures are then used to study the problem at the level of individual channels or nodes, groups of nodes, and all the nodes. This provides an understanding of how the brain organizes itself as it performs different tasks and the interrelationship between these different levels of description.

Deep learning techniques have also provided new opportunities and directions in studies of brain signals. It involves training a neural network to discover patterns in massive datasets. Statistical methods and deep learning techniques are usually used together. Statistical methods are typically used to pre-process the data, identify essential features, and identify the data set's dimensionality. At the same time, deep learning techniques allow studying the intricate relationships between the brain signals.

Despite the plethora of different techniques, our understanding of the brain is still in its nascent stage. Apart from the complexity originating from the brain as an organ, the methods used have limitations. For example, the properties of the network are sensitive to the methods used to construct the network itself. For instance, Pearson correlation based network construction is a linear correlation, and hence the network properties would be the ones that are best captured by such linear correlations. While the deep learning methods are certainly promising since they consider any nonlinear correlations, the advantages they provide compared to the other methods still need to be discovered.

Given the complexity of brain dynamics and the limitations of the different methods, we explore how well the various ways correlate in this thesis. Specifically, we have looked at the relationship between the fluctuations in the signals at a channel, the channel represented as a node in the brain's functional network, and the observations from deep learning techniques. Based on sliding window analysis, our main observation is that for resting state data, the mean and variance of the raw signal at a channel show a positive correlation to the fluctuations in the weighted degree of the node in the corresponding network. And a scatter plot of correlation values between different channels using simple statistical methods and deep learning-based methods gives information about the association and similarity between the two approaches in capturing the patterns of functional connectivity in the brain.

List of Figures

CHAPTER 1
Introduction

1.1 Brain

The human body's most intricate organ is the brain [1]. It controls everything we do, including our thoughts, feelings, and physical movements. It contains around 100 billion neurons, which are specialised cells that communicate with one another via electrical and chemical signals. These neurons are organised into various zones, each with a specific function.

One of the brain's primary functions is the processing of information. Our brain converts sensory input from our environment, such as sights and sounds, into signals, which are then interpreted to provide meaning. The brain significantly influences the ability to recall and learn new information. Additionally, it helps in memory development and information recall from the past.

Unfortunately, the brain can be impacted by numerous illnesses and ailments. A few typical examples include stroke, Parkinson's disease, and Alzheimer's disease. These conditions may significantly harm a person's quality of life.//

The brain can be spatially segregated into different regions based on the functions being carried out. Each brain hemisphere has four sections called lobes that control specific functions. The **Frontal lobe** [2] is the most significant part of the brain and controls personality traits, judgment, and movement. It is situated in the front of the head. The **Parietal lobe** [3], located in the middle of the brain, aids in object identification, understanding spatial relationships, pain, and touch in the body. The back portion of the brain that controls vision is called the **Occipital lobe** [4]. Short-term memory, speech, musical rhythm, and to some extent, smell identification are all functions of the **Temporal lobes** [5] on the sides of the brain.

1.2 Methods to obtain Brain Signals

The brain can be imagined to function at different hierarchical scales. The smallest part of the brain is known as the synapse, and the largest part is known as a region of the brain. Many synapses make neurons, and many neurons make a brain region. Many regions make the whole brain. Broadly, the different methods used to measure brain signals can be characterized into:

1. **Non-Invasive Methods [6] :** Techniques in which instruments or probes are not inserted into the brain or skull to obtain signals from the brain.
2. **Invasive Methods [7]:** Brain tissue or fluid is directly accessed using invasive techniques to obtain brain signals.

The different methods to record brain signals can also be differentiated based on their temporal and spatial resolution. The ability of a technology to record changes in brain activity over time determines its temporal resolution. In other words, it relates to the accuracy of determining when certain brain activities occur. Some techniques can quickly measure changes in brain activity on the order of milliseconds and therefore provide a high temporal resolution, and some techniques have a low temporal resolution. At the same time, some methods offer solutions in seconds and have a comparatively lower temporal resolution.

Contrarily, the spatial resolution of a method relates to its accuracy in precisely predicting the spatial location of a specific brain activity. A high spatial resolution lets us pinpoint which brain areas are active during a particular task or stimulus. Two of the standard non-invasive methods to record brain activities are fMRI and EEG, while fMRI provides high spatial but poor temporal resolution. EEG data has high temporal but poor spatial resolution.

1.3 fMRI(Functional Magnetic Resonance Imaging)

Functional Magnetic Resonance Imaging [8], or fMRI, is a non-invasive method of measuring brain activity. It uses a powerful magnet to generate magnetic feild and radio waves to create detailed brain images. Precisely, fMRI measures changes in blood flow and oxygenation levels in different brain areas in response to various stimuli, such as visual or auditory stimuli, or during the performance of specific tasks.

When neurons in the brain become active, they require more oxygen and glucose to support their increased metabolic demands.The outcome is increased blood flow to the brain, which activates an area and is known as the hemodynamic response. fMRI takes advantage of this by using the magnetic properties of hemoglobin to detect changes in the brain's oxygenated and deoxygenated blood.

The images produced by fMRI are incredibly detailed, allowing researchers and doctors to see which brain areas are most active during specific tasks or in response to particular stimuli. These images can be analyzed using sophisticated statistical methods to identify areas of the brain that are significantly more active during certain conditions than others.

fMRI uses the **BOLD (Blood Oxygen Level Dependent) [9]** concept. The BOLD signal measures the difference between the magnetic properties of oxygenated and deoxygenated hemoglobin. A higher BOLD signal is produced when the brain's neurons are engaged because more oxygenated hemoglobin is present in the blood vessels. The brain regions active during a specific task or stimulus are mapped using the BOLD signal. It may take several seconds to notice changes in brain activity.

1.4 EEG(Electroencephalogram)

The electrical activity produced by the brain can be measured using electroencephalography (EEG) [10]. EEG is a commonly used technique in clinical and research settings to understand brain function, diagnose neurological disorders, and track changes in brain activity over time. It involves placing electrodes on the scalp to measure the electrical signals generated by the brain's neurons.

The brain's millions of neurons produce EEG signals. These neurons generate electrical currents as they communicate, which can be measured by the electrodes placed on the scalp. EEG signals are typically recorded with the subject sitting or lying down with their eyes closed or open, and they can also be recorded during specific tasks or stimulation.

EEG signals are characterized by their frequency and amplitude. The signal frequency refers to how often the electrical activity repeats per second, measured in hertz (Hz). The signal's amplitude refers to the strength of the electrical activity, measured in microvolts (μV). Different frequency bands of EEG signals are associated with varying states of brain and cognitive processes.

The excellent temporal resolution of EEG is one of its key benefits. EEG is ideally suited for researching the timing of cognitive processes in the brain since it can accurately record changes in brain activity. In contrast to other neuroimaging methods, EEG has a lower spatial resolution, which restricts its capacity to precisely pinpoint the source of the electrical impulses in the brain.

1.5 Characteristics of Brain Signals

Brain signals have several characteristics that help in their analysis and interpretation. Some of these characteristics are:

1. **Amplitude :** A brain signal's amplitude describes its power or intensity. It is the vertical separation of a signal's highest and lowest points. The location of the brain from which a signal is recorded, the signal type (such as EEG or fMRI), and the activity being monitored can all affect the signal's amplitude.
2. **Frequency :** A brain signal's frequency is measured in oscillations or cycles per second. It is expressed in Hz or Hertz. In EEG signals, different frequencies, such as alpha, beta, theta, and gamma waves, are connected to various types of brain activity.
3. **Phase :** The relative position of a wave cycle at a certain instant in time is called the phase of a brain signal. It can be used to examine if certain brain regions are synchronized or desynchronized.

4. **Time :** A brain signal's time is the instant that it is recorded. It can be applied to research how connections develop as well as the temporal dynamics of brain activity.

5. **Spatial Location :** A brain signal's spatial placement relates to the particular brain area where it was captured. It can be used to examine how functionally connected various brain regions are to one another.

6. **Noise :** Unwanted impulses are called noise, which might obstruct examining brain signals. Internal factors like muscle or eye movements and external factors like electromagnetic radiation can bring it on.

Signals are classified into two categories based on their statistical properties:

1. **Stationary Signal :**

   A signal is considered stationary if its statistical characteristics don't change over time. In other words, the signal's mean, variance, and correlation do not change with time. Because stationary signals' statistical characteristics are constant and we can use statistical methods to analyze them, they are simpler to understand and model.

2. **Non-Stationary Signal :**

   Any signal whose statistical characteristics change over time is said to be non-stationary. For instance, the signal's mean, variance, and correlation could change with time. Because non-stationary signals are more complex than stationary signals, they must be analyzed using sophisticated signal processing methods.

1.6 Network construction using EEG signals

Analyzing the functional connectivity between various brain regions is a step in building networks using EEG readings. This can be accomplished by computing pairwise correlations or coherence between the EEG time-series data acquired at several electrode locations on the scalp. Since various frequency bands are believed to be connected to multiple brain networks and processes, these correlations are typically calculated within a specific frequency range.

The correlation values can then be used to build a network graph. Each node corresponds to a particular EEG electrode position on the scalp, and each edge to a statistically significant correlation between the time-series data from two electrode locations. The weight of the edge often indicates the strength of the correlation, with thicker or darker edges denoting more significant correlations.

The resulting network can be examined using graph theory tools to find significant nodes or hubs, sub-networks or communities, and patterns of connectivity or communication between various brain regions. These network analyses can show how the brain is functionally organized and adapts to multiple inputs or cognitive demands.

It is significant to note that proper preprocessing and analysis of the data are necessary when building networks using EEG signals to guarantee that the final network appropriately depicts the underlying brain activity. The selection of frequency bands, correlation measurements, and network analysis techniques can also impact the outcomes. It should be made carefully based on the study subject at hand.

1.7 Functional Connectivity

Functional connection [11] describes the statistical correlation or synchronization of neuronal activity among several brain regions, regardless of how physically distinct they are. In other words, when working on a task or relaxing, there is synchronized movement between various brain regions.

EEG, fMRI, and other methods, among others, can all be used to measure functional connectivity. Finding the degree of activity correlation between two brain areas is the fundamental goal of functional connectivity studies. This can be accomplished by computing the correlation coefficient, a metric for comparing the similarity of activity patterns across time, between the time series of each region.

Functional connectivity analysis is employed in neuroscience to understand how different brain regions interact and pinpoint the functional networks that underpin various cognitive processes, including attention, memory, language, and emotion.

There are two methods for analyzing functional connectivity: network-based and seed-based. In a seed-based analysis, a specific part of the brain (the seed) is chosen, and the functional connectivity of this part to the rest of the brain is assessed. In network-based analysis, the entire brain is viewed as a network, and multiple functional networks are identified by examining the connectivity between different regions.

Functional connectivity analysis has several uses in both fundamental and applied research. It has been applied to study how various neurological and psychiatric conditions affect the brain's functional connectivity, how it develops during childhood and adolescence, and how multiple interventions like medication, brain stimulation, and cognitive training affect brain function.

CHAPTER 2

Literature review

It is now possible to apply ideas from machine learning, neuroscience, and graph theory to various problems relevant to studying the human brain and treating disease, thanks to the advantages of non-invasive imaging techniques. Recent papers that relate to our findings and utilize the machine learning idea include the following:

1. **Functional brain network classification for Alzheimer's disease detection with deep features and extreme learning machine [12]**

2. **EEG functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia [13]**

The first article analyses AD (Alzheimer's disease) identification using fMRI data. A technique based on correlation is used to build a neural network. The definition of the Pearson correlation coefficient is

$$r_p = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{\Sigma_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\Sigma_{i=1}^{n}(x_i - \overline{x})^2 (y_i - \overline{y})^2}} \tag{2.1}$$

where

- x_i and y_i are the i-th values of the two variables
- $\bar{x}$ and $\bar{y}$ are the means of the two variables
- r_p is the Pearson correlation coefficient between the two variables, which ranges from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation.

is used to find the connectivity between different brain regions denoted as nodes in the network.

The authors of this study contend that methods that directly extract deep characteristics from brain networks outperform shallow learning techniques. How classifications based on brain network models compare to approaches based on deep learning is a crucial question. Does a strong association exist between the two?

In the first paper, they show the network model classification framework by which they have classified the networks based on the input. Using the data, a connectivity matrix was constructed from the fMRI images. The connectivity matrix can generate networks whose properties are used for feature selection. Alternatively, deep learning methods such as Convolutional Neural Network (CNN) [14] and Recurrent Neural Network (RNN)[15] can be directly used at this stage.

To learn some features, we feed the network into the RNN network, provide it to the fully connected layers, and then use the softmax activation function to finish.

In this paper, they learn the features of the network using

- **Regional connectivity positional features**
- **Adjacent positional features**

They have employed the CNN layer in the deep learning-based methods to learn Regional Connectivity Position Features. Convolution layers, max pool, average pool, and fully linked layers were all used in the design, along with ReLU as the activation function. Additionally, they used the RNN model in deep learning-based techniques to learn positional adjacency features.

The second paper investigates using EEG data to identify schizophrenia (SZ) and Alzheimer's disease (AD). They consider the network of connections between various brain regions and deep neural networks to distinguish between individuals with AD and SZ. We focus on the relationships between the electrodes that record the time series when the neural network only accepts raw time series or signals as input.

The strategy for categorizing EEG time series from healthy patients exhibiting AD and SZ is suggested in this research. The accuracy for both illnesses is near 100% using a matrix of connections as input for a tailored convolutional neural network (CNN) model. This study also suggests that connection matrices produce more beneficial outcomes. The Granger Causality [16] and Pearson Correlation Coefficient provide promising results for SZ. Any brain disorder's EEG data can be analyzed using the abovementioned framework.

EEG time series are used to create the first matrix of connections since they are artifacts-free. The strength of links between two brain regions has been measured using three different methods:

- **Granger causality test** [16]
- **Pearson Correlation Coefficient** [17]
- **Spearman's Rank Correlation** [18]

The convolutional layer performs convolution, a mathematical operation that can be done simultaneously in several dimensions. The weights of the artificial neurons (or filter) are represented by a tensor called a kernel. The convolutional layer outputs incorporate the input data's main features. The results of the convolution between neurons and kernels are feature maps. The convolutional layer's functionality is similar to that of the pooling layer, which decreases the dimensionality. The max-pooling function in this example minimizes the size of the feature map by returning the most significant value within an area of the tensor. The fully connected layer divides input data into numerous classes based on a training data set. Because the output correctly predicts the outcome of the input EEG data as healthy or unhealthy, the artificial neurons in the fully connected and max pooling layers are connected.

Here, two methods for the CNN architectures are suggested, one of which (CNNtuned) employs a tuning procedure and the other which (CNNuntuned) does not. Finding the values of hyperparameters to tune the CNN model's performance entails using optimization techniques. In the current work, three tuning strategies are employed:

- Random search [19]
- Hyper-band [20]
- Bayesian Optimization[21]

CHAPTER 3
Motivation

A node's measurement in a network built using EEG data can reveal information about the underlying brain activity at that particular brain region. For instance, a higher degree of centrality or betweenness centrality may indicate that the node is more significant in communicating information between other brain regions. A larger clustering coefficient, on the other hand, may imply that the node is more engaged in regional information processing inside a particular brain area.

We can better comprehend how these network measurements relate to the underlying brain activity by comparing them to the matching EEG signal for that node. An area of the brain with strong neural activity, as evidenced by a higher-amplitude EEG signal, may correspond to a node with a high degree of centrality, for instance. Additionally, alterations in network measurements over time might also be reflected in the corresponding EEG signal, which would represent alterations in the underlying brain activity.

The functional organization of the brain and the integration of neural activity across different brain regions can be learned by examining the relationship between measures of nodes in EEG-based networks and matching EEG signals.

By analyzing the correlation between node measurements in EEG-based networks and corresponding EEG signals, it is possible to learn about the functional organization of the brain and the integration of neural activity across various brain areas.

On the other hand, deep learning-based models can capture intricate nonlinear correlations between signals. These models, which may be applied to tasks like signal prediction, classification, and clustering, use neural networks to understand the correlations between the signals. For instance, convolutional neural networks (CNNs) can be used to categorize signals based on their features, and recurrent neural networks (RNNs) can be used to forecast the future time step of a signal based on its initial values. These models can also be applied to unsupervised learning tasks like dimension reduction and clustering, which can be utilized to find trends and connections in multivariate signals. However, the training and testing of these models are often computationally expensive and data-intensive.

CHAPTER 4
Dataset

The dataset we have used for our work is from Large-scale functional networks identified from resting-state EEG using spatial ICA [22] paper. The dataset is related to a study titled ”Mapping the human brain functional connectivity using EEG: A graph theory-based analysis of functional networks.”The dataset includes EEG recordings from 64 electrodes placed on the scalp of 13 individuals. The recordings were obtained during resting-state conditions, with participants asked to remain awake and relaxed with their eyes closed. To make it computationally light, we have selected some specific channels out of the 64, which are Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T7, T8, P7, P8, Fz, Cz, Pz, Oz. So we are working on these 19 channels for our work.

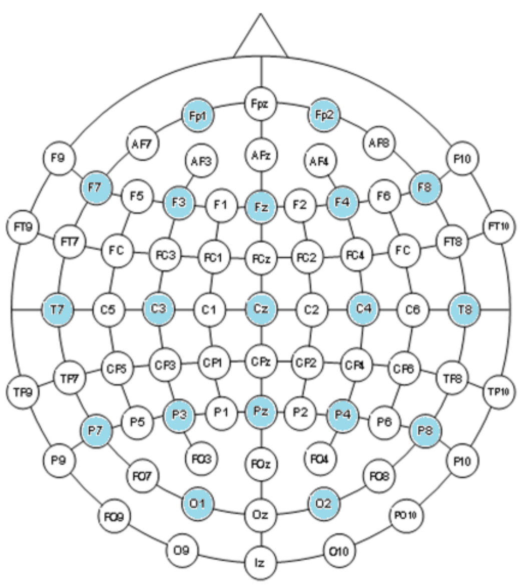

Figure 4.1: Brain Channels [23]

4.1 Resting State

When a person is not engaged in any particular task or is not paying attention to anything in particular, their brain is said to be in a "resting state." The brain is still functioning during this period, and spontaneous changes in brain activity occur. This state is crucial to study because it serves as a benchmark for understanding how the brain behaves in other conditions, such as when performing a task or experiencing different illnesses.

Several brain imaging methods, including fMRI and EEG, can be used to study the brain's resting state. Researchers use fMRI to detect changes in blood flow and oxygenation levels in various brain regions. Researchers used EEG to track the electrical activity produced by brain neurons. Both methods offer insightful data regarding the resting state, although fMRI has a higher level of spatial resolution while EEG has a higher temporal resolution.

Research on the brain's resting state [24] has also been applied to examine individual variations in brain activity. For instance, studies have revealed that people with high levels of anxiety exhibit increased activity in the amygdala, a part of the brain involved in processing emotions while resting. Additionally, individual variations in cognitive abilities like attention and memory have been predicted using resting state activity.

Research on the resting state is crucial to understanding how the brain functions in different states and how neurological and mental problems could hamper it.

CHAPTER 5
Methods

5.1 Data Preprocessing

Before getting into the analysis, the data has to be pre-processed to ensure minimal overlap between signals from different channels, separating the amplitude and phase components and looking at the signal in task-specific frequency bands. The different methods used for this purpose are discussed below.

5.1.1 Independent Component Analysis(ICA)

A statistical method called independent component analysis (ICA) [25] [26] separates independent and significant sources of signals from a jumble of visual signals. ICA is frequently used to extract functional brain networks from measurable data, such as EEG or fMRI signals, in the context of brain signals.

The basic idea behind ICA is to decompose measured signals into independent, non-gaussian components. The method assumes that the observed signals are a linear mixture of independent sources and uses a matrix factorization technique to estimate both the sources and the mixing matrix that produced the observed signals. The resulting sources are statistically independent and represent underlying neural processes not visible in the observed signals.

The cocktail party dilemma is a well-known illustration of the usefulness of independent component analysis (ICA). This issue distinguishes different sound sources in a noisy setting, similar to trying to make out a single conversation during a party in a packed room.

The extraordinary ability of the human brain to carry out this separation automatically can make it difficult to mimic this process using computers. But ICA has proven to be a potent tool for addressing this issue.

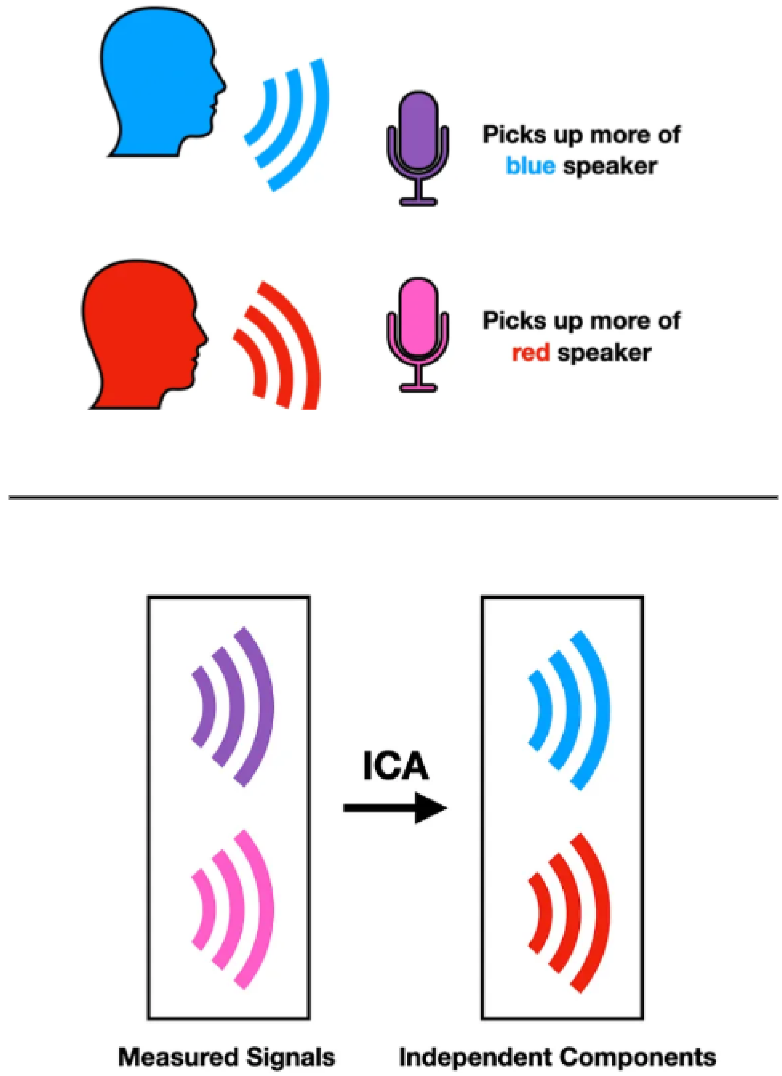

Figure 5.1: Schematic showing the concept behind the ICA [27]. In the top figure, each microphone has a mixture of the two human conversations. In contrast, the bottom figure shows ICA is taking the mixed signals as an input and giving the output as independent signals .

The cocktail party dilemma can be seen as a situation where various audio signals are combined to create a complicated waveform in the context of ICA. ICA assumes that the sources are statistically independent of one another and attempts to decompose this mixed signal into its underlying source signals, as seen in figure 5.1.

Using ICA, it is possible to decompose the mixed audio signal in the cocktail party problem into its underlying sound sources, such as individual conversations. This is achieved by determining the statistical correlations between the various audio sources, as in the bottom of the figure 5.1.

Statistical regularities in the mixed signal, including correlations or non-gaussian distributions, are recognized by ICA methods. The estimation of the mixing matrix, which defines how the various sources contribute to the mixed signal, is done using these regularities.

The mixed signal can be divided into its independent components using ICA after the mixing matrix has been determined. Using the estimated mixing matrix, this procedure includes splitting the mixed signal into a new group of statistically independent signals.

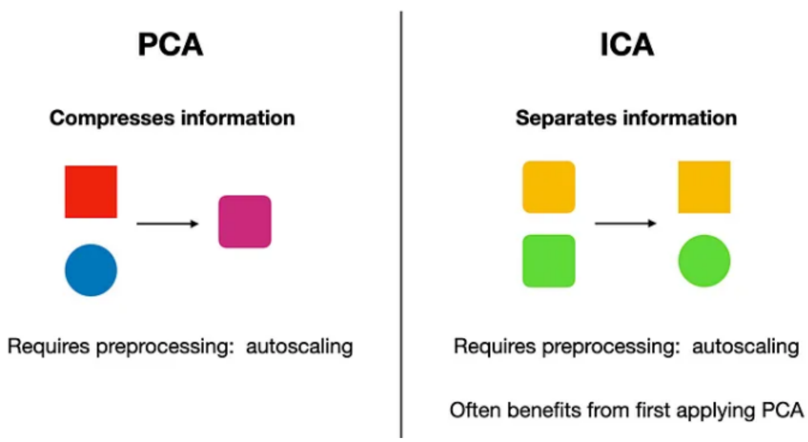

Figure 5.2: ICA vs PCA [27]

PCA(Principle Component Analysis) [28] is a linear approach, meaning it can only capture linear correlations in the data, but ICA can capture both linear and non-linear interactions. This is an essential distinction between PCA and ICA. While PCA assumes that the observed signal is a linear combination of gaussian variables, ICA assumes that the observed signal is a linear combination of non-gaussian and statistically independent source signals. As a result, ICA is better suited for studying complex, non-linear phenomena like brain signals.

PCA and ICA further differ in that PCA can only recognize orthogonal components while ICA can recognize non-orthogonal ones. In other words, whereas ICA components can be oriented in any direction concerning one another, PCA components are always perpendicular. These are the main reasons why we do not use PCA instead of ICA.

5.1.2 Band Pass Filter

A band-pass filter is a signal-processing instrument that attenuates (decreases) frequencies outside a specific frequency range while allowing frequencies within that range to pass through a signal. In other words, it removes the undesirable components while selectively amplifying or attenuating the signal components within a certain frequency range.

Combining low-pass and high-pass filters creates a band-pass filter. In contrast to the high-pass filter, which blocks low-frequency components below a given cutoff frequency, the low-pass filter eliminates high-frequency components above that cutoff frequency. These filters enable the signal to flow through a particular frequency range or passband. Band-pass filters are used to process EEG signals to remove undesired noise and artifacts and identify particular frequency components associated with brain activity.

Band-pass filters, such as Butterworth [29], Chebyshev [30], and Bessel [31] filters, come in various shapes and sizes. Each type has unique traits and trade-offs between ripple, frequency response, and filter order. We are using **Butterworth Band Pass Filter** in this thesis.

In the case of brain signals, the frequency components of interest are typically within a specific range, such as the alpha (8-13 Hz) or beta (13-30 Hz) and many more bands in EEG signals given in the figure.

Table 5.1: Frequency Bands and their Associated Brain Activities

Frequency Band	Frequency Range	Associated Brain Activities
Alpha	8-13 Hz	Relaxation, Focused Attention, Creative Flow
Beta	13-30 Hz	Alertness, Concentration, Problem Solving
Delta	0-4 Hz	Deep Sleep, Emotions
Gamma	30-100 Hz	Perception, Consciousness, Learning
Theta	4-8 Hz	Meditation, Creativity, Memory Retrieval

5.1.3 Hilbert Transform

The Hilbert Transform's [32] mathematical technique transforms a complicated time-domain signal into a frequency-domain output. The Hilbert Transform can be used in brain signals to determine the amplitude and phase of the various frequency components in a given signal.

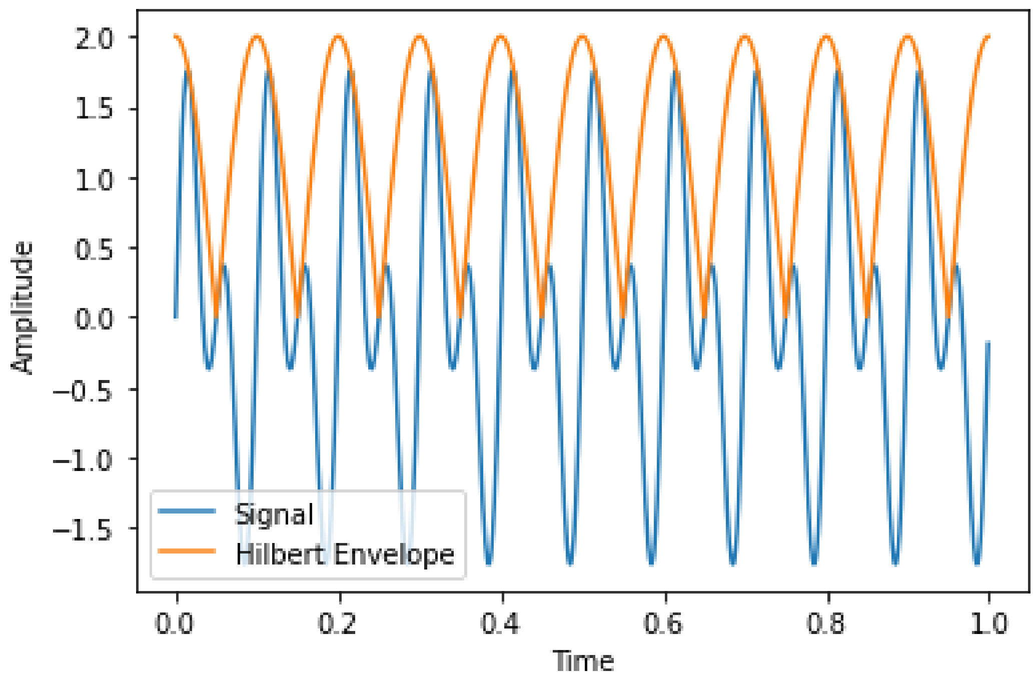

Figure 5.3: Hilbert Envelope VS Raw Signal

The resulting plot shows in figure 5.3 that the signal and its envelope are in the same plot, where the envelope appears as a smooth curve following the peaks and troughs of the original signal. This demonstrates the ability of the Hilbert transforms to extract the envelope of a signal, which can be useful in analyzing non-stationary signals with rapidly changing frequencies.

5.1.4 Pearson Correlation

Pearson correlation is a statistical tool used to assess the degree of linear relationship between two variables. Pearson correlation is utilized in the context of brain signals to evaluate functional connectivity between various brain areas.

$$r_p = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{\Sigma_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\Sigma_{i=1}^{n}(x_i - \overline{x})^2 (y_i - \overline{y})^2}} \tag{5.1}$$

where

- x_i and y_i are the i-th values of the two variables
- $\bar{x}$ and $\bar{y}$ are the means of the two variables
- r_p is the Pearson correlation coefficient between the two variables, which ranges from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation.

We first extract time-series data from various brain regions using fMRI or EEG. This data is then used to calculate Pearson correlation for brain signals. The degree of similarity or correlation between the time-series data from each pair of brain areas is then determined using Pearson correlation.

5.2 Method to construct and analyze Functional Connectivity at complete Network Level

In the first stage, we implemented a method to compute the correlation between pairs of brain regions. The flow chart for this is shown in Figure 5.4.

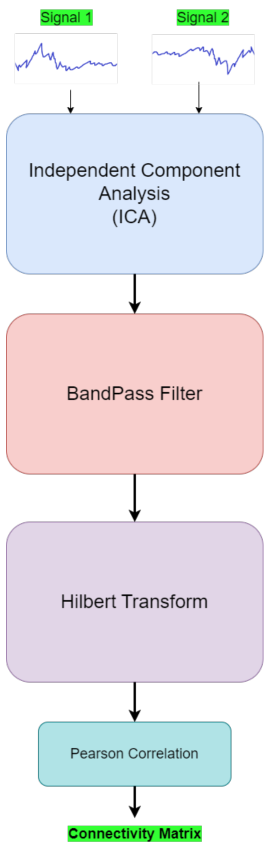

Figure 5.4: Flow Chart of Method 5.2

To obtain a connectivity matrix to create the functional network, the following steps are used, which are also mentioned in figure 5.4

- **Independent Component Analysis**
- **Band Pass Filter**
- **Hilbert Transform**
- **Pearson Correlation Coefficient**

All these components are explained in 5.1.

Figure 5.4 shows the flowchart for computing the correlation between pairs of brain regions in the first stage of the method. The steps involved include Independent Component Analysis (ICA), band pass filtering using a Butterworth filter, Hilbert transform, and calculating the Pearson correlation coefficient to obtain a connectivity matrix for creating the functional network.

5.3 Method to construct and analyze Functional Connectivity at Node Level

In this method, we utilized almost the same pipeline shown in Figure 5.4. Additionally, we have added some components to the pipeline, like Weighted Degree, Mean, and Variance, and computed the correlation between each other. However, we employed a Sliding Window based approach where the window length is set to 30 seconds, and the overlapping window size is set to 15 seconds.

Figure 5.5 shows the flow of the Sliding Window based approach used in the method, which involves calculating the correlation between pairs of brain regions for each window at the node level, generating an adjacency matrix, and computing the weighted degree. Mean and variance for each window for different frequency bands are also calculated, and the average correlation between weighted degree, mean, and variance is used to infer that the variance drives the weighted degree and that node-level connectivity influences functional connectivity.

The sliding window technique obtains time-varying functional connectivity in EEG signals. EEG signals have non-stationary characteristics, which means that the statistical properties of the signal, such as its mean and variance, are not constant over time. Therefore, using a static window for calculating functional connectivity may result in a loss of information, as the connectivity may change over time.

To overcome this issue, the sliding window technique is used, which involves dividing the EEG signal into several short segments and calculating the functional connectivity for each segment. By sliding the window along the signal, overlapping segments are obtained, which helps capture the connectivity's time-varying nature. This approach allows for examining dynamic changes in connectivity and provides a more detailed and accurate representation of brain activity.

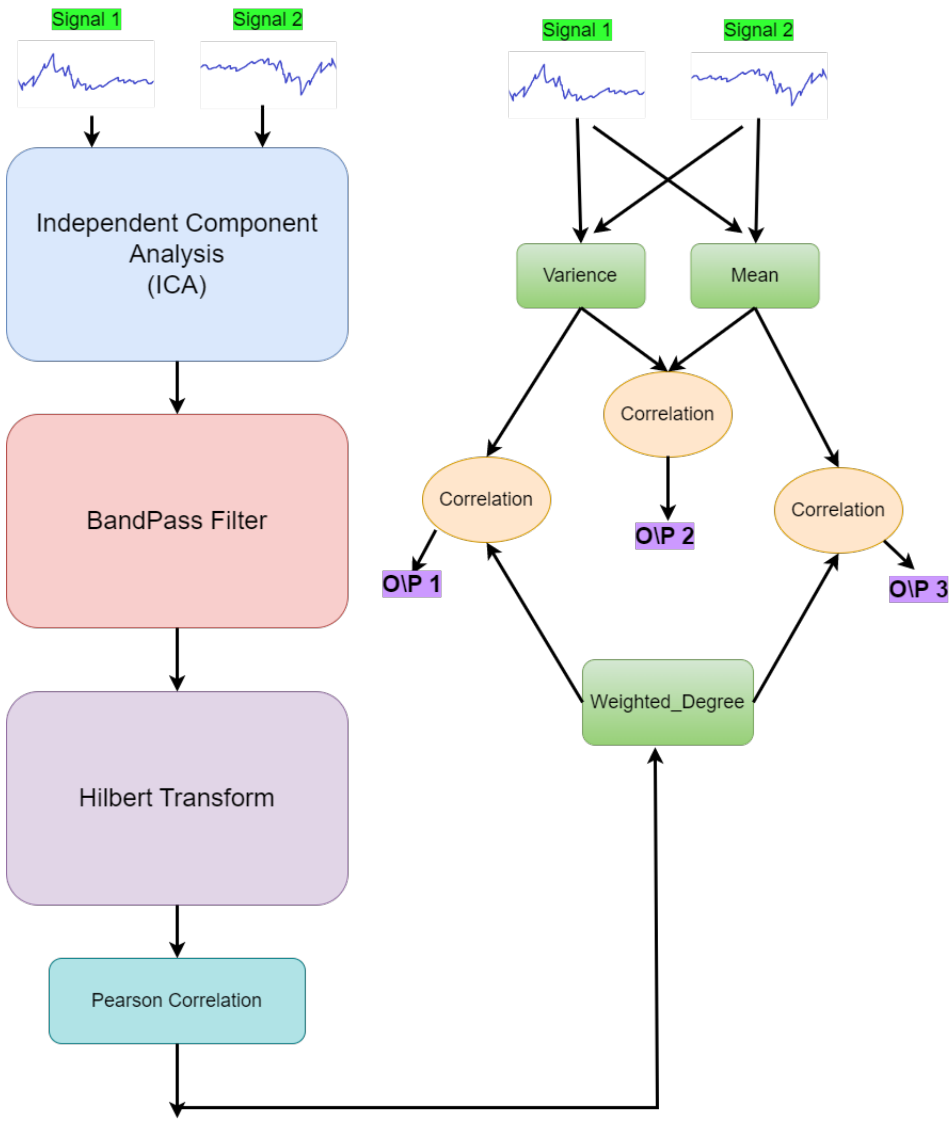

Figure 5.5: Flow Chart Method 5.3

The length of the sliding window can be adjusted depending on the frequency band of interest. For example, for high-frequency bands such as gamma, a shorter window length may be used to capture the rapid changes in connectivity. In contrast, for low-frequency bands such as alpha and theta, a longer window length may be used to capture the slower changes in connectivity.

The reason behind this method is to get connectivity at the node level. By using this approach, we were able to calculate the correlation between pairs of brain regions for that particular window at the node level and able to make an adjacency matrix. We also calculated the weighted degree by using the same adjacency matrix. We have also computed the mean and variance for each and every window for each band, like Alpha, Beta, Theta, Gamma, and Delta for each channel on the raw signals. And by calculating the correlation between the weighted degree and mean, mean and variance, and variance and weighted degree of a particular channel, we observe that the changes in the mean and the variance will also be responsible for changing the weighted degree.

A negative correlation in functional connectivity represents an inverse relationship between the time series of two brain regions, indicating that when one region is active, the other is inactive. However, a negative correlation is often found to be artifactual in functional connectivity analysis due to various factors such as head motion, physiological noise, and preprocessing techniques. These factors can introduce spurious negative correlations between brain regions without biological basis, leading to incorrect inferences about the brain's functional organization. That is the main reason we have removed or neglected the negative correlation.

5.4 ANN based Approach

In this procedure, we employed a Deep Learning model known as an ANN (Artificial Neural Network) [33]. This form of a neural network has four completely connected layers. The first layer uses the 'linear' activation function and includes nine input nodes. When using the linear activation function, the subsequent three layers have 6, 6, and 9 nodes, respectively. An identity function, or "linear" activation function, returns the same value as its input.

The model summary lists the parameters in each layer, including the input

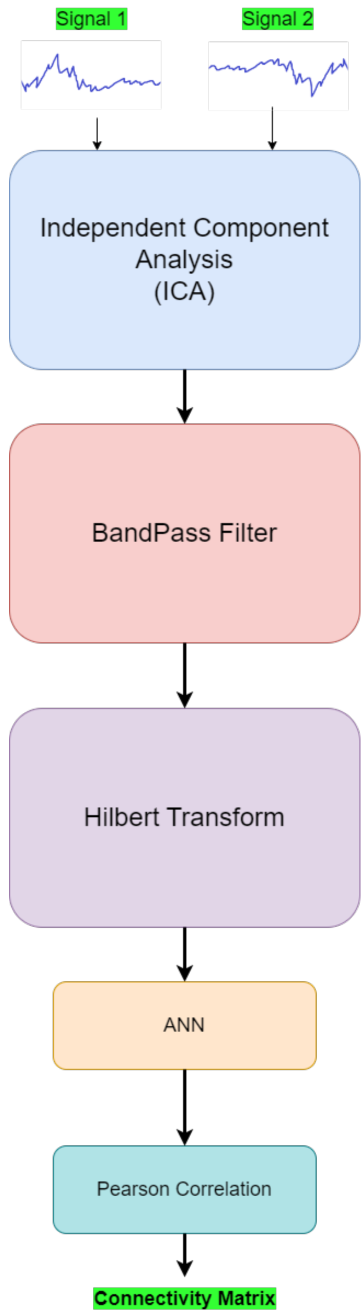

Figure 5.6: Flow Diagram of Method 5.4

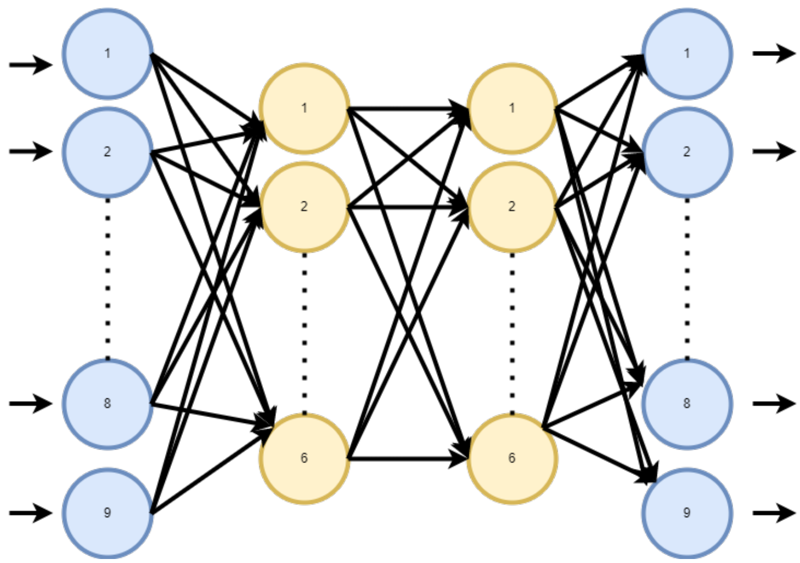

Figure 5.7: ANN Model Diagram

layer's 81 parameters (9 nodes x 9 input features). Just after the input layer, the two hidden layers and the last output layer have 42, 42, and 63 parameters, respectively. The model has 228 different trainable parameters in total. Figure 6.9 details the model's architecture.

The 'Adam' optimizer, a well-known optimization algorithm for training neural networks, is used to build the model. The loss function employed is the typical loss function for regression issues, known as "mean_squared_error." Measuring the average discrepancy between the predicted and actual values, "mse" (mean squared error) is the statistic used to assess the model's performance.

Our thesis work used a Z-score to normalize the brain signals. We separated the signals into training and testing datasets after normalization. By their index, this division randomly chose half of the signals. The testing set was then utilized to assess the model's performance once our model had been trained.
We employed the training and testing data to forecast the outcome as model input. After that, we estimated the correlation between the expected and actual outputs (the x_train and y_train signals). We could assess the model's predictions' accuracy thanks to this correlation.

CHAPTER 6
Result

By performing all the mentioned methods in 5.2, 5.3, and 5.4, we got some output as below:

6.0.1 Network obtained by Method mentioned in 5.2

By performing the steps mentioned in figure 5.4, we got the following kind of results for **Alpha Band** and **Beta band** mentioned in figures 6.1 and 6.3, respectively. These figures are symmetric because there is no direction in the correlation. In the context of functional connectivity analysis, each variable represents a brain region or channel, and the correlation coefficients in the heatmap indicate the pairwise correlations between these regions or channels. A high positive correlation coefficient suggests that the activity in the two regions or channels tends to vary together, while a high negative correlation coefficient suggests that the activity tends to vary in opposite directions. A correlation coefficient close to zero indicates little or no relationship between the variables.

Visualizing the correlation matrix as a heatmap allows patterns of connectivity or functional relationships between different brain regions or channels to be identified. This can help understand the brain's underlying network structure or functional organization and may provide insights into brain function, cognitive processes, or neurological disorders. Since the correlation between the same signals is significant, the maximum values are along the diagonal. The darker regions depict a stronger correlation in comparison to lighter ones. Our current work focuses on extracting the features corresponding to these networks.

1. **Alpha Band**

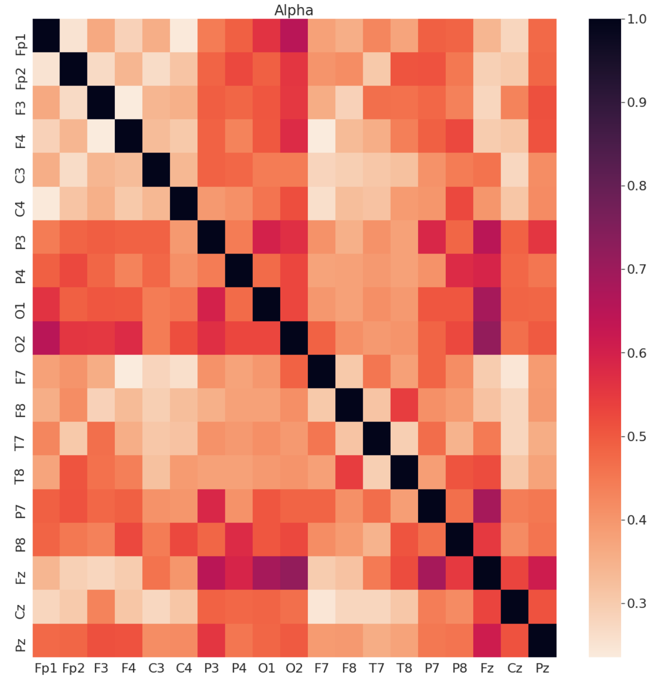

Figure 6.1: Connectivity Matrix using Alpha Band

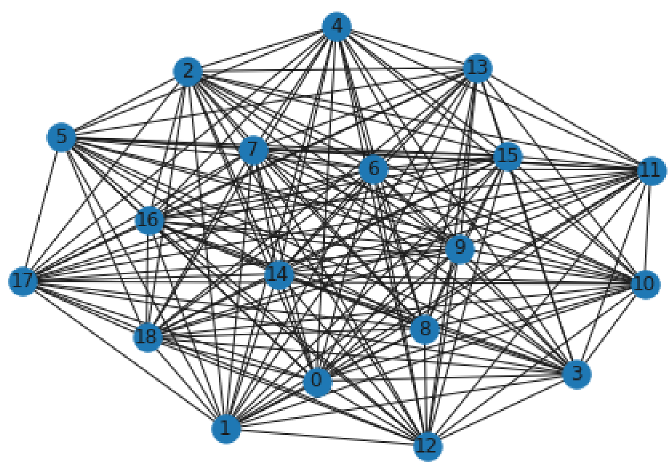

Figure 6.2: Network obtained by connectivity matrix mentioned in figure 6.1

2. **Beta Band**

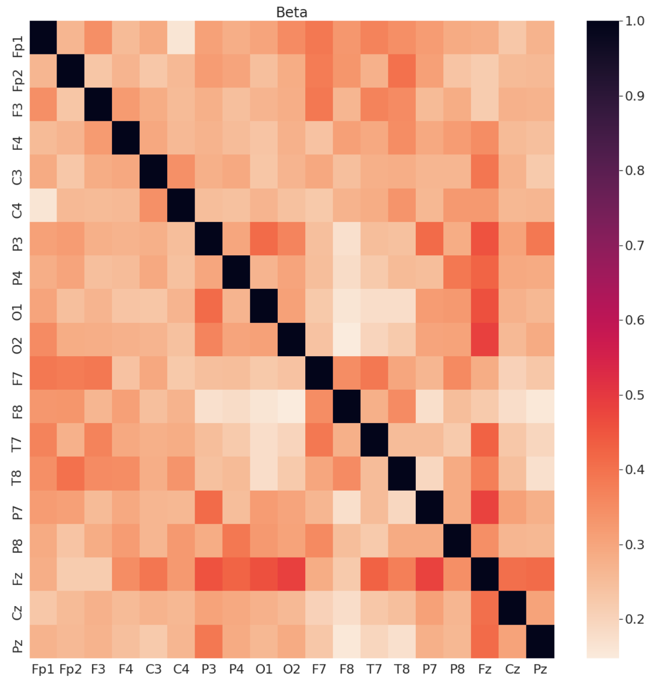

Figure 6.3: Connectivity Matrix using Beta Band

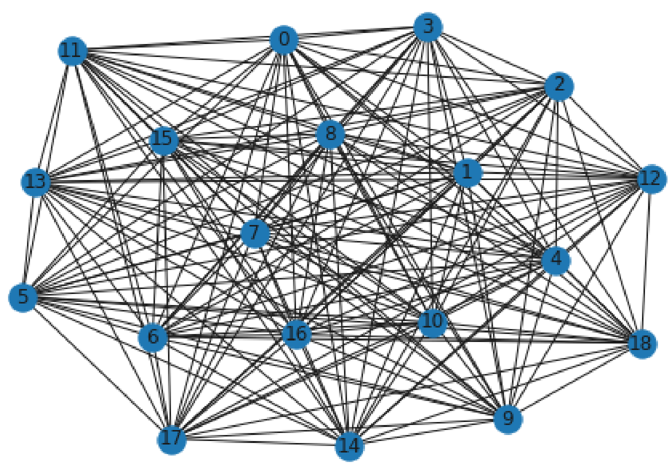

Figure 6.4: Network obtained by connectivity matrix mentioned in figure 6.3

6.0.2 Network obtained by Method mentioned in 5.3

By performing the steps mentioned in figure 5.5, we got the following kind of results for all frequency bands, but we are plotting only for some window for **Alpha frequency band**:

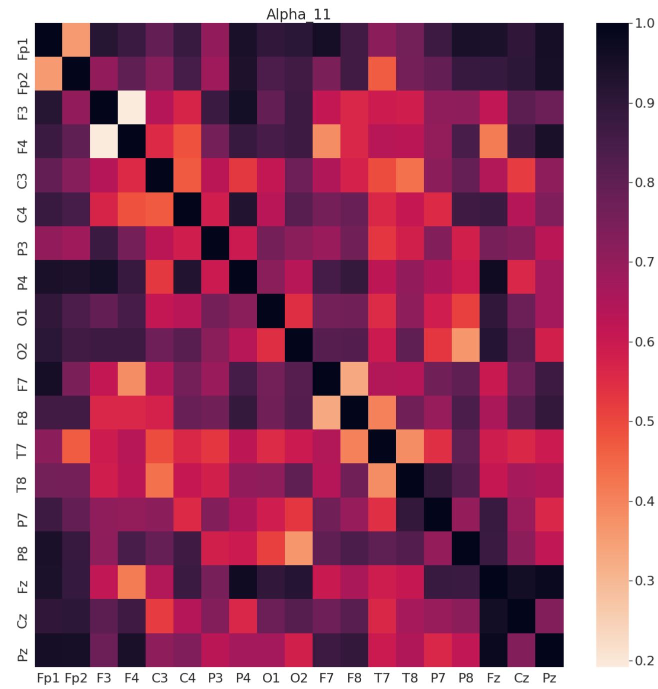

Figure 6.5: Connectivity Matrix using Alpha Band for window 11

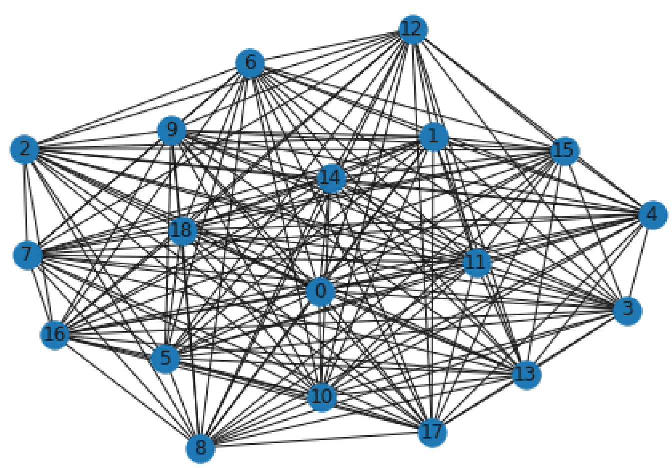

Figure 6.6: Network obtained by connectivity matrix mentioned in figure 6.5

The analysis of the figures 6.5, 6.7, and 6.9 shows variations in connectivity or correlation strength at specific nodes and time windows using the sliding win-

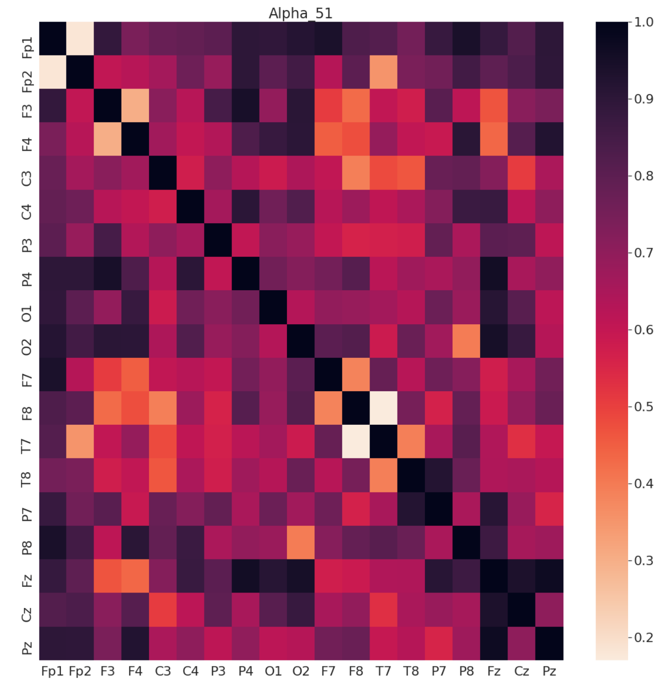

Figure 6.7: Connectivity Matrix using Alpha Band for window 51

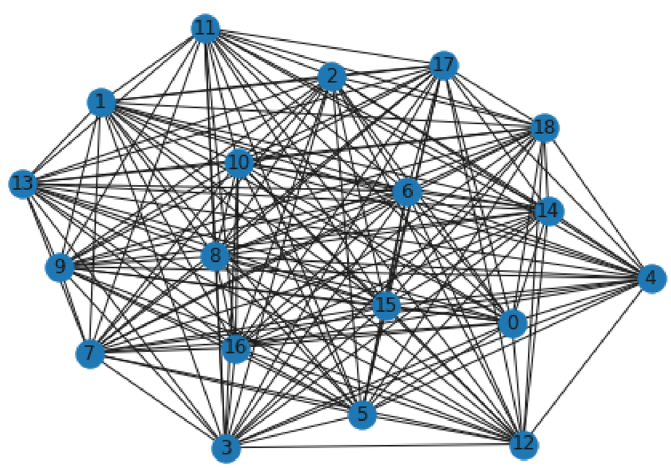

Figure 6.8: Network obtained by connectivity matrix mentioned in figure 6.7

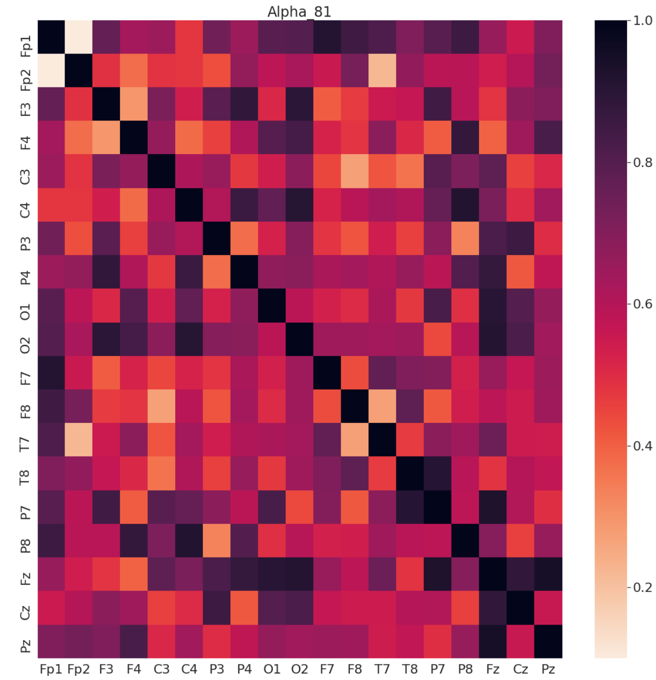

Figure 6.9: Connectivity Matrix using Alpha Band for window 81

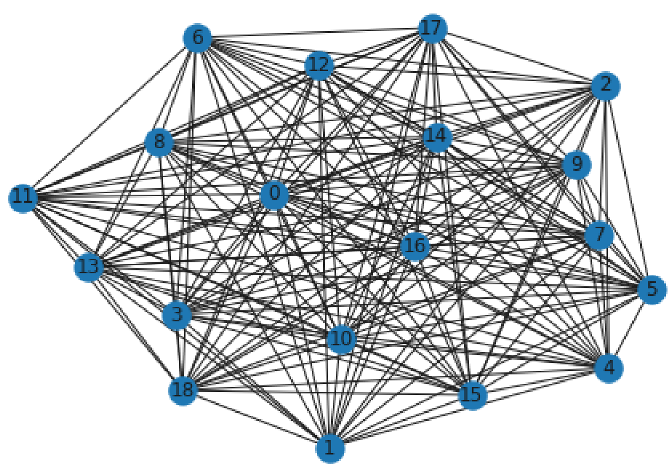

Figure 6.10: Network obtained by connectivity matrix mentioned in figure 6.9

dow approach. The figures display lighter or darker shades, indicating changes in connectivity or correlation patterns. Additionally, the network structure is observed to change in figures 6.6, 6.8, and 6.10, with nodes exhibiting alterations in properties such as degree.

Figure 6.11 demonstrates the weighted degree of the O1 channel across different windows. The slight variations in the weighted degree are responsible for modifying the network. This provides node-level information regarding the network, specifically highlighting nodes that can influence network dynamics through their changing characteristics. Our current focus is on interpreting these node-level representations in the context of complete network-level representations to determine their significance.

Furthermore, we investigated the relationship between Weighted Degree, Mean, and Variance by calculating the average correlation for specific channels. Figure 6.11 depicts the positive outcome of this analysis. These findings enable a better understanding of the network. Figure 6.12 presents the mean, variance, and weighted degree plots for the O1 channel. Additionally, we computed the correlation between mean and variance, variance and weighted degree, and weighted degree and mean for individual channels, as shown in Figure 6.13.

We have used the sliding window approach to break down complete signals into small windows and analyze them better at particular time intervals compared to analyzing the whole signal at once. In figure 6.11, We have taken three different windows, whose numbers are 11, 51, and 81, and plotted the weighted degree of **O1** channels for all the mentioned windows. Looking into figure 6.11, we can see how the weighted degree changes in a particular time window, such as the network. In figure 6.12, we plot the average of mean, average of variance, and average of weighted degree of all the subjects that we have taken into the dataset for each window.

In our study, we performed correlation analyses between the mean and variance, variance and weighted degree, and weighted degree and mean of functional connectivity data. The correlation coefficients for each channel were compiled in Figure 6.13. Moreover, we generated plots depicting the mean, variance, and weighted degree values specifically for the O1 channel, as presented in Figure 6.12. This analysis aimed to examine the relationships between these metrics and

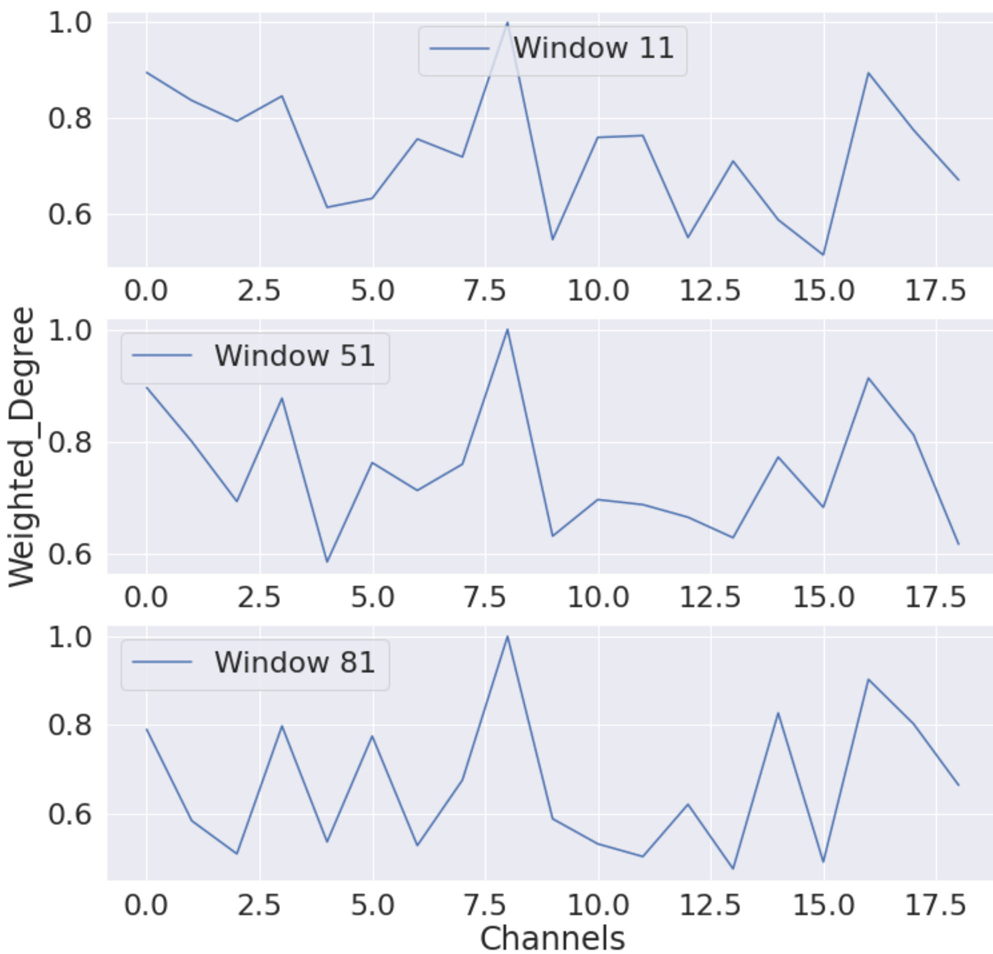

Figure 6.11: weighted degree of O1 channel in different window

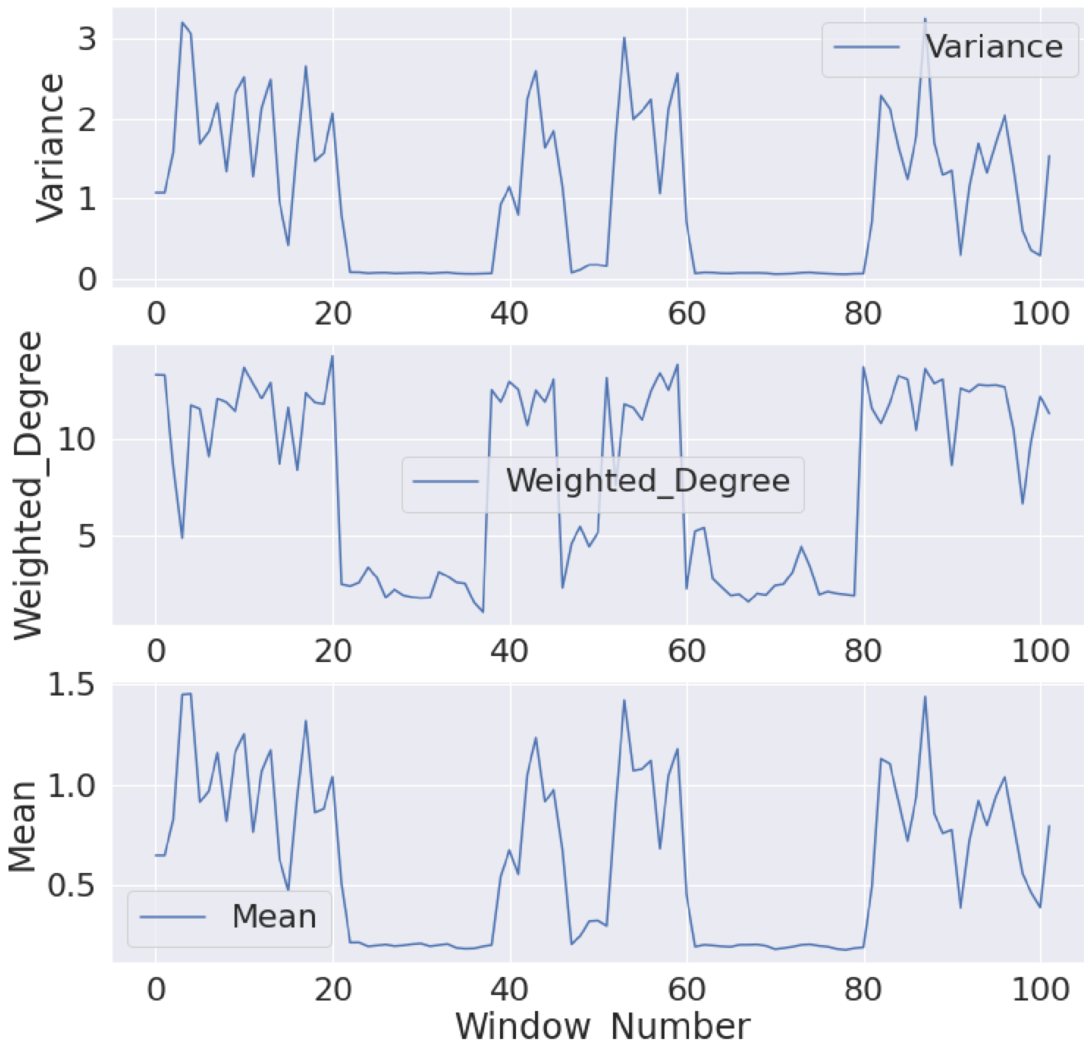

Figure 6.12: Mean, Variance of raw signal of a **O1** channel and Weighted Degree of **O1** channel after getting the adjacency matrix for all window

their potential implications within the context of brain network dynamics. By exploring the correlations and visualizing the O1 channel characteristics, we gained insights into the functional properties and dynamics of the occipital lobe, which is primarily associated with visual processing.

As we know that the Occipital lobe of the brain manages vision-related things. So as we selected 19 channels, O1 and O2 are on the brain's occipital lobe. We have used the resting state dataset in which subjects have to blink their eyes, which means they perform vision-related activities. That is the main reason for plotting the result related to the O1 channel.

The correlation between the mean and variance of EEG brain signals can provide insights into the Signal-to-Noise Ratio (SNR). SNR measures the strength of the brain signal relative to the level of background noise present in the signals.

If the correlation between mean and variance is high, it indicates that the variability in the EEG signals (noise) is proportional to the mean activity level. This suggests that the noise level increases as brain activity increases, potentially reducing the SNR. In such cases, it becomes more challenging to separate the meaningful brain signals from the noise, resulting in a lower SNR.

Conversely, if the correlation between mean and variance is low, it suggests that the variability in the EEG signals is not strongly related to the mean activity level. This implies that the noise level remains relatively constant regardless of the brain activity level, which is favorable for SNR. In such scenarios, the brain signals are more distinguishable from the background noise, resulting in a higher SNR.

The Contrast-to-Noise Ratio (CNR) can be understood by looking at the correlation between the mean and variance of EEG brain signals. The CNR measures the difference in brain activity (contrast) about the signal's amount of noise.

If the correlation between mean and variance is high, it indicates that the variability in the EEG signals (noise) is proportional to the mean activity level. This suggests that the noise level is relatively consistent across different brain states or conditions, which might impact the ability to distinguish meaningful brain activity from noise. The CNR may be lower in such cases, making detecting and differentiating specific brain responses more challenging.

On the other hand, if the correlation between mean and variance is low, it suggests that the variability in the EEG signals is not strongly related to the mean activity level. This can indicate a favorable scenario for CNR, as the noise level may be relatively independent of the brain activity, allowing for better differentiation between meaningful signals and noise.

Channel List	Varience vs Weighted Degree	Varience vs Mean	Mean vs Weighted Degree
Fp1	0.076126	0.912443	0.19048
Fp2	0.146044	0.925285	0.276789
F3	0.461823	0.980436	0.460861
F4	0.442954	0.985684	0.437445
C3	0.380957	0.984551	0.376001
C4	0.362754	0.984773	0.360199
P3	0.476282	0.987306	0.483611
P4	0.417709	0.989319	0.432117
O1	0.470217	0.989088	0.481226
O2	0.489678	0.990042	0.505532
F7	0.426594	0.949017	0.409304
F8	0.441749	0.984423	0.432246
T7	0.392127	0.985273	0.359176
T8	0.454304	0.989683	0.445124
P7	0.515165	0.989461	0.519643
P8	0.449012	0.990758	0.457963
Fz	0.443021	0.979445	0.444659
Cz	0.44483	0.977034	0.450617
Pz	0.414705	0.984339	0.417423

Figure 6.13: Correlation between Mean and Variance, Variance and Weighted Degree and Weighted Degree and Mean

6.0.3 Network obtained by Method mentioned in 5.4

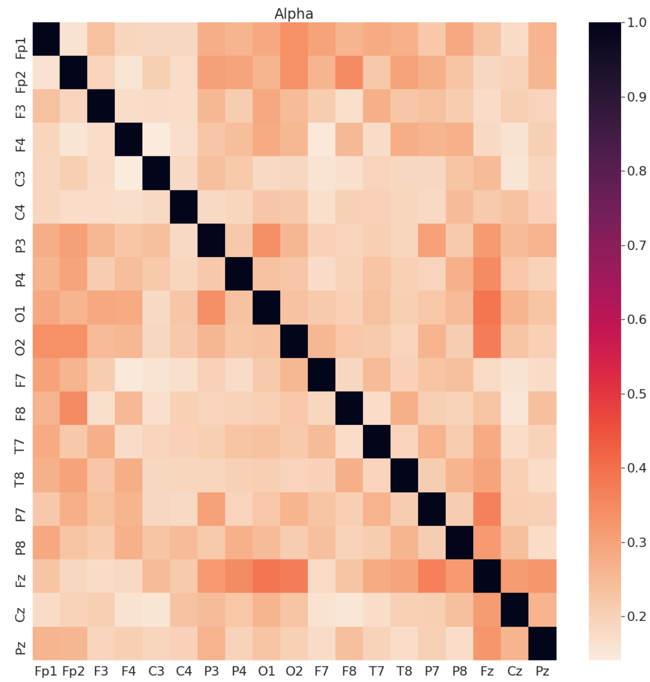

Figure 6.14: Alpha Frequency band using ANN

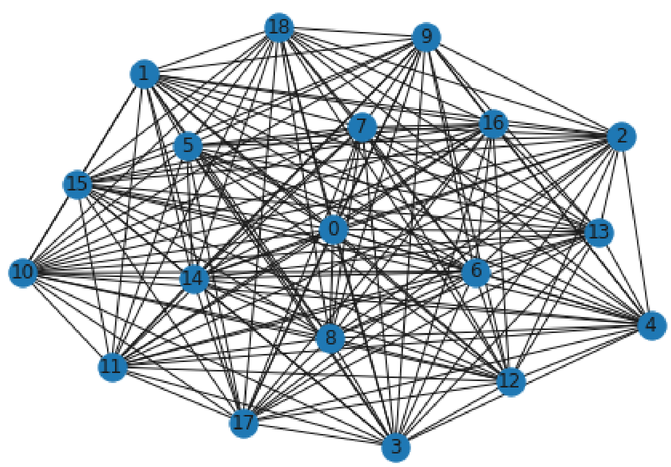

Figure 6.15: Network obtained by connectivity matrix mentioned in figure 6.14

In figure 6.14, we get a correlation matrix that is the average of all the subjects for a symmetric alpha band. The diagonal elements have the highest and perfect correlation. We can see in figure 6.14 that the correlation between the different channels differs from the simple statistical method for the alpha band shown in figure 6.1 because deep learning methods have the potential to capture non-linear and complex relationships between variables that simple statistical methods may

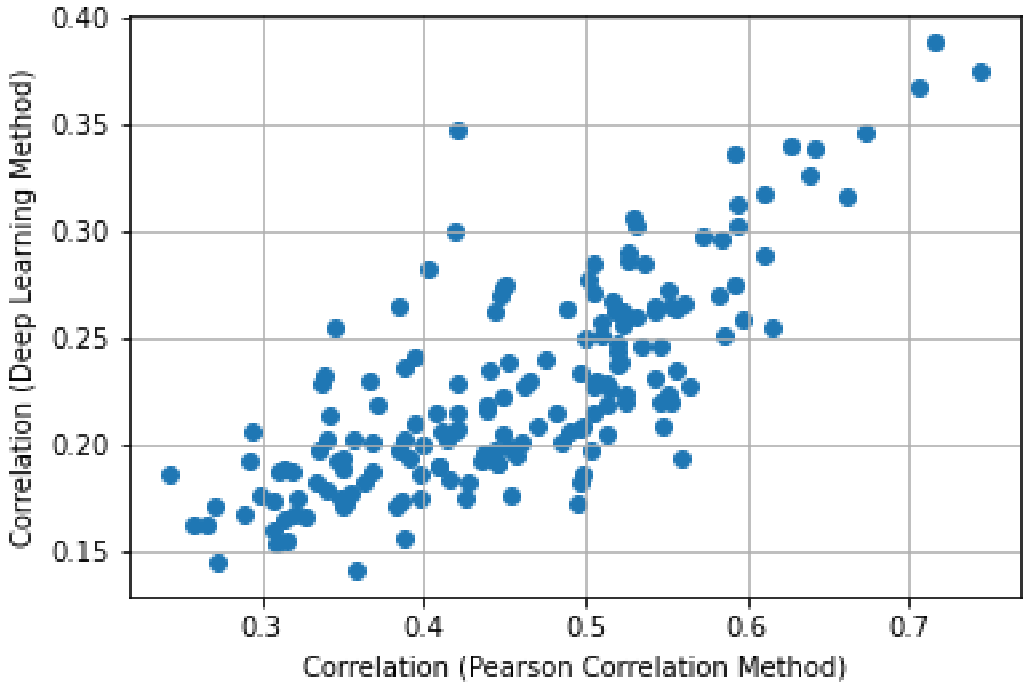

Figure 6.16: Scatter Plot of correlation between Deep Learning based and Pearson Correlation Method

miss. So we have tried to plot a scatter diagram in figure 6.16 between the correlation measured by the method mentioned in 5.2 and method 5.4. Figure 6.16 shows the correlation pattern between the simple statistical method and the deep learning-based method. By identifying the patterns from the scatter plot, we can also get information on the relation between the methods like a Positive Linear Relationship, Negative Linear Relationship, Non-Linear Relationship, etc. If a non-linear relationship is available, we can get information about it, which is our main motive for using Deep Learning based methods. By analyzing it, we can get information about the complex network.

The scatter plot visually compares the correlation values from simple statistical and deep learning-based methods. It helps understand the degree of agreement, consistency, and ability of the deep learning-based method to capture non-linear relationships, highlighting its potential advantages over traditional statistical approaches in uncovering complex brain connectivity patterns.

Deep learning-based methods often capture complex patterns and relationships in data, making them effective for various tasks, including brain signal analysis. When it comes to functional connectivity between brain regions, deep learning methods can outperform simple statistical methods for several reasons:

1. **Non-Linear Relationships :** Brain signals are highly dynamic and non-linear in nature. Simple correlation methods like Pearson are limited to capturing linear relationships, whereas deep learning models can handle non-linear dependencies, allowing them to capture more intricate interactions between brain regions.

2. **Feature Representation :** Deep learning models can automatically learn relevant features from the data, reducing the need for manual feature engineering. This ability to learn meaningful representations from raw brain signals enables deep learning models to better extract the underlying patterns, contributing to improved functional connectivity estimation.

3. **Temporal Dependencies :** Many deep learning models, such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, can capture temporal dependencies in time-series data. In brain signals, temporal dependencies are crucial for understanding the sequential nature of neural activity, which is not fully captured by simple correlation methods.

4. **Robustness to Noise :** Deep learning models can be designed to be robust to noise and artefacts commonly present in brain signals. They can be trained to focus on relevant signal components while suppressing noise, leading to more accurate and robust functional connectivity estimates.

5. **Handling Missing Data :** Deep learning models can handle missing data points more effectively, allowing for more flexible and complete analyses of brain signals even with some missing or noisy data.

However, it's essential to note that the success of deep learning methods heavily depends on the quality and quantity of the data, appropriate model selection, and hyperparameter tuning. In some cases, simple correlation methods might still be sufficient, especially if the brain signals are relatively simple or linearly related. Therefore, it is crucial to carefully consider the data characteristics and research goals when choosing between deep learning-based methods and traditional correlation techniques for functional connectivity analysis in brain signals.

CHAPTER 7
Conclusions

Using EEG data and various analysis techniques, we have examined the functional connectivity of brain networks in this thesis work. The primary study topic was whether or not node-level analysis can be transferred into network-based analysis. The research also investigated how to categorize the models or methodologies based on the input and how to determine the link between brain regions that can also be non-linear.

This study used three methodologies one to get the network-level information, one to get node-level information, and the last one based on the Deep Learning model. The study used a dataset with 19 channels of interest and 13 individuals' resting-state EEG recordings. This thesis presented functional connectivity matrix results for various frequency bands and techniques for node and complete network levels. However, it is important to note that deep learning methods have the potential to capture non-linear and complex relationships between variables that may be missed by simple statistical methods such as Pearson correlation. Therefore, it is possible that the deep learning method may reveal important features or relationships that were not captured by simple statistical methods.

The correlation between the mean and variance of EEG brain signals provides valuable insights into the Signal-to-Noise Ratio (SNR) and the Contrast-to-Noise Ratio (CNR). A high correlation suggests that the noise level increases with the mean activity, potentially reducing the SNR and impacting the ability to distinguish meaningful brain signals from noise. Similarly, it may decrease the CNR, making it more challenging to differentiate brain activity from background noise. Conversely, a low correlation indicates a more favorable scenario for SNR and CNR, where the noise level remains relatively constant regardless of brain activity, allowing for better detectability and distinguishability of brain signals. Therefore, understanding the correlation between the mean and variance is crucial for assessing the reliability, quality, and interpretability of EEG signals in studying brain activity.

Deep learning-based methods offer the potential to uncover complex brain connectivity patterns, improve prediction accuracy, and advance our understanding of brain function and neurological disorders.

CHAPTER 8
Future Work

1. Use different datasets to understand the brain's functional connectivity while doing some different activities.

2. Analysing the node level network and complete network using graph-based methods like degree centrality, betweenness centrality, and many more methods. These methods help identify the critical nodes in the network, which can help in understanding the organization and function of the network. They can be used to study the functional connectivity of the brain, etc. By analyzing the node-level and complete network using these methods, we can obtain insights into the organization and functioning of the network.

3. Implement 1D CNN and RNN to predict the next signals and compute their non-linear correlation.

4. The classification of brain diseases based on EEG signals, because it is an important task that can be achieved using machine learning and deep learning techniques. These methods can provide accurate and reliable diagnosis of brain diseases, which can lead to better patient outcomes and improved quality of life.

References

[1] Alvaro Pascual-Leone and Roy Hamilton. The metamodal organization of the brain. *Progress in brain research*, 134:427–445, 2001.

[2] Walle JH Nauta. The problem of the frontal lobe: A reinterpretation. *Principles, Practices, and Positions in Neuropsychiatric Research*, pages 167–187, 1972.

[3] Leonardo Fogassi and Giuseppe Luppino. Motor functions of the parietal lobe. *Current opinion in neurobiology*, 15(6):626–631, 2005.

[4] Jane E Adcock and Chrysostomos P Panayiotopoulos. Occipital lobe seizures and epilepsies. *Journal of Clinical Neurophysiology*, 29(5):397–407, 2012.

[5] Larry R Squire, Craig EL Stark, and Robert E Clark. The medial temporal lobe. *Annu. Rev. Neurosci.*, 27:279–306, 2004.

[6] Seung-Schik Yoo, Hyungmin Kim, Emmanuel Filandrianos, Seyed Javid Taghados, and Shinsuk Park. Non-invasive brain-to-brain interface (bbi): establishing functional links between two brains. *PloS one*, 8(4):e60410, 2013.

[7] Andreas K Engel, Christian KE Moll, Itzhak Fried, and George A Ojemann. Invasive recordings from the human brain: clinical insights and beyond. *Nature Reviews Neuroscience*, 6(1):35–47, 2005.

[8] Seong-Gi Kim and Seiji Ogawa. Biophysical and physiological origins of blood oxygenation level-dependent fmri signals. *Journal of Cerebral Blood Flow & Metabolism*, 32(7):1188–1206, 2012.

[9] Owen J Arthurs and Simon Boniface. How well do we understand the neural origins of the fmri bold signal? *TRENDS in Neurosciences*, 25(1):27–31, 2002.

[10] Fabrice Wendling, Karim Ansari-Asl, Fabrice Bartolomei, and Lotfi Senhadji. From eeg signals to brain connectivity: a model-based evaluation of interdependence measures. *Journal of neuroscience methods*, 183(1):9–18, 2009.

[11] Andrew A Fingelkurts, Alexander A Fingelkurts, and Seppo Kähkönen. Functional connectivity in the brain—is it an elusive concept? *Neuroscience & Biobehavioral Reviews*, 28(8):827–836, 2005.

[12] Xin Bi, Xiangguo Zhao, Hong Huang, Deyang Chen, and Yuliang Ma. Functional brain network classification for alzheimer's disease detection with deep features and extreme learning machine. *Cognitive Computation*, 12(3):513–527, 2020.

[13] Caroline L Alves, Aruane M Pineda, Kirstin Roster, Christiane Thielemann, and Francisco A Rodrigues. Eeg functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia. *Journal of Physics: Complexity*, 3(2):025001, 2022.

[14] Teja Kattenborn, Jens Leitloff, Felix Schiefer, and Stefan Hinz. Review on convolutional neural networks (cnn) in vegetation remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 173:24–49, 2021.

[15] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*, 2014.

[16] Anil Seth. Granger causality. *Scholarpedia*, 2(7):1667, 2007.

[17] Pearson correlation coefficient. `https://en.wikipedia.org/wiki/Pearson_correlation_coefficient`.

[18] Leann Myers and Maria J Sirois. Spearman correlation coefficients, differences between. *Encyclopedia of statistical sciences*, 12, 2004.

[19] Zelda B Zabinsky et al. Random search algorithms. *Department of Industrial and Systems Engineering, University of Washington, USA*, 2009.

[20] Lisha Li, Kevin Jamieson, Afshin Rostamizadeh, and Ameet Talwalkar. Parallelizing hyperband for large-scale tuning. *En: SysML*, 2018.

[21] Martin Pelikan. Bayesian optimization algorithm. In *Hierarchical Bayesian optimization algorithm*, pages 31–48. Springer, 2005.

[22] Stéphane Sockeel, Denis Schwartz, Mélanie Pélégrini-Issac, and Habib Benali. Large-scale functional networks identified from resting-state eeg using spatial ica. *PloS one*, 11(1):e0146845, 2016.

[23] Brain 64 channels. https://www.fieldtriptoolbox.org/template/layout/.

[24] Claudio Babiloni, Claudio Del Percio, Anna Caroli, Elena Salvatore, Emanuele Nicolai, Nicola Marzano, Roberta Lizio, Enrica Cavedo, Susan Landau, Kewei Chen, et al. Cortical sources of resting state eeg rhythms are related to brain hypometabolism in subjects with alzheimer's disease: an eeg-pet study. *Neurobiology of aging*, 48:122–134, 2016.

[25] B Gohel, P Lee, M-Y Kim, Kiwoong Kim, and Yong Jeong. Meg based functional connectivity: Application of ica to alleviate signal leakage. *Irbm*, 38(3):127–137, 2017.

[26] James V Stone. Independent component analysis: an introduction. *Trends in cognitive sciences*, 6(2):59–64, 2002.

[27] Ica_schematics. https://towardsdatascience.com/introduction-to-ica-independent-component-analysis-b2c3c4720cd9.

[28] Sam Roweis. Em algorithms for pca and spca. *Advances in neural information processing systems*, 10, 1997.

[29] SS Daud and R Sudirman. Butterworth bandpass and stationary wavelet transform filter comparison for electroencephalography signal. In *2015 6th international conference on intelligent systems, modelling and simulation*, pages 123–126. IEEE, 2015.

[30] Yi-Chyun Chiou, Jen-Tsai Kuo, and Eisenhower Cheng. Broadband quasi-chebyshev bandpass filters with multimode stepped-impedance resonators (sirs). *IEEE transactions on microwave theory and techniques*, 54(8):3352–3358, 2006.

[31] Lorenz Trachsel. Hartley transforms and narrow bessel bandpass filters produce similar power spectra of multiple frequency oscillators and all-night eeg. *Sleep*, 16(6):586–594, 1993.

[32] Hilbert transform. https://en.wikipedia.org/wiki/Hilbert_transform.

[33] Daesoo Lee, Seung-Jae Lee, and Yu-Jeong Seo. Application of recent developments in deep learning to ann-based automatic berthing systems. *International Journal of Engineering and Technology Innovation*, 10(1):75–90, 2020.